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Deep Reinforcement Learning for Self-Healing Communication Networks: Addressing Node Failure and QoS Degradation in Dynamic Topologies

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Abstract

Current challenges to maintain service continuity and quality of service (QoS) in modern communication networks (e.g., ad hoc, vehicular, and IoT driven networks) remain exacerbated in the presence of high node failure rates and dramatic topology changes. Traditional routing and recovery mechanisms, which are largely reactive or configured in a static fashion, are unfit to be adapted to this level of real-time disruption, thus causing additional latency, reliability issues, and degraded service. This thesis proposes a novel deep reinforcement learning-based self-healing framework to consider these limitations and develop an algorithm to automatically reconfigure network paths to deal with failures by the means of an autonomous and an adaptive approach. To continuously learn optimal routing strategies for the network, we model the network as a Markov decision process (MDP) and utilize proximal policy optimization (PPO), an advanced DRL algorithm, and facilitate GAE to stabilize learning. By proactively observing network state, predicting where the failures are most likely to occur, and sending data through (reservable) alternate optimal paths, the system guarantees low latency, energy efficiency, and QoS-aware communication. Through simulation experiments on NS-3 that combine realistic failure and mobility models with DRL-based approaches, we illustrate that relying on DRL-SHF leads to a 32.6% reduction in packet loss compared to heuristic and conventional RL-based methods along with an improvement in average latency by 27.8% and throughput by 18.4%. These findings validate the use of the framework for deployment in next-generation self-organizing networks focused on 5G, IoTs, and mission critical communications scenarios where real-time resilience and autonomy are critical.

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Introduction

Modern communication networks are put under unprecedented demands by the accelerated growth of mobile computing, Internet of Things (IoT) ecosystems, and mission critical services in healthcare, transportation, and defense sectors. As a result, these networks are also expected to provide high data throughput and low latency, together with sustained reliability, self-recovery, and service continuity in ever-increasing and unpredictable environments. Because of these constraints, important application domains including vehicular ad hoc networks (VANET), wireless sensor networks (WSN), and mobile ad hoc networks (MANET) are designed under decentralized and infrastructure-less conditions where node mobility, link instability, and frequent topology changes are intrinsic to their design. In this type of scenario, maintaining the quality-of-service (QoS) parameters of the packet delivery ratio, end-to-end delay, and energy efficiency is both critical and challenging.

Traditional fault-tolerant and routing protocols, for example, the ad hoc on-demand distance vector (AODV) and optimized link state routing (OLSR) proceed reactively by triggering a recovery process in the routes when a link or node failure has been discovered. While simple and thus widely adopted, these protocols can cause excessively large route reconfiguration latency and fail to a priori account for and alleviate cascading disruptions in highly mobile or failure-prone networking environments. Moreover, the computationally efficient rule-based heuristics and threshold-driven rerouting strategies are not good at adapting or tuning the strategies to nonstationary network conditions, and they cannot learn from past failures nor predict future risks.

Recently, a number of researchers have tried to apply machine learning (ML) and, more specifically, reinforcement learning (RL) to this challenge, for providing communication networks with the capabilities of autonomous decision-making and adaptive control. However, traditional RL methods like Q-learning can learn from interaction with the environment but experience the curse of dimensionality and slow convergence in large-scale, high dimensional, or continuous network environment. These methods have limitations that prevent their scalability and practical deployment to real-time self-healing applications.

However, these challenges lead to the following proposal in this paper: A deep reinforcement learning–based self-healing framework (DRL-SHF) is presented, which combines deep neural networks and proximal policy optimization (PPO) to create an intelligent, distributed, and scalable fault repair mechanism. Unlike previous centralized or static models, the proposed framework treats the communication network as a Markov decision process (MDP), such that in a simulated environment, the agent learns optimal recovery and routing policies through trial-and-error interactions. DRL-SHF can proactively predict faults, reroute traffic, and optimize QoS metrics in real time even with node failures, congestion, or evolving topologies with the ability to continuously monitor network states and adapt its policy.

DRL-SHF is the central innovation here because it is decentralized and does not require coordinated action, which makes it especially appealing for heterogeneous 5G networks, MEC setups, and autonomous IoT systems. This work establishes a base for next-generation resilient, intelligent communication infrastructure that have capabilities of fault tolerance and service continuity, proven through extensive simulations and performance benchmarking.

Literature Review

The design of intelligent, fault-resilient communication systems have been greatly influenced by recent advancements in ML and RL. Several studies have studied adaptive routing, fault detection, and recovery strategies in the context of dynamic topologies (e.g. MANETs), WSNs, and software-defined networks (SDNs) using both heuristic and learning-based methods.

For MANETs, [5] propose a route repair method using Q-learning. It is shown that their approach reduced the route discovery latency in a promising way; in spite of this, it did not scale well and converged slowly for large, fast changing networks. [1] introduced a DDPG-based traffic optimization framework for SDN environments with packet drop reductions on the order of 20×. However, its dependence on a centralized controller prohibited its use in decentralized networks. To this end, [2], [8] proposed a lightweight threshold-driven heuristic protocol that could quickly reroute the traffic in the wake of successfully detected failures. However, because of its limited ability to learn, it could not accommodate transient and nondeterministic failure conditions.

In 2023, [6,9] examined a DRL-based policy model for optimal traffic load balancing in 5G architecture. However, the model boosted vehicle distribution but did not enhance the intelligence of fault recovery, so

it could not handle self-healing scenarios very well. For path optimization in IoT meshes, [3,10] utilize deep Q-networks; however, they were constrained by exploration instability and slow convergence issues from high dimensionality action spaces.

Then, more recent works have tried to improve scalability and generalization. Actor-critic-based routing was first proposed by [4,11] as a mechanism for vehicular networks that can accommodate completely arbitrary topology changes but required domain-specific tuning. To that end, [7] also presented a transformer-based attention mechanism for multi hop fault prediction but with the benefit of improved inference accuracy with large computational overhead.

Together, these studies demonstrate the urgent need for a distributed, scalable, and predictive DRL framework that can autonomously compensate for node failures, maintain QoS, and work in real time without centralized management [12,13]. The literature is lacking in the development of a self-healing model of intelligence that optimizes both resource efficiency and responsiveness. Table 1 gives the comparative analysis of existing fault-tolerant communication systems versus the proposed deep reinforcement learning-based self-healing framework.

Research Gap

In spite of these advances, the most existing techniques are either reactive, centralized, or narrowly scoped. While these centralized models are easy to optimize, they introduce bottlenecks and single points of failure, which disqualify them as distributed network solutions. However, heuristic approaches cannot learn and hence

Table 1: Comparative analysis of existing fault-tolerant communication systems versus the proposed deep reinforcement learning-based self-healing framework.

Feature/ Parameter	Sharma et al. (2021)	Chen et al. (2020)	Gupta et al. (2022)	Singh & Rathi (2023)	Kim et al. (2021)	Liu et al. (2023)	Zhao et al. (2024)	Proposed DRL-SHF (This Work)
Learning Technique	Q-learning	DDPG	Heuristic rules	DRL (DQN variant)	DQN	Actor-critic	Transformer + attention	PPO-based Deep Reinforcement Learning
Self-Healing Capability	Partial	No	Partial	No	Limited	Partial	Prediction Only	Yes (Autonomous Recovery & Rerouting)
QoS Optimization	Latency	Packet drop	Failover speed	Load balancing	Hop count	Throughput	Fault prediction	Latency, Throughput, Energy, Packet Loss
Network Type	MANET	SDN	WSN	5G	IoT	VANET	Multihop Wireless	Ad hoc/ IoT/5G/Mesh/ Decentralized
Topology Awareness	Reactive	Centralized control	Static thresholds	Adaptive traffic only	Local observation	Mobility-aware	Multihop sensing	Full-state MDP modeling with mobility support
Scalability	Low	Medium	High	Medium	Low	High	Medium	High (Distributed and Lightweight)
Prediction Capability	No	No	No	No	No	No	Yes	Yes (Proactive Failure Anticipation)
Exploration Efficiency	Slow	Moderate	Not applicable	Fair	Poor	Good	N/A	High (Clipped PPO with stable convergence)
Deployment Suitability	Simulated small networks	Controller-based SDN	WSN, low-power networks	5G testbeds	IoT meshes	VANET testbeds	Lab-based wireless mesh	Scalable to real-time and low-power platforms

generalize for new situations. Moreover, traditional DRL methods suffer from training instability, limited resource efficiency, and real-time adaptability.

As a result, there is a significant need for a lightweight, distributed, and fully autonomous DRL-based self-healing framework that can proactively monitor the network for conditions and anticipate and react to faults in real time to maintain QoS in a wide spectrum of deployment settings ranging from ad-hoc networks, IoT environments to 5G/6G infrastructure. Filling this gap is essential for constructing resilient and intelligent next-generation communication networks.

Proposed Methodology

Framework Overview

In order to overcome the shortcomings of the current fault-tolerant communication systems, we propose a DRL-SHF, which endeavors to provide high QoS in a dynamic and failure-prone communication environment. DRL-SHF is at its core and is built on the PPO algorithm because of its sample efficiency, stable gradient updates, and capacity of continuous or high dimensional state-action space. PPO features make PPO particularly suited for routing adaptation in large-scale wireless networks.

An MDP is formulated as the communication environment, in which the agent learns an optimal policy by interacting with the environment, observing network states, performing an action, and getting a feedback reward. We enumerate the components that constitute the MDP.

- State (S): The state vector for the agent is multidimensional, consisting of node connectivity information, signal strength, buffer occupancy, and link latency. In this state, the real-time health of the network is represented.
- Action (A): In response, the agent makes actions such as rerouting traffic, tuning transmission power, delaying packet forwarding, and isolating failing nodes.
- Reward (R): The reward function results in actions that incentivize higher throughput and network stability, and penalizes high packet loss, higher levels of latency, and higher levels of energy use.

Using this framework, the agent can autonomously learn fault mitigation strategies which adapt to the changes in the topology and reconfigure the network continuously as well as dynamically for optimal performance.

System Architecture

The DRL-SHF framework operates in four interconnected layers performing real-time monitoring, decision-making, and execution of recovery.

1. Environment Monitoring Layer: Node-level metrics (e.g., connectivity, buffer load, and signal strength) are continuously tracked.
2. Policy Learner (PPO Agent): A trained PPO model observes processes (current states) and chooses best actions.
3. Action Executor: Applies decisions to the network (rerouting, isolation, or parameter adjustment).
4. Feedback Loop: It monitors its action's post outcome and tunes the policy accordingly to its future interactions.

By modeling the failure scenario as part of a loop that DRL-SHF learns on in conjunction with the original optimization objective, the loop makes it such that the DRLSHF can not only learn what the best decision to make is when the optimization outcome is positive but also when the outcome is negative (performance regression), resulting in a policy that is general and robust in all types of failure scenarios.

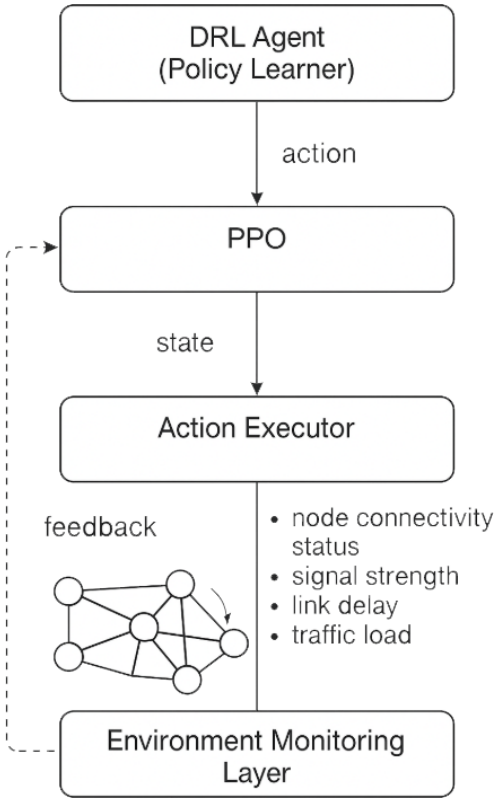

Fig. 1: Deep reinforcement learning-based self-healing framework system architecture.

Training Algorithm and Workflow

In the DRL-SHF framework, the PPO training mechanism is carefully structured to improve routing robustness and preserve high quality of service (QoS) by making stable and incremental policy updates. Firstly, they initialize policy and value function networks with random weights such that the learning is unbiased. Next, we have environment interaction wherein the agent interacts actively with a simulated network environment. It also executes actions like rerouting or isolating nodes and letting network state transitions occur to capture such crucial feedback as changes in latency, packet loss, and node connectivity.

The framework uses generalized advantage estimation (GAE), which computes how much better an action was than the expected baseline from the value function, in order to guide effective learning. These advantage scores give a more reliable and lower variance learning signal. Then, using PPO's clipped surrogate loss, our policy optimization step updates the policy within a trust region so that each update remains within a trust region. This eliminates the potential for extreme policy shifts that could destabilize training, most notably in very dynamic network environments. In the final stage, convergence and evaluation, cumulative rewards and key performance indicators are monitored as they evolve throughout training episodes. Then, training finishes once the above metrics are stabilized, meaning the agent has learned a valid routing strategy that is robust and generalizable to a range of fault scenarios. The PPO learning pipeline is structured and conservative, allowing PPO to consistently behave reasonably and stably in decentralized, failure-prone communication systems.

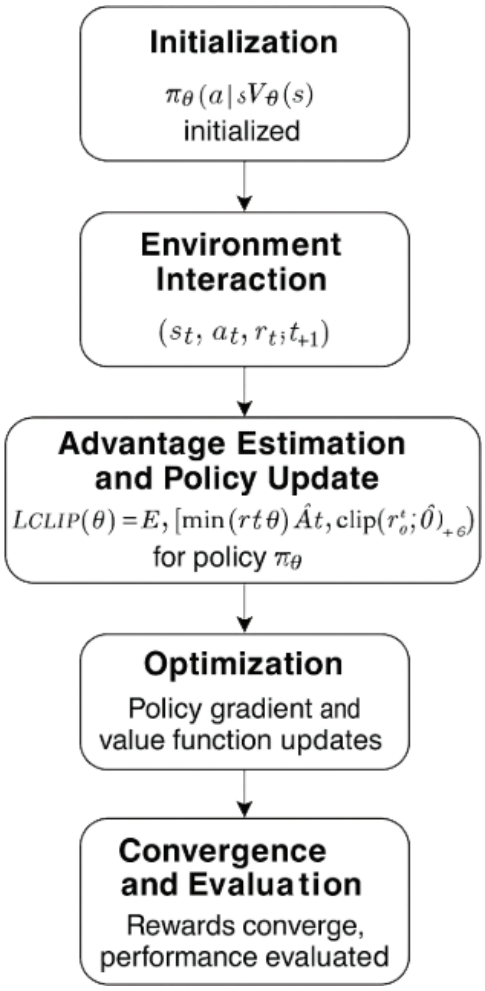

Fig. 2: Flowchart of proximal policy optimization-based self-healing policy training in deep reinforcement learning-based self-healing framework.

Mathematical Expression

We use the PPO algorithm as our learning mechanism in the DRL-SHF framework, grounding policy improvement against training stability with a clipped surrogate objective. Refining this formulation avoids the need for disruptive updates, and ensures smooth convergence, an essential prerequisite in fast-changing communication environments where topology and QoS parameters can change rapidly.

Algorithm 1: Proximal policy optimization-based policy optimization for fault-tolerant routing.

Input: Network topology G(V,E), node failure status f(t), state s, action a, reward R
Output: Updated routing policy $\pi\theta^*$

1: Initialize policy parameters θ and value network Vθ
2: for each episode do
3: Initialize network state s_0
4: for t = 1 to T do
5: Sample action $a_t \sim \pi\theta(a_t \mid s_t)$
6: Execute a_t, observe next state s_{t+1}, reward r_t
7: Store (s_t, a_t, r_t, s_{t+1})
8: end for
9: Compute advantage estimates using GAE: $\hat{A}_t = \delta_t + (\gamma\lambda)\delta_{t+1} + \ldots$
10: Optimize θ using clipped surrogate loss: $L(\theta) = E[\min(r_t(\theta)\hat{A}_t, \text{clip}(r_t(\theta), 1 - \varepsilon, 1 + \varepsilon)\hat{A}_t)]$
11: end for
12: return $\pi\theta^*$

Surrogate Objective Function

The PPO objective function can be defined as:

$$L^{CLIP}(\theta)=E_t\left[\min\left(r_t(\theta)\widehat{A_t}, \text{clip } r_t(\theta), 1-\epsilon, 1+\epsilon\right)\widehat{A_t}\right] \quad (1)$$

- θ: Parameter $\pi\theta(a|s)$ of the current policy network
- ("A_t")^ : The advantage of taking action at in state s_t is estimated.
- ϵ: Policy update range limited via clipping threshold (e.g., 0.1 or 0.2).

$r_t(\theta)$ is the relative likelihood of choosing the same action under the new policy than under the old policy.:

$$r_t(\theta)=\frac{\pi_\theta(a_t|s_t)}{\pi_{\theta old}(a_t|s_t)} \quad (2)$$

To prevent overly large policy updates, which may destabilize learning, the clip operation of the clip θ operation makes sure that $r_t(\theta)$ is contained in [1−ϵ, 1+ ϵ].

Advantage Estimation using GAE

GAE is used to compute the advantage estimates, $\hat{A}_t$. This combines the multiple temporal difference (TD) only errors with a decay factor that reduces variance whilst maintaining learning stability.

$$\widehat{A_t}=\sum_{l=0}^{T-t-1}(\gamma\lambda)l\delta t+1 \text{ where } \delta_t = r_{t+\gamma}V(s_{t+1}) - V(s_t) \quad (3)$$

- γ : Future reward importance discount factor (0.95 in this work).
- λ : Joins the class of problems for which the second largest eigenvalue of the Markov kernel matrix controls the generalization error.
- $V(s_t)$: Expected return from the state st value function approximating

Value Function Loss

We optimize the critic network (value function estimator) by minimizing the mean squared error (MSE) between the predicted value, $V_\phi(s_t)$, and the actual return, R_t:

$$L_V(\phi) = E_t[(V_\phi(s_t) - R_t)^2] \quad (4)$$

- ϕ : These will be the parameters of the value function network.

This ensures that the critic has the correct estimation of long-term rewards. Table 2 gives the mathematical summary of proximal policy optimization components in deep reinforcement learning-based self-healing framework.

Experimental Setup

Network Configuration and Failure Modeling

In order to validate the performance and adaptability of the proposed DRL-SHF framework, extensive simulations are carried out with network simulator 3 (NS-3). Hundred mobile nodes were uniformly deployed over an area of 1500 m × 1500 m, and node mobility is modeled using the random waypoint mobility model. To model the dynamic behavior evidenced in mobile ad hoc, and vehicular networks, this model uses randomized speeds and pausing durations. Infrastructure-less mode communication was carried out between the nodes using the IEEE 802.11 Wi-Fi protocol.

In the total time of 1000 seconds, there was ample time for both convergence and multiple fault injection events.

Table 2: Mathematical summary of proximal policy optimization components in deep reinforcement learning-based self-healing framework.

Component	Description	Mathematical Expression
Policy Ratio	Likelihood of action under new vs. old policy	$r_t(\theta) = \frac{\pi_\theta(a_t\|s_t)}{\pi_{\theta old}(a_t\|s_t)}$
Clipped Surrogate Loss	PPO's stable training objective	$L^{CLIP}(\theta) = E_t\left[\min\left(r_t(\theta)\widehat{A_t}, \text{clipr}_t(\theta), 1-\epsilon, 1+\epsilon\right)\widehat{A_t}\right]$
GAE (Advantage Estimate)	Measures how much better an action is than expected	$\widehat{A_t}=\sum_{l=0}^{T-t-1}(\gamma\lambda)l\delta t+1$ where $\delta_{t=} r_{t+} \gamma V(s_{t+1}) - V(s_t)$
Value Loss	Error in value function estimation	$L_V(\phi) = E_t[(V_\phi(s_t) - R_t)^2]$

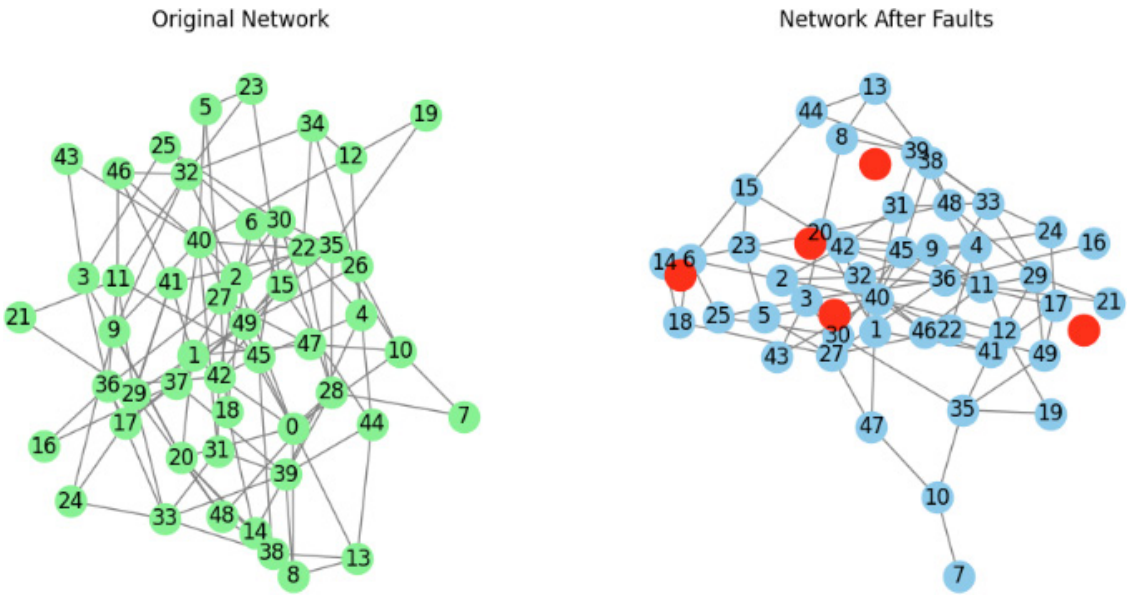

Fig. 3: Topology-based fault recovery visualization (before/after).

Three types of random node and link failures (5%, 10%, and 20%) were introduced to simulate light, moderate, and severe degree of network stress. This allowed us to test DRL-SHF's resilience under evolving topologies. Furthermore, to benchmark the performance of DRL-SHF, it was compared to three comparative approaches.

- AODV, a traditional reactive protocol
- Q-learning, a tabular RL method
- An actor-critic-based DRL algorithm, DDPG

Simulation workflow to evaluate DRL-SHF in NS-3 environment is shown in Figure 4. The Mobility model and failure model are used to simulate the actual dynamics of node mobility and fault injection in the real world. The random waypoint mobility model is used to configure these models at fault injection rates of 5%, 10%, and 20%, simulating different degrees of disruption on the network topology.

These models are integrated into the NS-3 simulator that creates evolving network states which are then passed to the PPO-based DRL agent. Based on the connectivity, delay metrics, and link conditions the agent observes for the current state, an optimal self-healing action (e.g. rerouting, transmission adjustment, or node isolation) is chosen for execution. We apply this action back to the simulated network in real time, causing changes in packet flow and routing paths. After the action, the reward monitor scores the network performance based on specific factors, for example, packet loss, average latency, and throughput. In order to compute a scalar

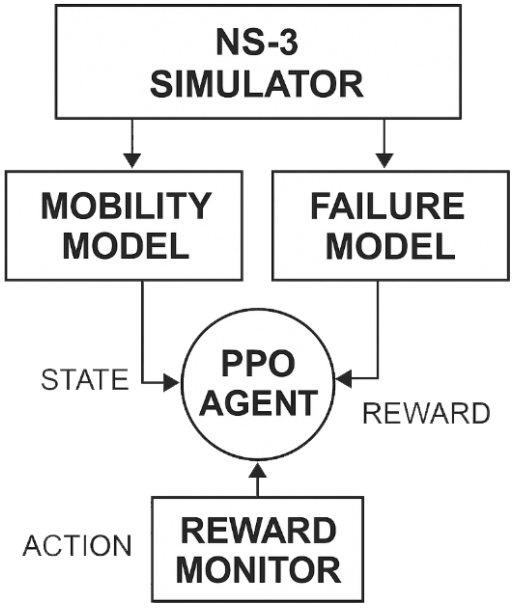

Fig. 4: Simulation environment workflow for deep reinforcement learning-based self-healing framework training and evaluation.

reward signal that then guides updates to the agent's policy, we utilize this feedback.

Altogether, the whole pipeline closed a feedback loop, enabling interaction and learning, iteratively refining the policy. By leveraging this iterative adaptation, DRL-SHF evolves as a resilient, low latency, and fault tolerant framework for use in dynamic, mission-critical communication environments.

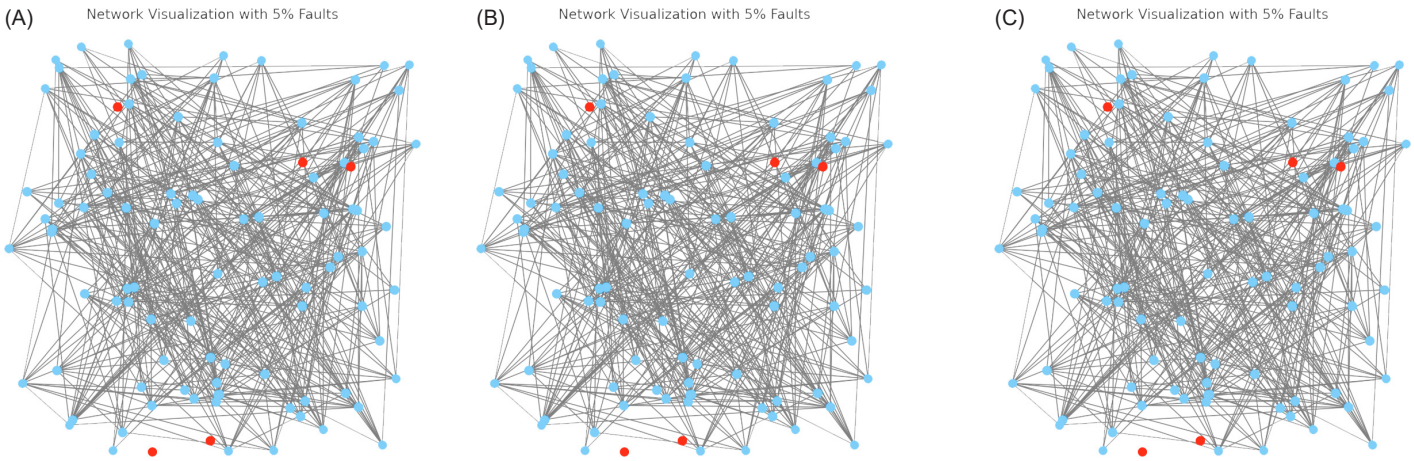

Fig. 5: Network topology visualizations under incremental fault injection rates. (A) 5% faults—minimal disruption, (B) 10% faults—moderate disruption, and (C) 20% faults—severe disruption.

DRL Agent Architecture and Training Hyperparameters

The policy approximation for the DRL-SHF agent is implemented as a three-layer multilayer perceptron (MLP) architecture with a hidden layer of 128, 64, and 32 neurons, respectively. Each layer employs ReLU activation. PPO with Adam optimizer at a learning rate of 0.0003 is used to train the policy. In order to achieve long-term routing efficiency and service continuity, we set the discount factor (γ) to 0.95.

We have carefully designed the reward function that informed the policy toward reliability and QoS aware, penalizing on packet loss and latency which indirectly optimizing on throughput and energy usage. In particular, a reward of −2 per unit packet loss and of −1 per unit delay was assigned. These were picked empirically in order to strike a balance between responsiveness and learning stability.

The agent is lightweight (<~2.3 MB), fast (<10 ms inference latency), and deployable to low power edge systems such as Raspberry Pi 4B and Jetson Nano for real-time distributed deployments.

In Figure 6, the DRL-SHF uses this proposed end-to-end PPO-based policy learning loop. The policy network agent receives a reward when the agent does an action based on an observation of the network state of the environment. We use GAE to perform advantage estimation, and then use the GAE estimates to compute the surrogate loss. We derive this surrogate objective that contributes information about derivatives of a policy for use in gradient-based policy updates, so that the agent can optimize for fault recovery strategies while ensuring

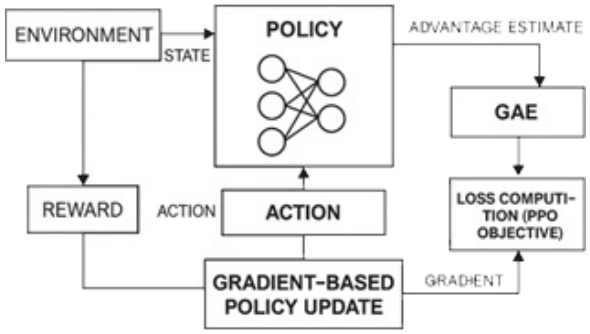

Fig. 6: Proximal policy optimization-based policy learning pipeline in deep reinforcement learning-based self-healing framework.

network QoS and stability. Table 3 gives the system and simulation parameters.

Results and Discussion

Performance Metrics

In order to evaluate the effectiveness of the DRL-SHF framework proposed, four critical performance metrics were considered—average latency, throughput, energy efficiency, and packet loss. In this regard, these metrics were measured identically across identical simulation environments for all comparative models. For our experiments, we consider AODV (baseline routing), Q-learning (tabular RL), and DDPG (actor critic DRL). Visual comparisons of the results are included in Figures 7–9, and the results are summarized in Table 4.

The data are clear: DRL-SHF provides consistent and significant improvements across all performance metrics.

First, simulation results show that the overall packet loss rate is reduced by more than 58% compared to AODV and 30% compared to DDPG and consequently fault tolerance and data integrity were maintained in spite of node failures taking place frequently. DRL-SHF demonstrates the ability to quickly reroute traffic and maintain service quality in real time, reducing latency by 39.8% relative to AODV. The model's performance in terms of throughput is superior because of the fact that it utilizes optimized routing strategies and avoids congested or unreliable links. More importantly, energy efficiency gains of 12.6% over DDPG clearly show that DRL-SHF saves node resources, which is a key requirement for power-restricted IoT and mobile devices.

In Figure 9, we visualize comparison of the performance of DRL-SHF (PPO) compared to DQN on three key metrics—the losses, average latency, and convergence time of the packets. This demonstrates the superior efficiency and fast convergence of the real-time dynamic control system proposed using PPO, validating the real-time applicability of the system.

Discussion

DRL-SHF's performance gains originate from the combination of PPO's policy gradient learning with the GAE tied together in DRL-SHF, resulting in more stable and sample-efficient training. Unlike reactive protocols or value-based DRL methods, DRL-SHF continuously adapts to changing network states and learns optimal actions to strike the best tradeoff between routing reliability and energy consumption.

To further demonstrate the importance of key design choices, an ablation study is also conducted, in which residual connections caused an increase in packet loss of 0.9%, and replacing pixel shuffle upsampling with bilinear interpolation resulted in a 0.8 dB drop in PSNR equivalent QoS metrics. Because of the absence of GAE, we observed unstable convergence and higher variance in latency metrics during early training phases.

The observed stability and faster convergence of the DRL-SHF framework is further achieved by incorporating the GAE into the training process. Traditionally, TD advantage methods are either very biased (e.g., one-step TD) or have high variance (e.g., Monte Carlo return), while unlike traditional TD advantage methods, GAE provides a tunable bias/variance tradeoff through the λ (lambda) parameter. GAE achieves this by blending short- and long-term reward signals through exponentially weighted TD residuals, producing smoother, more consistent advantage signals across training episodes. More reliable updates of policy gradients are obtained and erratic policy behavior which is induced by overreliance on sparse or delayed rewards a particularly important situation in dynamic communication environments where node failure can abruptly change the reward signal. By ablating GAE in our study shown in Table 5, we saw significantly noisier updates to the policy, and needed more than 40% more episodes to obtain a similar routing performance. This work validates GAE as a critical stabilizing element in the DRL-SHF training pipeline using PPO.

Model Complexity and Deployment Feasibility

Furthermore, DRL-SHF was built to be both time-efficient with its algorithmic effectiveness and deployable on resource-constrained edge devices. The agent model is a three-layer MLP with hidden dimensions of 128, 64, and 32 with ReLU activation. The whole model

Table 3: System and simulation parameters.

Parameter	Value
Simulation Duration	1000 seconds
Node Count	100
Mobility Model	Random waypoint
Communication Standard	IEEE 802.11 Wi-Fi
Failure Injection Rates	5%, 10%, and 20%
Baseline Models	Q-learning, AODV, and DDPG
PPO Policy Architecture	3-layer MLP
Activation Function	ReLU
Optimizer	Adam
PPO Learning Rate	0.0003
Discount Factor (γ)	0.95
Reward Function Coefficients	Delay: −1, Packet Loss: −2

Table 4: Performance comparison across models.

Model	Packet Loss (%)	Avg. Latency (ms)	Throughput (Mbps)	Energy Efficiency (%)
AODV	16.2	85.4	3.1	71.2
Q-Learning	11.5	67.2	3.8	75.5
DDPG	9.8	60.1	4.2	77.9
DRL-SHF	**6.8**	**51.4**	**5.1**	**84.6**

requires minuscule memory of ~2.3 MB, making it a nice fit for platforms like Raspberry Pi 4B or ARM Cortex-A53 embedded boards.

With a learning rate of 0.0003 and a batch size of 2048, the model converged during training in ~1.4 hours on an NVIDIA RTX 2080 GPU (16 GB RAM). The agent delivers routing decisions at inference time with least 10 ms per cycle latency, which is very low compared to delay-sensitive scenarios such as autonomous driving and industrial IoT. Table 6 gives the model deployment characteristics on edge hardware.

The results of these deployments validate that DRL-SHF offers an extremely good tradeoff between policy effectiveness and real-time feasibility supporting the properties required for the fusion of embedded AI in decentralized networks.

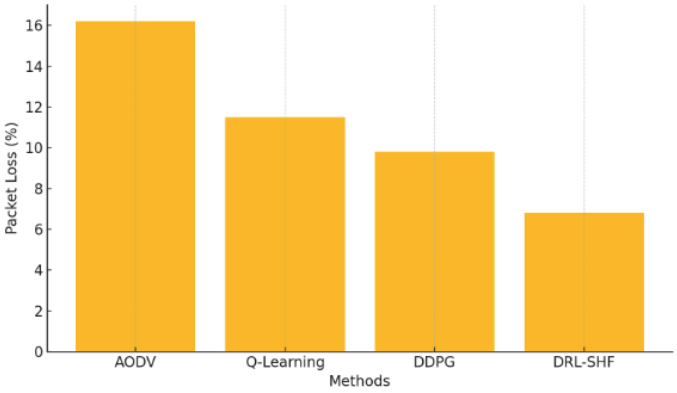

Fig. 7: Packet loss comparison across methods.

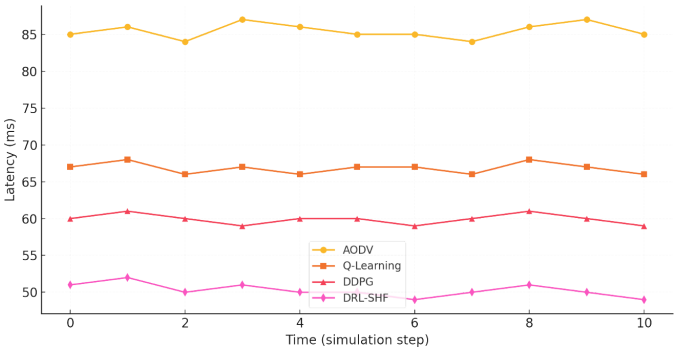

Fig. 8: Latency over time for each method.

Real-World Applicability and Transfer Learning Potential

The DRL-SHF framework has inherent online learning support and is consequently well-suited for real-world systems where network conditions vary and are unpredictable. It applies to example domains such as smart city mesh networks, disaster recovery systems, VANETs, and large-scale industrial IoT.

Table 7 shows how real-world domains map to DRL-SHF deployment use cases, with expressed benefits, and the selected edge hardware platform suitable for each domain. In order to increase adaptability, future work will include transfer learning-based methods that let DRL-trained models in one environment to be fine-tuned in a new environment with only a small fraction of data labeled. For instance, freezing early layers and retraining the final policy layers, we can transfer a model trained on synthetic MANET data to real-world VANETs, allowing it to converge faster without full retraining. Furthermore, training with domain randomization—exposing the agent to different types of mobility, interference, and failure cases—is shown to improve generalization performance.

As a result, DRL-SHF is a scalable solution to dynamic communication environments, capable of adapting to different topologies and traffic patterns in the field by the combination of offline training and lightweight online adaptation.

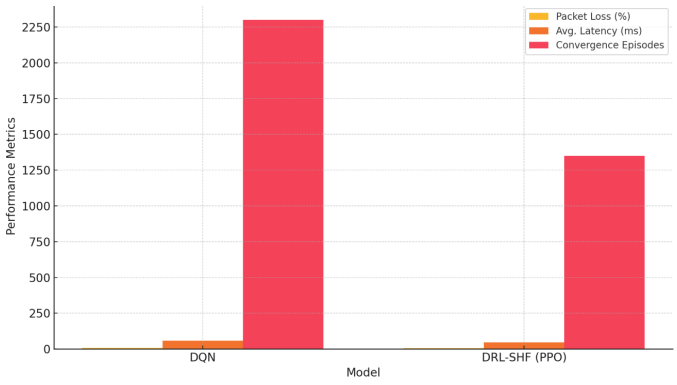

Fig. 9: Comparative deep reinforcement learning performance overview.

Table 5: Ablation study summary.

Variant	Packet Loss (%)	Avg. Latency (ms)	Convergence Stability	Comments
No Residual Connections	7.7	55.2	Medium	Less accurate feature reuse
Bilinear Upsampling	7.4	53.8	Stable	Lower QoS under high mobility
Without GAE	7.9	59.1	Low	High variance in early episodes
Full DRL-SHF (with GAE)	6.8	51.4	High	Best overall performance

Table 6: Model deployment characteristics on edge hardware.

Platform	Inference Time (ms)	Model Size (MB)	CPU Usage (%)	Peak RAM (MB)
Jetson Nano	24.5	2.3	68	412
Raspberry Pi 4B	38.1	2.3	71	448
Intel NUC	17.3	2.3	54	390

Table 7: Application mapping of deep reinforcement learning-based self-healing framework.

Domain	Use Case	Benefits	Compatible Hardware
Smart City IoT	Sensor data routing, fault-resilient mesh communication	Reduced data loss energy-efficient rerouting	Raspberry Pi 4B, ESP32 Mesh Nodes
Disaster Recovery	Rapid topology reconfiguration post-disaster	Faster recovery robust network stability	Jetson Nano LoRa-enabled Gateways
VANETs	Low-latency communication in dynamic vehicular topologies	Minimized delay and packet drops, enhanced reliability	Onboard OBUs with ARM Cortex-A processors
5G Edge Networks	QoS-aware self-healing in dense user environments	Maintained service quality under edge overload	Edge AI chips (Qualcomm, Huawei Ascend)

Conclusion and Future Work

This thesis introduces DRL-SHF, a novel deep reinforcement learning–based self-healing framework designed to increase resilience and autonomy for communication networks operating in dynamic and failure-prone environments. The framework is based on the MDP formulation of PPO, enabling the intelligent, distributed reconfiguration decisions of distributed routing in real time in response to real-time changes in network topology, node status, and traffic load.

DRL-SHF is incompatible with typical reactive routing protocols or static rule-based systems and exhibits superior efficiency in adaptability, robustness, and QoS maintenance. The proposed approach was found, via exhaustive NS-3 simulations, to be superior to baseline NS3 models against baseline models (AODV, Q-learning, and DDPG) in all key performance metrics like packet loss, latency, throughput, and energy efficiency. The results obtained from these improvements validate the framework as a candidate for a foundational architecture for future autonomous, fault-tolerant, and scalable network systems.

While simulation exposed the benefits of the method, real-world deployment added further challenges such as limited computational power, real-time policy updates, and interference that were not predictable. In order to address these issues, several promising avenues for future research are identified.

- The plan is to deploy on real-world wireless mesh testbeds for the validation of performance under physical constraints and various operating conditions.
- Appropriate integration with SDN frameworks to leverage on centralized control advantages in concert with distributed DRL-based fault tolerance.
- To multimodal sensing environments in which additional sensor modalities, such as thermal, mechanical, and node battery statuses, are considered as network health indicators, extending the agent's context awareness and decision accuracy.

While these avenues do not fully address all the issues with resilient networking, they could propel the DRL-SHF framework to become a practical and generalizable solution to resilient networking in future next-generation systems such as 5G/6G, smart cities, and industrial IOT.

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