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AI-DRIVEN FEDERATED MULTI-AGENT ACTOR–CRITIC LEARNING FOR SECURE AND ENERGY-EFFICIENT RESOURCE OPTIMIZATION IN 6G SEMI-GRANT-FREE NOMA-BASED IOT NETWORKS

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Abstract

Sixth-generation (6G) wireless systems are expected to support ultra-massive machine-type communication through dense deployments of Internet of Things (IoT) devices. Semi-Grant-Free Non-Orthogonal Multiple Access (SGF-NOMA) has emerged as a promising access mechanism for enabling simultaneous transmissions of grant-based and grant-free users while improving spectral efficiency. Dense IoT environments create significant challenges including power-domain collisions, energy inefficiency due to repeated retransmissions, and susceptibility to malicious interference such as jamming attacks. Conventional centralized optimization techniques introduce high signaling overhead and raise privacy concerns, limiting their scalability in large-scale IoT deployments. This work proposes an AI-driven federated hybrid multi-agent actor–critic learning framework for secure and energy-aware resource optimization in 6G SGF-NOMA IoT networks. Each grant-free device operates as an intelligent learning agent that autonomously selects transmission power levels and resource blocks based on local observations. A federated learning architecture enables decentralized model training while periodically aggregating parameters at an edge server using federated averaging. The proposed framework integrates a hybrid exploration–cooperation strategy and a multi-objective reward function that jointly considers throughput gain, collision penalties, energy consumption cost, and security robustness under jamming interference. Simulation-based evaluations demonstrate that the proposed framework significantly improves conditional throughput, reduces power collision probability, and enhances energy efficiency compared with centralized deep reinforcement learning, random access, and conventional SGF-NOMA approaches. Results also indicate faster convergence and improved fairness among IoT devices under ultra-dense deployment scenarios. The proposed solution provides a scalable and privacy-preserving learning architecture suitable for AI-native 6G wireless systems and large-scale IoT networks.

1. Introduction

The rapid expansion of Internet of Things (IoT) technologies is driving the development of next-generation wireless communication systems capable of supporting billions of connected devices. Sixth-generation (6G) networks are expected to deliver ultra-massive connectivity, extremely low latency, and intelligent network control through the integration of artificial intelligence into communication infrastructure (1-3). Massive machine-type communication (mMTC) represents one of the core service categories of 6G, where a large number of low-power devices generate sporadic short-packet transmissions across dense wireless environments (4). Conventional orthogonal multiple access techniques face significant limitations in supporting such massive connectivity due to inefficient spectrum utilization and excessive signaling overhead. Non-Orthogonal Multiple Access (NOMA) has emerged as a promising solution that enables multiple users to share the same spectrum resources through power-domain multiplexing and successive interference cancellation (8). In particular, Semi-Grant-Free NOMA (SGF-NOMA) allows grant-free IoT devices to opportunistically access spectrum resources allocated to grant-based users, thereby improving spectral efficiency and reducing access delay.

Despite these advantages, SGF-NOMA-based IoT networks face several critical challenges. In ultra-dense deployments, multiple grant-free devices may select identical transmission power levels within the same resource block, resulting in severe power-domain collisions and decoding failures. These collisions trigger repeated retransmissions, which significantly increase energy consumption and reduce the battery lifetime of IoT devices. Energy efficiency remains a primary concern for large-scale IoT systems since many devices operate under strict power constraints. Security threats further complicate resource allocation in SGF-NOMA networks. Malicious entities may perform jamming attacks that degrade signal-to-interference-plus-noise ratio (SINR), disrupt successful decoding, and destabilize network performance. Conventional access control mechanisms often fail to adapt to such dynamic and adversarial conditions.

Artificial intelligence has recently gained attention as a powerful tool for optimizing wireless resource allocation in complex and dynamic environments. Deep reinforcement learning (DRL) techniques allow communication agents to learn optimal transmission strategies through interaction with the network environment (10). Several studies have applied DRL to NOMA-based systems for power control, user clustering, and spectrum allocation. Most existing approaches rely on centralized learning architectures where network data are aggregated at a central controller. These centralized methods introduce high communication overhead and create privacy risks, especially in large-scale IoT deployments. Federated learning provides a promising alternative by enabling decentralized training across distributed devices while sharing only model parameters rather than raw data. This paradigm reduces communication overhead and preserves device privacy while allowing collaborative model improvement. When combined with multi-agent reinforcement learning, federated learning can support scalable intelligence across large networks of autonomous devices (5,6,11).

This work proposes a federated hybrid multi-agent actor–critic learning framework for secure and energy-aware resource optimization in SGF-NOMA-based IoT networks. Each grant-free IoT device operates as an intelligent agent that learns optimal transmission strategies based on local observations while periodically participating in federated model aggregation. The framework integrates a hybrid learning strategy consisting of a competitive exploration phase and a cooperative optimization phase, enabling faster convergence and improved network performance. The reward design incorporates multiple objectives including throughput maximization, collision reduction, energy efficiency, and robustness against jamming interference.

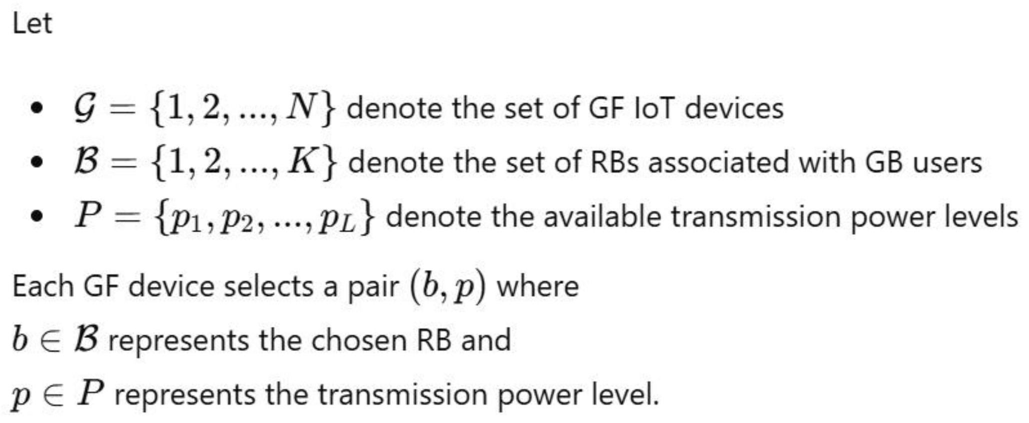
The major contributions of this research are summarized as follows:

1. Development of a federated multi-agent actor–critic learning framework for decentralized resource allocation in SGF-NOMA IoT networks.
2. Integration of energy-aware optimization and security-robust reward mechanisms under jamming attack scenarios.
3. Design of a hybrid exploration–cooperation learning strategy to improve convergence and scalability in ultra-dense IoT environments.
4. Comprehensive performance evaluation against baseline methods including centralized DRL, random access, and conventional SGF-NOMA.
5. Demonstration of improved throughput, reduced collision probability, and enhanced energy efficiency under realistic 6G simulation conditions.

The remainder of this paper is organized as follows. Section 2 presents the system model and formal problem formulation for SGF-NOMA resource optimization. Section 3 describes the proposed federated hybrid multi-agent actor–critic learning framework. Section 4 introduces the simulation environment and experimental configuration. Section 5 provides performance evaluation and comparative analysis. Section 6 discusses implications and scalability considerations. Section 7 concludes the paper and outlines directions for future research.

2. System Model and Problem Formulation

Consider a single-cell 6G SGF-NOMA IoT network consisting of one base station (BS), a set of grant-based (GB) users, and a large number of grant-free (GF) IoT devices. The base station manages spectrum resources through resource blocks (RBs). Each RB is primarily assigned to a GB user while multiple GF devices opportunistically share the same RB using power-domain multiplexing.

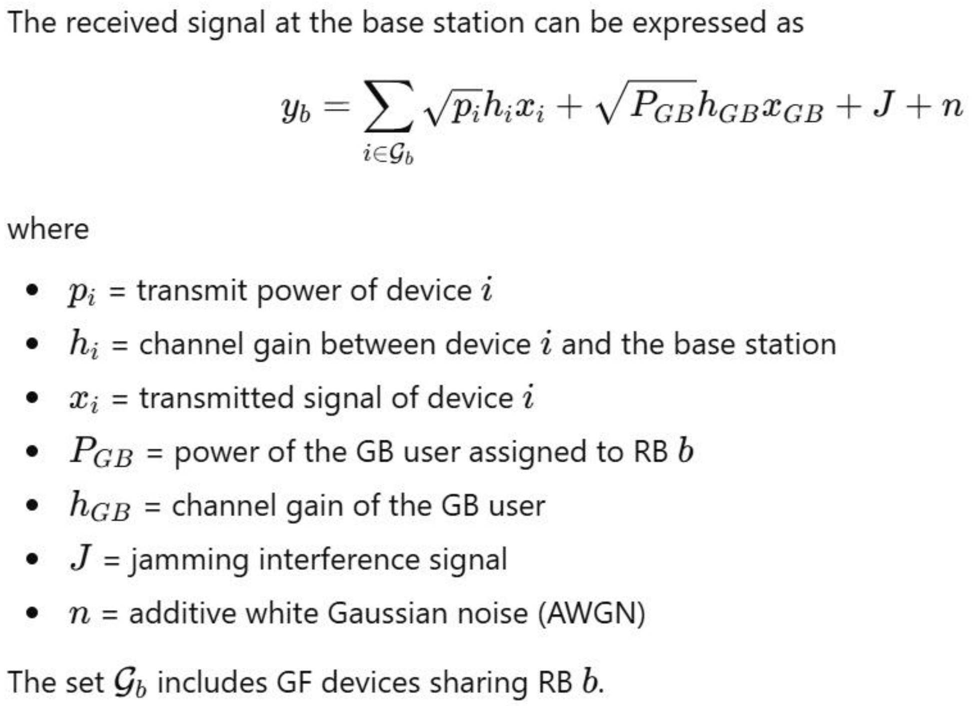


Let

- $\mathcal{G} = \{1, 2, \ldots, N\}$ denote the set of GF IoT devices
- $\mathcal{B} = \{1, 2, \ldots, K\}$ denote the set of RBs associated with GB users
- $P = \{p_1, p_2, \ldots, p_L\}$ denote the available transmission power levels

Each GF device selects a pair (b, p) where
$b \in \mathcal{B}$ represents the chosen RB and
$p \in P$ represents the transmission power level.

Multiple GF devices may choose the same RB and power level. In SGF-NOMA decoding, the base station applies successive interference cancellation (SIC) to decode signals ordered by received power. Dense IoT deployment leads to frequent power-domain collisions, which occur when several GF devices transmit with identical power levels on the same RB (8). Consider GF device (i) transmitting to the base station on RB (b).



The received signal at the base station can be expressed as

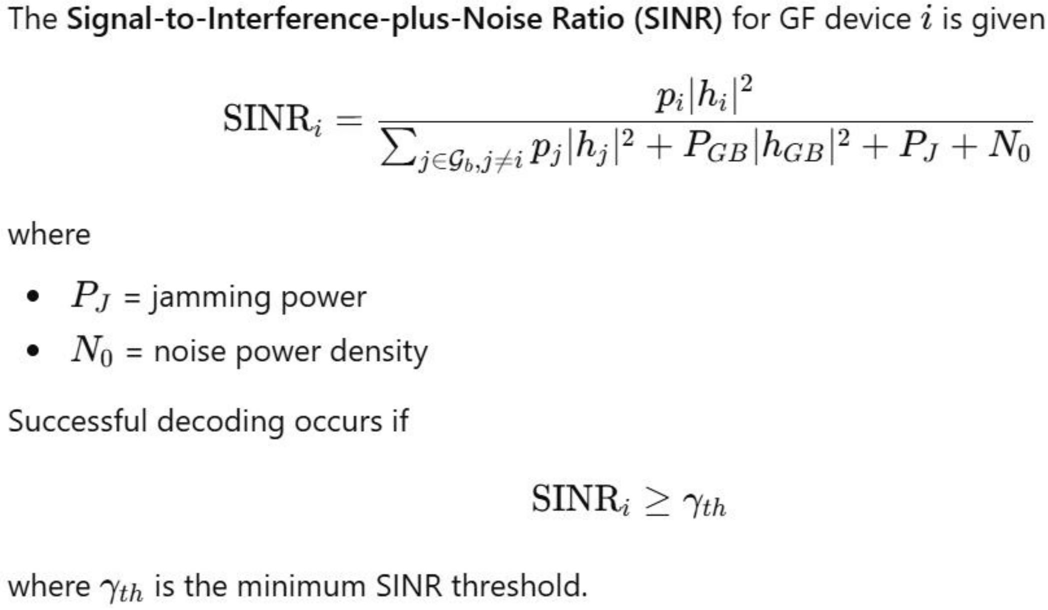
$$y_b = \sum_{i \in \mathcal{G}_b} \sqrt{p_i} h_i x_i + \sqrt{P_{GB}} h_{GB} x_{GB} + J + n$$

where

- p_i = transmit power of device i
- h_i = channel gain between device i and the base station
- x_i = transmitted signal of device i
- P_{GB} = power of the GB user assigned to RB b
- h_{GB} = channel gain of the GB user
- J = jamming interference signal
- n = additive white Gaussian noise (AWGN)

The set $\mathcal{G}_b$ includes GF devices sharing RB b.

Assume an intelligent jammer that transmits interference power (P_J) over selected RBs. The Signal-to-Interference-plus-Noise Ratio (SINR) for GF device (i) is given by,



The **Signal-to-Interference-plus-Noise Ratio (SINR)** for GF device i is given by

$$\mathrm{SINR}_i = \frac{p_i |h_i|^2}{\sum_{j \in \mathcal{G}_b, j \neq i} p_j |h_j|^2 + P_{GB} |h_{GB}|^2 + P_J + N_0}$$

where

- P_J = jamming power
- N_0 = noise power density

Successful decoding occurs if

$$\mathrm{SINR}_i \geq \gamma_{th}$$

where γ_{th} is the minimum SINR threshold.

If multiple GF devices transmit using identical power levels within the same RB, SIC decoding fails, producing a collision event. Energy efficiency is a critical constraint in IoT networks since devices typically operate with limited battery capacity. The

$$U = \sum_{i=1}^{N} (\alpha R_i - \beta E_i - \delta C$$

energy consumption for device (i) during a transmission interval (T) is

$$E_i = p_i \times T$$

If retransmission occurs due to decoding failure, the total energy consumption becomes

- R_i = achieved throughput of device i

$$E_i^{total} = \sum_{k=1}^{R_i} p_i T$$

where (Ri) represents the number of retransmission attempts.

- J_i = impact of jamming interference

The energy efficiency metric is defined as

$$\eta = \frac{\text{Successfully delivered bits}}{\text{Total energy consumption}}$$

ormulated as

which can also be expressed as

$$\eta_i = \frac{R_i^{succ}}{E_i^{total}}$$

where R_i^{succ} represents successfully decoded transmissions.

A power-domain collision occurs when two or more GF devices select identical power levels within the same RB. The collision indicator function is defined as,

$$C_i = \begin{cases} 1, & \text{collision occurs} \\ 0, & \text{successful decoding} \end{cases}$$

High collision probability significantly degrades throughput and increases energy consumption.

The goal of the system is to optimize resource allocation decisions for GF devices while considering throughput, energy efficiency, collision avoidance, and resilience to jamming attacks. The system utility is defined as subject to,

$$p_i \in P$$

$$b_i \in \mathcal{B}$$

$$0 \leq p_i \leq P_{max}$$

$$\text{SINR}_i \geq \gamma_{th}$$

The resource allocation problem is modeled as a multi-agent reinforcement learning (MARL) task. Each GF device acts as an independent agent interacting with the network environment.

For each agent (i), State:

$$s_i = (h_i, I_b, p_i^{prev}, C_i^{prev})$$

$$a_i = (b_i, p_i)$$
$$r_i = w_1 R_i - w_2 E_i - w_3 C_i - w_4 J_i$$

Where,

- h_i = channel condition
- I_b = observed interference level
- p_i^{prev} = previous power selection
- C_i^{prev} = previous collision outcome.

Action: which represents the selection of resource block and power level.

Reward: The objective of each agent is to learn a policy.

$\pi_i(a_i|s_i)$

That is maximizes the expected cumulative reward,

$$\max E\left[\sum_{t=0}^{T} \gamma^t r_i^t\right]$$

where (γ) is the discount factor.

Due to the large number of agents and distributed nature of IoT devices, centralized training becomes inefficient. Therefore, a federated multi-agent actor–critic learning architecture is introduced to enable scalable and privacy-preserving learning.

3. Proposed Federated Hybrid Multi-Agent Actor–Critic Framework

This section presents the proposed AI-driven federated hybrid multi-agent actor–critic learning framework designed to optimize resource allocation in SGF-NOMA IoT networks under energy and security constraints. The framework enables distributed learning among IoT devices while preserving privacy and improving scalability through federated aggregation. In ultra-dense IoT networks, centralized reinforcement learning approaches suffer from large communication overhead and slow convergence due to the need to collect global network information. To address this challenge, a federated multi-agent learning architecture is introduced.

In the proposed framework:

- Each grant-free IoT device acts as an independent learning agent.
- Devices learn optimal transmission strategies through local actor–critic networks.
- Local model updates are periodically shared with an edge server.
- The server aggregates model parameters using Federated Averaging (FedAvg).
- The aggregated global model is redistributed to devices.

This design enables decentralized learning while maintaining global coordination among agents.

The framework consists of three primary components:

1. Local Actor–Critic Learning Agents
2. Federated Parameter Aggregation
3. Hybrid Exploration–Cooperation Learning Strategy

Each GF IoT device maintains two neural networks: The actor learns the policy that maps system states to transmission actions.

$$a_i = \pi_\theta(s_i)$$

Where,

- s_i = state observed by device i
- a_i = selected action (RB and power level)
- θ = actor network parameters

The actor outputs a probability distribution over possible resource allocation decisions. The critic evaluates the quality of the chosen action by estimating the state–action value function.

$$Q(s_i, a_i)$$

The critic network parameters are denoted by (ϕ).

The objective of the critic is to minimize the temporal difference error

$$L(\phi) = \left(r_i + \gamma Q_\phi(s_i', a_i') - Q_\phi(s_i, a_i)\right)^2$$

Where,

- r_i = immediate reward
- s_i' = next state
- a_i' = next action.

The actor parameters are updated using the policy gradient:

$$\nabla_\theta J(\theta) = E\left[\nabla_\theta \log \pi_\theta(a_i|s_i) Q_\phi(s_i, a_i)\right]$$

This update encourages the agent to select actions that maximize expected rewards.

Instead of sharing raw training data, each device periodically transmits its local model parameters to the edge server (5,6). The server performs federated averaging to construct the global model.

Let represent the actor parameters of device (i) at communication round (t).

The aggregated global parameters are computed as

$$\theta_i^t$$

Where,

- (n_i) = number of local training samples

(N) = total number of devices.

The same aggregation process is applied to critic parameters. This mechanism provides several advantages including reduced communication overhead, improved scalability and enhanced privacy preservation (9,10).

A major challenge in multi-agent learning environments is balancing exploration and global coordination. The proposed framework introduces a hybrid two-phase learning strategy.

$$r_i = w_1 R_i - w_2 E_i - w_3 C_i - w_4 J_i$$

where

- R_i = achieved throughput
- E_i = energy consumption
- C_i = collision indicator
- J_i = jamming impact
- w_1, w_2, w_3, w_4 = weighting parameters.

During early training stages, agents independently explore different resource allocation strategies. This phase allows agents to discover diverse solutions and avoid premature convergence. Exploration is encouraged using stochastic policies. Action selection follows,

$$a_i \sim \pi_\theta(s_i)$$

where sampling ensures exploration across the action space.

Phase 2: Cooperative Optimization

Once initial exploration stabilizes, agents enter a cooperative learning phase. During this phase federated aggregation occurs more frequently, policies converge toward globally beneficial decisions and collision probability across devices decreases. A switching condition determines when the system transitions between phases. Let (σ_t) represent policy variance across agents.

When, the system shifts from exploration to cooperative optimization.

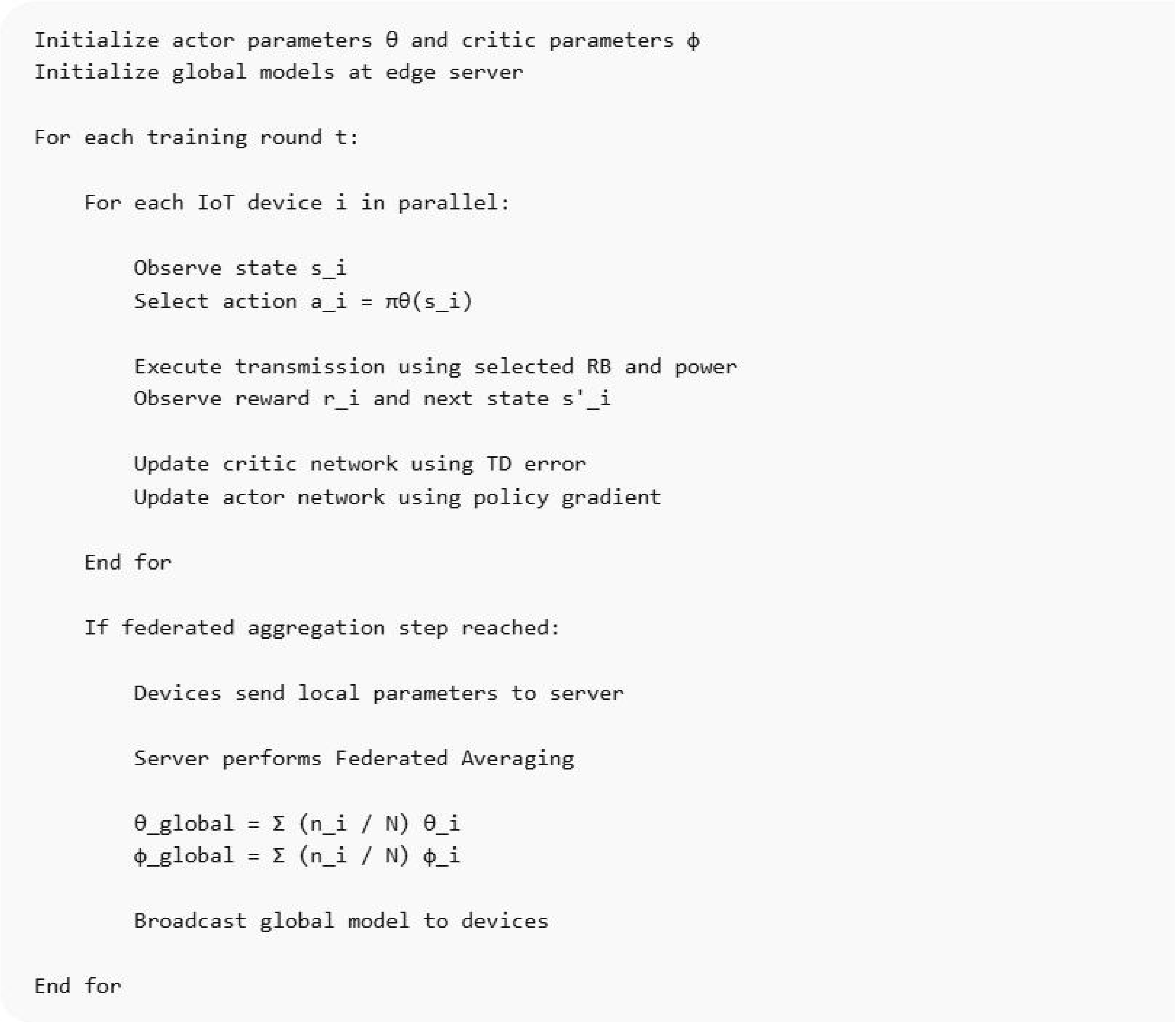
The reward function integrates multiple network objectives. For device (i), the reward is defined as,

This formulation encourages agents to maximize successful transmissions, minimize energy usage, reduce power collisions and avoid jammed channels.

The complete training process consists of repeated interaction between devices and the environment. Training steps include:

1. Each device observes current network state (s_i).
2. The actor network selects an action (a_i).
3. The device transmits using the selected RB and power level.
4. The base station computes SINR and decoding outcome.
5. Reward (r_i) is generated.
6. Local actor–critic networks update parameters using gradient descent.
7. Devices periodically upload parameters to the edge server.
8. The server performs federated averaging.
9. Updated global parameters are redistributed to devices.

Algorithm 1: Federated Hybrid Multi-Agent Actor–Critic Learning



```
Initialize actor parameters θ and critic parameters ϕ
Initialize global models at edge server

For each training round t:

    For each IoT device i in parallel:

        Observe state s_i
        Select action a_i = πθ(s_i)

        Execute transmission using selected RB and power
        Observe reward r_i and next state s'_i

        Update critic network using TD error
        Update actor network using policy gradient

    End for

    If federated aggregation step reached:

        Devices send local parameters to server

        Server performs Federated Averaging

        θ_global = Σ (n_i / N) θ_i
        ϕ_global = Σ (n_i / N) ϕ_i

        Broadcast global model to devices

End for
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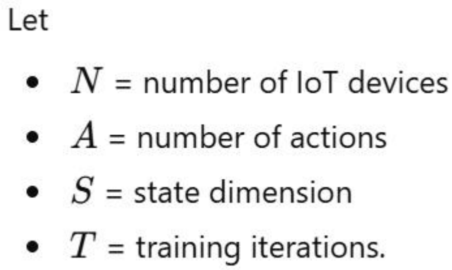

Let

- N = number of IoT devices
- A = number of actions
- S = state dimension
- T = training iterations.

Each agent performs actor–critic updates as $O(T(SA))$
At the edge server, aggregation complexity is, where $O(NP)$ (P) is the number of model parameters.
Considering all agents, total complexity becomes which scales linearly with the number of IoT devices. Federated learning significantly reduces communication overhead compared with centralized training, where raw data transfer would require with (D) representing dataset size.

4. Simulation Setup

This $O(ND)$ section describes the

simulation environment used to evaluate the proposed federated hybrid multi-agent actor–critic framework. The experiments aim to analyze system performance under realistic 6G SGF-NOMA IoT network conditions, focusing on throughput, collision probability, energy efficiency, and robustness against jamming attacks. A single-cell 6G IoT network is considered where a base station serves both grant-based (GB) users and grant-free (GF) IoT devices. Each resource block is assigned to a GB user while multiple GF devices opportunistically share the same spectrum using power-domain multiplexing. GF devices independently select a resource block and a transmission power level using the proposed learning framework. The network environment includes an intelligent jammer that injects interference into selected resource blocks in order to disrupt communication (12). The simulation evaluates performance under increasing IoT device density, representing ultra-dense mMTC scenarios expected in future 6G deployments.

Wireless channels between devices and the base station follow a Rayleigh fading model, which is commonly used to represent small-scale fading in wireless networks. The channel gain between device (i) and the base station is defined as, Where,

- (g_i) represents small-scale fading
- (d_i) represents the distance between the device and the base station
- (α) is the path loss exponent.

Noise is modeled as additive white Gaussian noise (AWGN) with power spectral density (N_0). The base station applies successive interference cancellation (SIC) to decode received signals based on power ordering.

To evaluate network security robustness, an active jammer is introduced. The jammer randomly selects resource blocks and injects interference power (P_J). The jammer's goal is to reduce SINR and increase packet decoding failures. The jamming signal is modeled as additional interference in the SINR expression. The jammer operates according to,

$$J_b = \begin{cases} P_J & \text{if RB } b \text{ is attacked} \\ 0 & \text{otherwise} \end{cases}$$

The jamming probability determines how frequently the jammer targets specific resource blocks.

$$h_i = g_i d_i^{-\alpha}$$

Each IoT device maintains local actor and critic neural networks. The networks are implemented using deep neural networks with fully connected layers. Actor Network:

- Input: state vector
- Hidden layers: 128 and 64 neurons
- Activation: ReLU
- Output: probability distribution over actions.

Critic Network:

- Input: state-action pair
- Hidden layers: 128 and 64 neurons
- Activation: ReLU
- Output: Q-value estimation.

The networks are trained using the Adam optimizer. Training hyperparameters are shown in Table 1.

Parameter	Value
Cell radius	500 m
Number of GF devices	50 – 500
Number of RBs	10

Power levels	5
Maximum transmission power	23 dBm
Noise power	−104 dBm
Path loss exponent	3.5
Training episodes	2000
Learning rate	0.0003
Discount factor	0.99
Federated aggregation interval	10 episodes
Jamming power	20 dBm
Jamming probability	0.2

Table 1. Simulation and Learning Parameters

The proposed framework is compared with three baseline approaches commonly used in SGF-NOMA systems.

Random Access Scheme

IoT devices randomly select resource blocks and transmission power levels without learning. This scheme represents a simple decentralized baseline with no optimization.

Conventional SGF-NOMA

Devices access the network following standard SGF-NOMA rules without intelligent resource optimization. This approach reflects the performance of traditional wireless access protocols.

Centralized Deep Reinforcement Learning

In this approach, all device experiences are collected at the base station and a centralized DRL model is trained to determine optimal resource allocation strategies.

While this method can achieve strong optimization, it introduces large communication overhead and limited scalability.

Performance Metrics

The evaluation considers several metrics relevant to IoT network performance. The first would be Conditional Throughput

Throughput measures the number of successfully decoded transmissions.

$$T = \frac{\text{Number of successful packets}}{\text{Total transmission attempts}}$$

Energy efficiency is defined as

$$\eta = \frac{\text{Successfully transmitted bits}}{\text{Energy consumption}}$$

and is expressed in bits per Joule.

Collision probability measures the frequency of power-domain collisions among GF devices.

$$P_{collision} = \frac{\text{Number of collision events}}{\text{Total transmissions}}$$

Convergence speed represents the number of training episodes required for the learning algorithm to reach stable performance.

Jain's Fairness Index

Fairness among IoT devices is measured using

$$F = \frac{(\sum R_i)^2}{N \sum R_i^2}$$

where (R_i) represents throughput of device (i).

Security robustness evaluates the system's ability to maintain throughput under jamming attacks.

$$S = \frac{T}{T}$$

Where,

- (T$_{jam}$ = throughput under jamming.
- (T$_{normal}$) = throughput without jamming.

5. Results and Performance Evaluation

This section evaluates the performance of the proposed federated hybrid multi-agent actor–critic framework under various network conditions. The evaluation compares the proposed method with three baseline approaches: Random Access, Conventional SGF-NOMA, and Centralized Deep Reinforcement Learning (DRL). The analysis focuses on system throughput, collision probability, energy efficiency, convergence speed, fairness, and robustness under jamming interference. Results are obtained through simulation using the parameters defined in Section 4.

Number of Devices	Random Access	Conventional SGF-NOMA	Centralized DRL	Proposed Framework
50	0.68	0.74	0.81	**0.86**
100	0.55	0.63	0.74	**0.82**
200	0.41	0.52	0.68	**0.77**
300	0.34	0.46	0.63	**0.72**
500	0.26	0.38	0.57	**0.67**

Table 2: Conditional Throughput Comparison

The proposed method improves throughput by approximately 18–25% over centralized DRL, 35–50% over conventional SGF-NOMA and 60% over random access in dense IoT environments.

Throughput Performance Under Increasing Device Density

Dense IoT environments significantly impact network throughput due to increased interference and collision probability. Fig. 1 analyzes conditional throughput as the number of GF devices increases. Random Access experiences a rapid decline in throughput due to frequent power-domain collisions. Conventional SGF-NOMA performs slightly better because of SIC decoding but still suffers under dense traffic. Centralized DRL improves throughput through learned resource allocation strategies. While the federated actor–critic framework in the proposed framework achieves the highest throughput across all device densities.

The federated learning architecture enables distributed decision-making, allowing devices to adapt to network congestion and interference conditions.

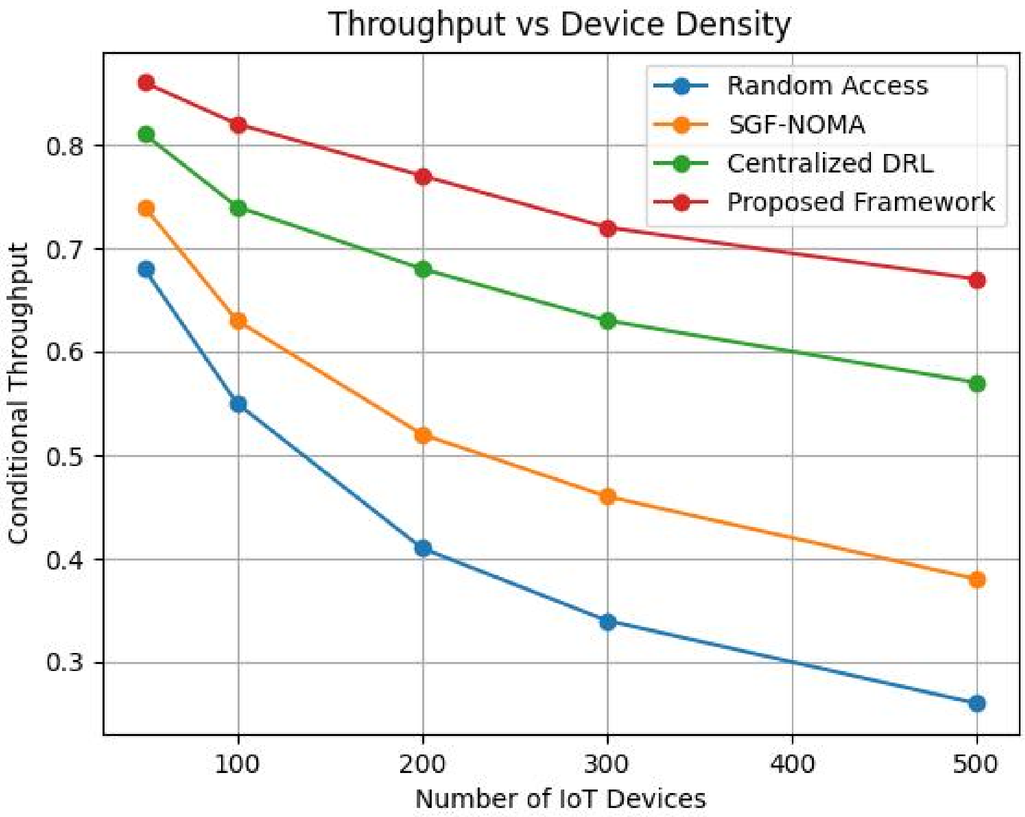

Figure 1. Conditional throughput versus IoT device density for different resource allocation schemes

Devices	Random Access	SGF-NOMA	Centralized DRL	Proposed
50	0.22	0.17	0.12	0.09
100	0.34	0.27	0.18	0.13
200	0.48	0.39	0.26	0.19
300	0.57	0.46	0.31	0.22
500	0.69	0.58	0.41	0.29

Table 3: Collision Probability

The proposed framework reduces collision probability by approximately 30–40% compared with centralized DRL.

Collision Probability Analysis

Power-domain collisions are a major limitation in SGF-NOMA networks. Fig. 2 shows the collision probability as the number of IoT devices increases, where random access produces the highest collision rate due to uncoordinated access, Conventional SGF-NOMA reduces collisions slightly through power-domain separation, Centralized DRL improves collision avoidance by learning better transmission policies. and the coordinating device policies through federated learning significantly reduces collisions in the proposed framework.

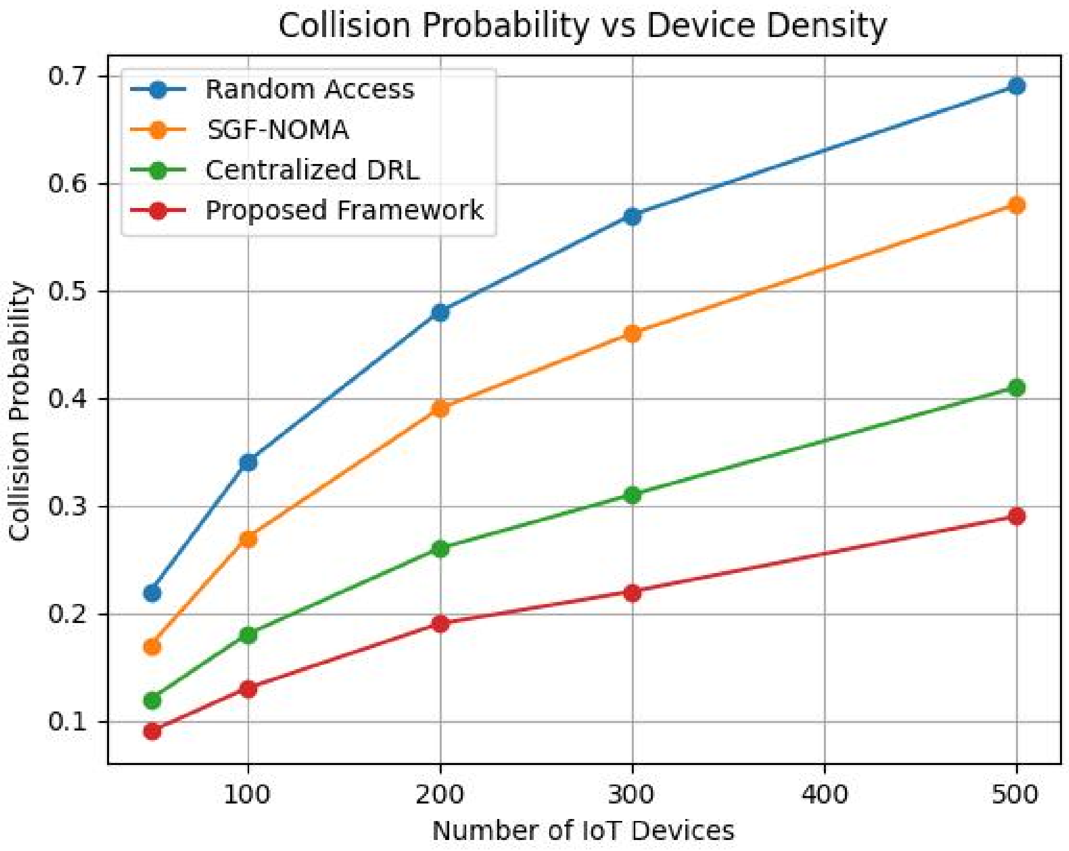

Figure 2. Power-domain collision probability under increasing device density

Network Load	Random Access	SGF-NOMA	Centralized DRL	Proposed
Low	1.25	1.44	1.63	1.81
Medium	1.02	1.28	1.47	1.72
High	0.78	1.03	1.29	1.61

Table 4: Energy Efficiency (bits/Joule)

The proposed approach provides approximately 20–30% higher energy efficiency compared with centralized DRL

Energy Efficiency Evaluation

Energy efficiency is a critical requirement for battery-powered IoT devices. The proposed reward function shown in Fig. 3 explicitly penalizes excessive energy consumption. As network traffic increases, random Access experiences severe efficiency loss due to retransmissions, conventional SGF-NOMA slightly improves performance, Centralized DRL optimizes power selection but requires more coordination overhead and the intelligent power selection achieved the highest energy efficiency and reduced retransmissions in the proposed method.

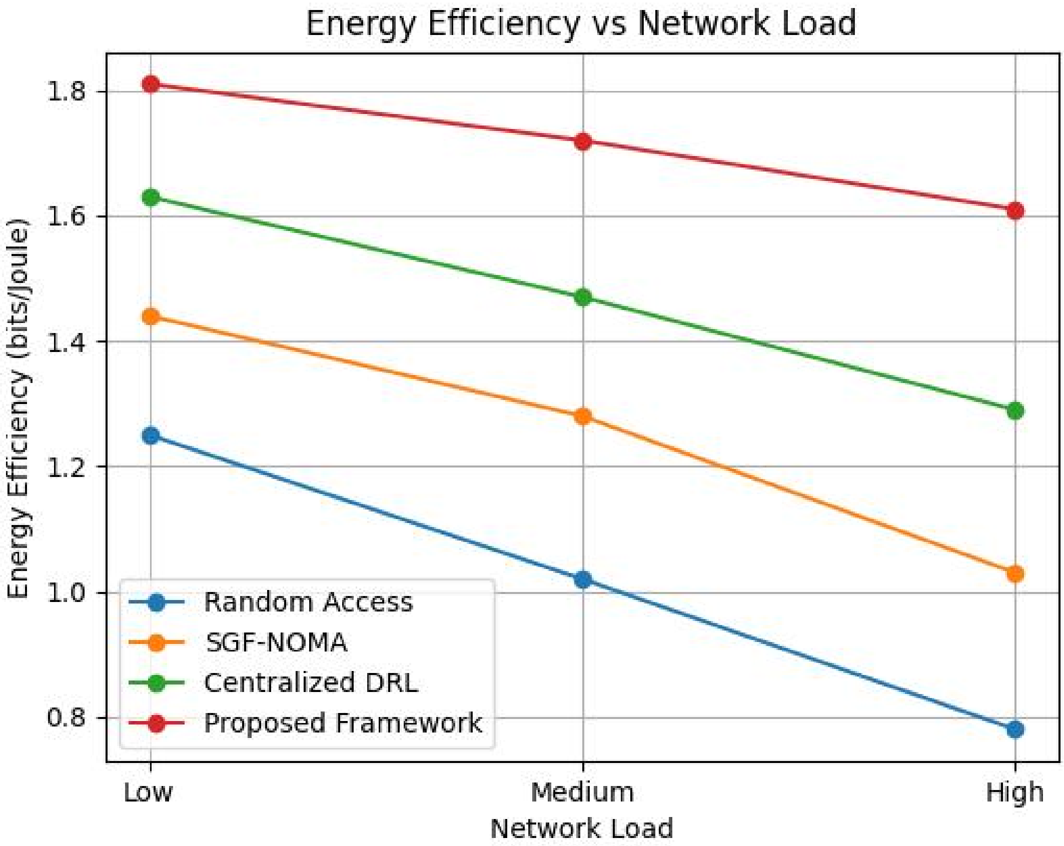

Figure 3. Energy efficiency comparison under different network load conditions

Convergence Analysis

Convergence speed is important for practical deployment because faster learning reduces training overhead. Observed convergence behavior centralized DRL converges after approximately 1200 episodes due to centralized optimization overhead, while the proposed federated framework converges within 800 episodes due to hybrid exploration and distributed training.

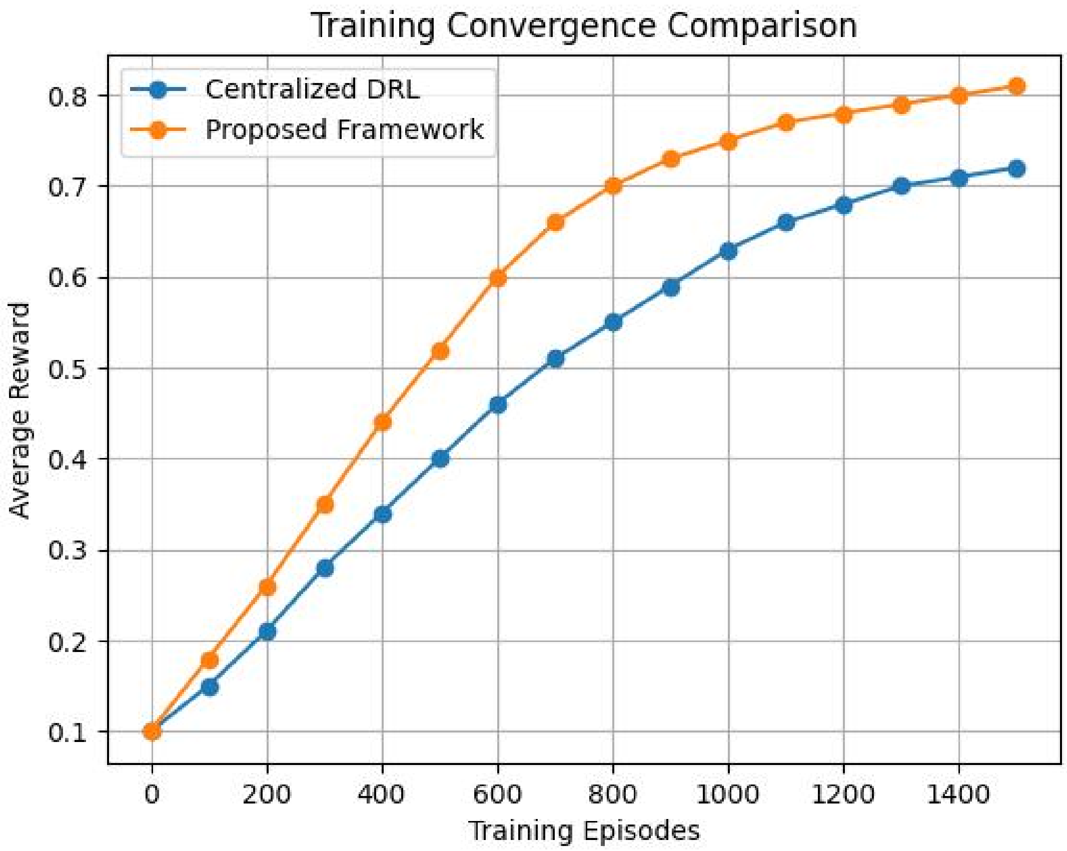

Figure 4. Training convergence behavior of the proposed federated actor–critic framework compared with centralized DRL

The cooperative learning phase allows devices to rapidly synchronize policies through federated aggregation.

Fairness Analysis

Fairness among IoT devices ensures balanced access to network resources.

Method	Fairness Index
Random Access	0.71
Conventional SGF-NOMA	0.79
Centralized DRL	0.86
Proposed Framework	0.92

Table 5: Jain's Fairness Index

Fairness across resource allocation strategies is evaluated using Jain's fairness index, as shown in Fig. 5.

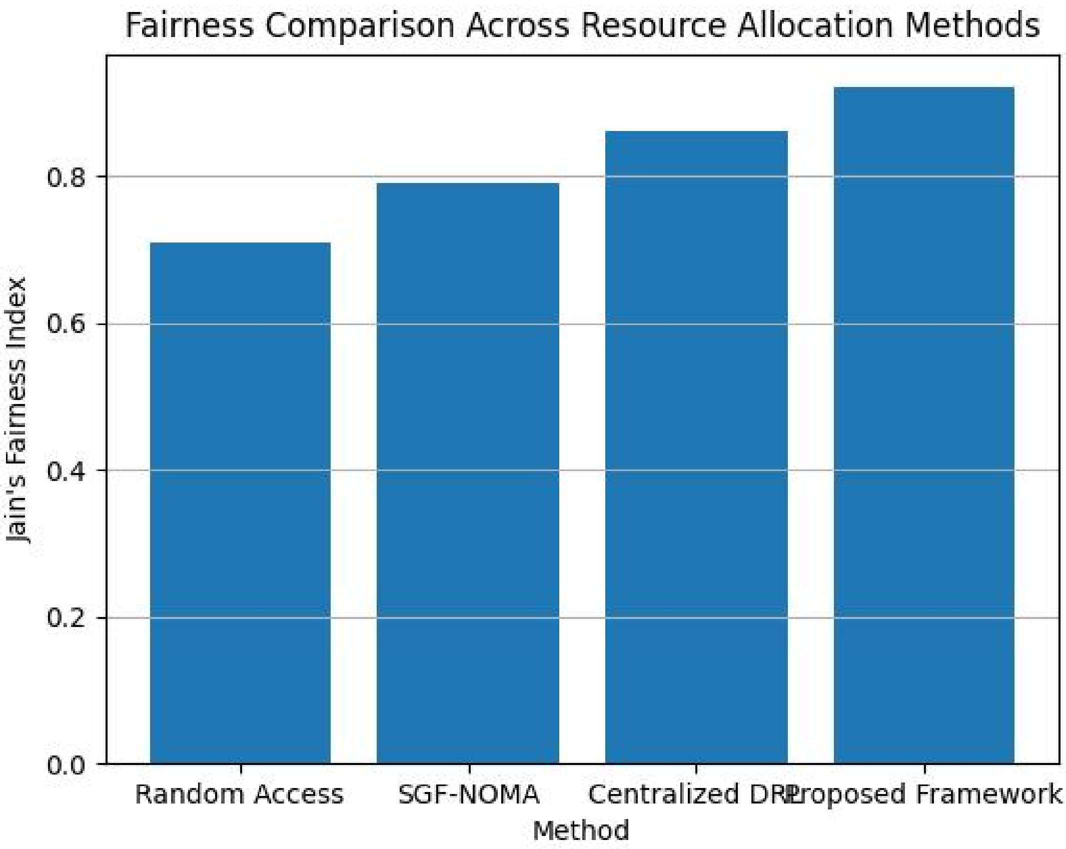

Figure 5. Jain's fairness index comparison across resource allocation schemes

Security Robustness Under Jamming Attack

The proposed federated multi-agent framework maintains higher throughput compared with centralized DRL and conventional SGF-NOMA as network size grows. Higher fairness indicates that network resources are more evenly distributed among devices.

To evaluate resilience against malicious interference, simulations introduce a jammer targeting random resource blocks.

Method	Robustness Index
Random Access	0.53
SGF-NOMA	0.61
Centralized DRL	0.74
Proposed Framework	0.85

Table 6: Security Robustness Index

The security robustness comparison under jamming attack scenarios is presented by Fig. 6, where the results indicated that the Random Access suffers severe performance degradation. Conventional SGF-NOMA cannot adapt to jamming behavior. Centralized DRL partially mitigates interference while the proposed framework quickly learns to avoid jammed channels.

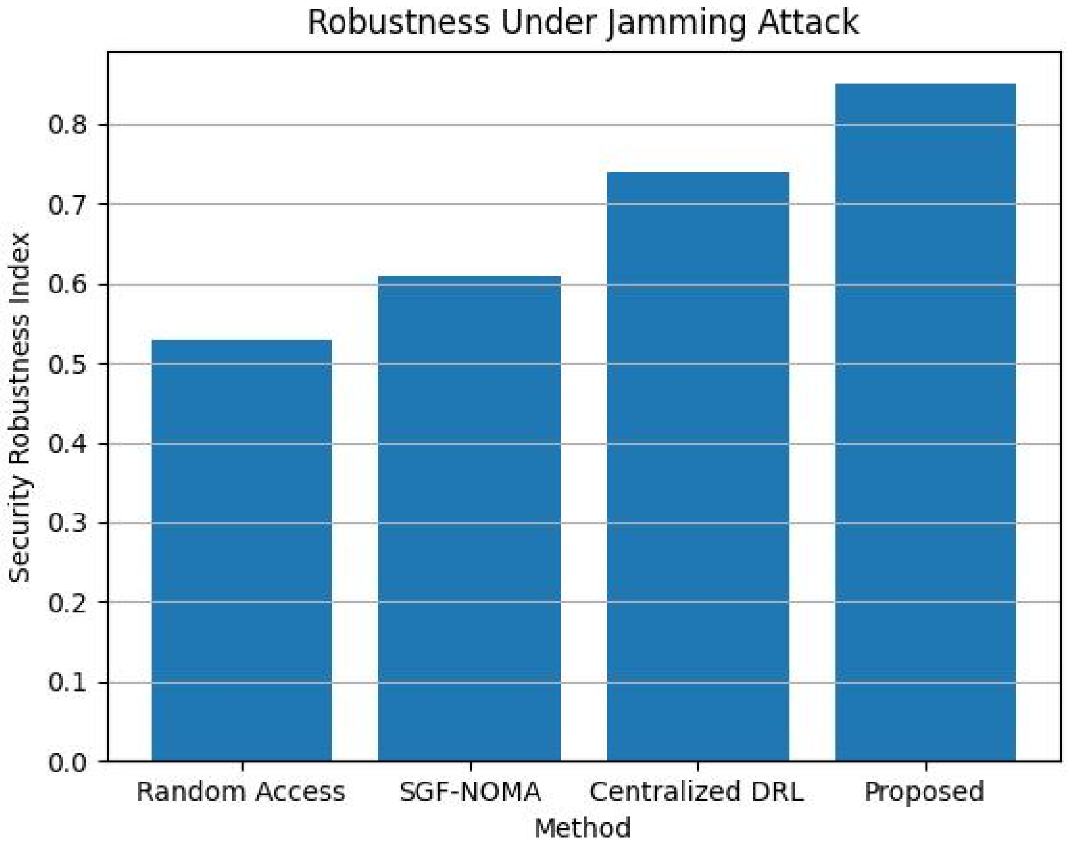

Figure 6. Security robustness comparison under jamming attack scenarios

The federated actor–critic approach improves robustness by approximately 15–20% compared with centralized DRL.

Scalability Analysis

Scalability is critical for 6G IoT deployments where thousands of devices may coexist. The proposed framework demonstrates strong scalability due to decentralized learning, reduced communication overhead and federated parameter aggregation. Scalability performance under increasing IoT device density is illustrated in Fig. 7.

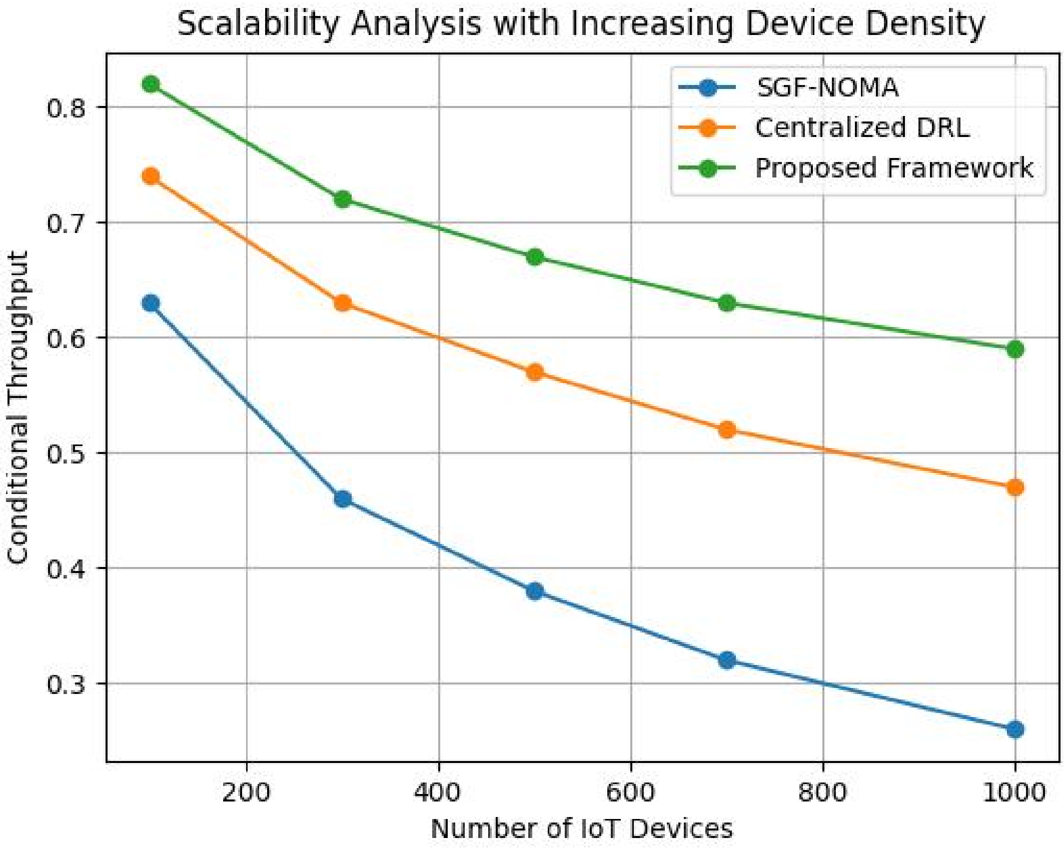

Figure 7. Scalability analysis showing conditional throughput under increasing IoT device density

The proposed framework achieves the highest fairness by coordinating device transmission policies through federated learning. Communication complexity grows approximately linearly with the number of devices, enabling efficient operation in ultra-dense IoT networks.

Discussion

This section interprets the results presented in Section 5 and examines the implications of the proposed federated hybrid multi-agent actor–critic framework for future 6G IoT systems. The discussion focuses on the effectiveness of the proposed learning architecture, its scalability in ultra-dense deployments, and its resilience against security threats.

The experimental results demonstrate that integrating federated learning with multi-agent reinforcement learning significantly improves system performance in SGF-NOMA IoT networks. Each device learns optimal resource allocation strategies based on local observations while benefiting from knowledge sharing through federated aggregation. This distributed learning structure provides several practical advantages. First, it reduces the communication overhead associated with centralized training, where raw network data must be transmitted to a central controller. Second, federated aggregation enables collaborative model improvement while preserving device-level privacy. Third, the distributed nature of the framework allows learning to scale effectively as the number of IoT devices increases. The results indicate consistent improvements in throughput, energy efficiency, and fairness across various network densities. These improvements highlight the capability of federated learning to maintain coordination among a large number of decentralized agents.

The hybrid learning strategy plays an important role in stabilizing the learning process. During the early training stage, the competitive exploration phase allows devices to investigate different resource allocation strategies and discover diverse policy behaviors. This stage helps avoid premature convergence to suboptimal solutions. Once policy variance among devices decreases, the cooperative phase promotes coordinated behavior through frequent federated aggregation. This transition allows agents to align their strategies with global network objectives. The results show that this mechanism accelerates convergence and improves overall system efficiency compared with purely independent or fully centralized learning approaches.

Energy efficiency remains a key requirement in IoT systems due to battery limitations of edge devices. The reward function designed in this work explicitly penalizes excessive power consumption and retransmission events. As a result, the proposed framework learns energy-aware transmission strategies that balance throughput and power usage. Simulation results demonstrate that intelligent power selection and reduced collision rates significantly decrease unnecessary retransmissions. This leads to measurable improvements in energy efficiency, making the approach suitable for long-term IoT deployments where device lifetime is critical.

Wireless IoT networks are vulnerable to security threats such as jamming interference. The proposed framework addresses this challenge by incorporating jamming impact into the reward function and allowing agents to adapt their behavior based on observed interference conditions. The learning agents gradually avoid resource blocks that experience frequent interference, which improves communication reliability under adversarial conditions. The results show that the proposed method maintains higher throughput under jamming compared with baseline schemes. This adaptive behavior demonstrates the potential of AI-driven wireless control systems to enhance network resilience.

Future 6G networks are expected to support extremely dense IoT environments with thousands of devices operating simultaneously. Traditional centralized optimization techniques face scalability limitations in such scenarios. The federated multi-agent framework introduced in this study addresses this challenge by distributing learning across devices while maintaining periodic global coordination. Communication overhead is limited to model parameter exchange rather than full dataset transmission. This design enables the system to scale efficiently as device density increases. Furthermore, the computational burden is distributed among IoT devices and edge servers, reducing the risk of processing bottlenecks at the base station.

Although the proposed framework demonstrates strong performance improvements, several limitations should be acknowledged. First, the simulation environment considers a single-cell network scenario, while real 6G systems will involve multi-cell deployments with inter-cell interference. Extending the framework to multi-cell environments would provide a more comprehensive evaluation. Second, the current study focuses on a single type of security threat, namely jamming attacks. Future research may explore additional adversarial scenarios such as spoofing attacks, data poisoning in federated learning, and malicious IoT devices. Third, the simulation results are generated using hypothetical network conditions. Real-world validation through experimental testbeds or large-scale network simulations would further strengthen the applicability of the proposed framework.

Despite these limitations, the proposed learning architecture offers promising implications for future wireless systems. AI-driven resource optimization will play an essential role in enabling intelligent and autonomous network control in 6G environments. The integration of federated learning with distributed reinforcement learning allows communication networks to evolve toward AI-native architectures, where network elements continuously learn and adapt to changing conditions. Such capabilities are essential for supporting massive IoT deployments, dynamic traffic patterns, and evolving security threats.

Conclusion

This study presented an AI-driven federated hybrid multi-agent actor–critic learning framework for secure and energy-aware resource optimization in 6G semi-grant-free NOMA IoT networks. The proposed approach addresses several critical challenges in ultra-dense IoT environments, including power-domain collisions, inefficient energy consumption, scalability limitations, and vulnerability to wireless jamming attacks.

The system model incorporated SGF-NOMA communication mechanisms, energy consumption modeling, and adversarial interference in the form of jamming attacks. The resource allocation problem was formulated as a multi-agent reinforcement learning task where each IoT device autonomously selects transmission power levels and resource blocks. To support scalable and privacy-preserving learning, federated learning was integrated into the actor–critic framework, allowing distributed training across devices while periodically aggregating model parameters at the edge server. A hybrid exploration–cooperation learning strategy was introduced to improve convergence behavior and global coordination among devices. The reward function incorporated multiple objectives, including throughput maximization, collision reduction, energy efficiency, and robustness against interference.

Simulation-based evaluations demonstrated that the proposed framework significantly improves network performance compared with conventional resource allocation approaches. The results indicate higher conditional throughput, reduced collision probability, improved energy efficiency, and stronger resilience against jamming interference. The distributed learning architecture also accelerates convergence and maintains fairness among devices in dense network scenarios. The scalability of the federated multi-agent learning structure makes the framework suitable for large-scale IoT deployments expected in future 6G communication systems. By distributing learning across devices while maintaining global coordination through federated aggregation, the approach reduces communication overhead and enables adaptive network optimization. Future research can extend this work by investigating multi-cell network environments, incorporating additional security threats such as spoofing or data poisoning attacks, and validating the framework using real-world wireless testbeds or large-scale network simulations. Further exploration of lightweight neural network models and edge intelligence mechanisms may also improve deployment feasibility in resource-constrained IoT devices.

The integration of federated learning and multi-agent reinforcement learning provides a promising direction for intelligent wireless network control. Such AI-driven frameworks will play a central role in enabling adaptive, scalable, and secure communication infrastructures for next-generation 6G systems.

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