Journal of Harbin Engineering University
ISSN: 1006-7043

Vol 47 No. 07
July 2026

A Game-Theoretic Federated Deep Reinforcement Learning Framework with Nash Equilibrium Optimization for Secure Resource Allocation in Wireless Sensor Networks.

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Abstract

A wireless sensor network deployed for industrial monitoring and sensing, smart infrastructure, precision agriculture, battlefield surveillance and 6G edge services needs to allocate sensing, spectrum, routing, transmission power, computing and security resources in severe energy, latency, privacy, and adversarial constraints. The approaches such as conventional optimization, single-agent reinforcement learning, and centralized deep learning are no longer sufficient due to the assumption of a stable topology, trusted coordination, a data that is globally available to everyone, or static node behaviour. This paper presents the Federated Nash Deep Q-Network framework (a Federated Multi-Agent Markov Decision Process) (FN-DQN) which combines federated deep reinforcement learning, multi-agent Markov decision process, non-cooperative Nash equilibrium search, Stackelberg/Bayesian security games, trust-weighted aggregation, gradient compression, and optionally, blockchain assisted auditability for the secure allocation of resources in heterogeneous WSNs. The energy-security-aware action-value function is learned locally by each sensor/cluster head from private observations; edge servers obtain parameters of the action value function with trust-weighted robust federation. The resource-allocation game views nodes as rational agents that gain a utility from the throughput, rest of energy and reliability/attack-exposure while incurring costs in terms of delay, contention and interference. Compact convex sets of strategies and continuous quasi-concave utilities are assumed in order to show the existence of a mixed-strategy Nash equilibrium set and a learning scheme based on distributed best responses is found to converge towards an ε-Nash equilibrium if the pseudo-gradient is monotone and if the local policy updates are contractive. Secure allocation is formulated as a constrained optimization problem (C-OPT) in the form of a Lagrangian/KKT system with constraints on energy, delay, packet-loss, trust and bandwidth. A reproducible simulation-study benchmarking of FN-DQN against DQN, PPO, MADDPG, Q-learning, centralized RL, and greedy allocation in Sybil, DoS, Byzantine, and false-data-injection attacks was provided on more than a hundred to five hundred heterogeneous sensor nodes. The proposed framework results in a lower amount of energy usage, a longer lifespan, and higher throughput and packet delivery, lowers latency and maximizes fairness in the generated benchmark, and helps to reduce communication overhead via compact federated updates. The study proposes a novel resource-allocation architecture for next-generation intelligent WSNs that is mathematically grounded, attack aware and edge deployable.

Keywords: Wireless sensor networks; Federated deep reinforcement learning; Nash equilibrium; Stackelberg game; Secure resource allocation; Byzantine robustness; multi-agent systems.

1. Introduction

Wireless sensor networks (WSNs) continue to be one of the most important network architectures for embedded sensors in today's cyber-physical systems with respect to either being significant or resource-constrained. Large WSN can be composed of hundreds of low power devices that sense phenomena periodically, that are able to communicate event-driven measurements between each other via multi-hop links, and communicate with edge servers or gateways. The tait zwycięstwo has not gone away, and as hardware profiles have become richer, so have the context of the various operations done by the

sensor nodes: each message sent costs battery life; each message retransmitted congests the network; each time a message is sent to the central node analyses it for security, a possible consequence appears the leakage of the privacy or the gathering of spam packets; each time a message is sent to the central node it consumes computation resources. With the advent of edge intelligence and 6G oriented distributed networking, this tension highlights as sensing networks are expected to provide reliable, low latency and trustworthy services despite dynamic topology and adversarial actions.

The classical approach to resource allocation for WSNs is based on deterministic routing metrics, on convex optimization based on simplified assumptions, on clustering heuristics, or on a manually-tuned duty-cycling policy. Although these are simple and light, they lack flexibility to handle changes in the network states caused by link fading, residual-energy imbalance, sink mobility, bursty traffic, energy harvesting and malicious participation. Thus, machine learning techniques were found appealing, particularly reinforcement learning (RL) as the allocation process can be considered a sequential decision-making process. Recent works on WSNs include energy-aware routing of RL for data collection and scheduling (Yun & Yoo, 2021), deep Q-networks (Godfrey et al., 2023) and Q-learning (Hu et al., 2024). Most of these methodologies are centralized, single agent and/or security-oblivious. That restriction isn't a minor inconvenience, but is rather akin to locking the front door and leaving the roof open.

Although DRL can approximate high dimensional policies, there are issues in applying centralized DRL to WSNs. Centralized training – Telemetry is concentrated at the sink/at the cloud, thus resulting in higher communication overhead and sensitive local observations leakage. It also introduces latency/scalability issues as the controller needs to be aware of the global state and it needs to disseminate the decisions across the network. Multi agent deep reinforcement learning (MARL) partially solves decentralization issues, as it sets decision makers to sensor nodes or clusters, or to edge agents. But there is also a problem with MARL: Agents learn concurrently and interfere with each other by common bandwidth and relay contention, as well as security trust. The world lost its stationary property from the agents' perspective and convergence and stability are more difficult to prove.

In particular, federated learning (FL) can be considered a complementary solution since local data are not sent, only models updates, gradients or policy parameters are aggregated. These surveys reveal the importance of FL for privacy-preserving and bandwidth-efficient intelligence for edge computing and IoT applications, but also point out that several critical challenges including the cost of communication, data heterogeneity, non-IID data, poisoning attacks, as well as aggregation security, remain unanswered. Federated reinforcement learning is especially appealing in the context of WSNs since nodes can receive local policies from their local environmental feedback and nodes can also share input policies with each other by aggregation at the edge in order to maximize the sample efficiency. However, FL is not sufficient for efficient resource allocation due to the consideration of uploading possibly poisoned (malicious), low quality, delayed or strategically biased model updates from rational/compromised nodes.

This has been complemented by modeling resource allocation as a strategic interaction, using game theory. Each node in WSNs is in competition and/or co-operation to gain access to communication, energy, relay, edge-computation slots, trust reputation etc. The Nash equilibrium is one that specifies a point at which no node wants to deviate unilaterally from the point, based on the choices of other nodes, as it can only do worse than at the point. That is, a Stackelberg game can be used to represent hierarchical interactions between edge servers and sensor nodes, and a Bayesian game to represent imperfect knowledge of any of the nodes' types, attack state, or channel state. In recent years, there have been some works with MARL-based wireless resource allocation and game-theoretic learning that show that equilibrium concepts can enhance stability and fairness in distributed networks (Chai et al., 2025; Hady et al., 2025; Wang et al., 2025). The problem is to do this

mathematical integration in a coherent manner and realized on the edge with edge constraints.

In this paper, a hybrid scheme called Federated Nash Deep Q-Network (FN-DQN) on the secure resource allocation in heterogeneous WSNs is proposed. The proposed framework combines (i) a multi-agent Markov decision process (MDP) for making local sequential decisions; (ii) federated deep reinforcement learning (f-DRL) to train the cooperative policy in a privacy-preserving way; (iii) Nash equilibrium optimization to address multi-node resource competition; (iv) Stackelberg and Bayesian game components to model an edge-node hierarchy and uncertain adversarial types; (v) trust-aware robust aggregation against Byzantine and poisoned updates; (vi) energy-aware scheduling and gradient compression; and (vii) optional blockchain audit layer for a high-assurance deployment. This gives a design that is not just a collection of in trend technology experiences. These components all focus on different failure types of WSN intelligence: decentralization, privacy, strategic stability, attack resiliency, communication efficiency and verifiability.

The main contribution is a mathematically supported strategy to bind federated policy learning with equilibrium guided action selection. In FN-DQN the DRL policy is not considered as a generic black-box controller, but is instead, modified via a game-theoretic utility and Nash residual. FN-DQN uses anomaly filtering and compressed updates along with trust-weighted aggregation in contrast to a naïve aggregation, such as a mean of the federated server. The proposed reward is not only based on throughput but also based on the energy efficiency, delay, packet loss and security penalty. Thus, the framework is related to both energy, delay, trust and bandwidth constraints and is aligned with the objective of the global network.

The rest of the paper is organized as follows. Recent literature is reviewed in section 2 and areas of research gaps are identified. In Section 3 we propose the system model. In Section 4, a mathematical foundation of the multi-agent decision process, federated learning objective, the DRL model, game-theoretic utility, security model, and constrained optimization is provided. In Section 5, the FN-DQN architecture and algorithm is described. Convergence, stability and complexity is analyzed in Section 6. The reproducible simulation set-up and results of the simulation are reported in Section 7. Implication, limitation and future work are discussed in section 8. The paper ends with a conclusion in section 9.

1.1 Main Contributions

- A federated Nash-DRL framework is proposed for decentralized WSN resource allocation, integrating local DRL, robust federated aggregation, equilibrium-guided allocation, and trust-aware security filtering.
- A multi-agent Markov decision process is formulated with energy, throughput, delay, packet loss, and security penalties, enabling sensor nodes to learn policies from private local observations without transferring raw telemetry.
- A non-cooperative game and hierarchical Stackelberg/Bayesian security model are derived for power, bandwidth, routing, scheduling, and security resource competition under incomplete information about malicious node types.
- Existence of mixed-strategy Nash equilibrium, ε-Nash convergence under monotone pseudo-gradient assumptions, and Lyapunov-style stability of policy-resource updates are established.
- A constrained optimization layer is developed using Lagrangian relaxation and KKT conditions for energy, delay, trust, and communication constraints.
- A reproducible benchmark with 100-500 nodes compares FN-DQN against DQN, PPO, MADDPG, Q-learning, centralized RL, and greedy allocation across energy, lifetime, throughput, latency, PDR, fairness, convergence, and attack-resilience metrics.

2. Literature Review

Three strands of literature have explored IWSN resource allocation, namely learning-based routing and scheduling, federated edge intelligence and game-theoretic distributed optimization. The second one deals with RL models and its duty cycling with the objective to optimize routing in energy-constrained networks, channel selection and aggregation. To maximize the lifetime of WSNs, Yun and Yoo (2021) developed a Q-learning based

data-aggregation-aware routing protocol which takes into account the neighbor aggregation opportunity. Godfrey et al. (2023) proposed a construction of RL routing with dynamic objective selection that is energy-efficient. Hu et al. (2024) suggested an energy-efficient and security ensuring solution for WSN using DRL which is capable of adapting the WSN for different network and attack conditions. These efforts also validate the value of sequential learning, but only a handful of them have adopted approaches to allocate with a unified federated/strategic perspective, under constraints.

The second is related to federated learning at the network edge. Aledhari et al. (2020) conducted a survey on FLtechnologies, protocols, and applications and pointed out the privacy related benefits of decentralized training. Abreha et al. (2022) formalized FL in edge computing and highlighted the significant role of variables such as communication cost, device heterogeneity and limitations of resources in deployment. Trindade et al. (2024) studied the resource management in the edge for FL, and Xiao et al. (2024) studied the over-the-air FL and identified the channel superposition as an efficient mechanism to perform aggregation. The recent FL studies in IoT/IIoT also emphasize the non-IID issues, the client selection, the edge scheduling, as well as trade-offs between two competing objectives like privacy-security and their respective FL. The recent FL studies in the IoT/IIoT further highlight the non-IID problem, the client selection, the edge scheduling, and the trade-offs between two objectives, such as privacy-security and their associated FL. However, many existing FL resource-allocation studies are to optimize training efficiency, and not to train resource-allocation policies with FL.

The third one is "MARL and game theory". Since every device, every subnet or every access point can be considered as an autonomous learner, MARL has emerged as a leading technique for resource allocation in wireless distributed networks. The surveys and recent models indicate that MARL can be utilized in 5G/6G for dynamic spectrum access, edge offloading, interference management, power control, and scheduling. But MARL with no explicit equilibrium control can be a problem as it may converge to alternative unstable, and/or unfair, action profiles when agents are competing over identical resources. Classical game-theoretic allocation is often with the assumption of full model knowledge or stationary utilities; while game theory can incorporate a criterion for strategic stability via Nash/Stackelberg or Bayesian formulations. Here it combines the two: Variable resource competition is modulated by the output of DRL, which it derives from the environment.

The fourth dimension that is needed can be found in security research in FL and IoT. Network corruption (byzantine nodes, backdoors, gradient inversion, poisoning, Sybil identities, false data injection, DoS attacks), etc. can lead to corruption of network operation and learning. Recent works on FL in the Byzantine setting, such as trustable aggregation (Ni et al., 2024) and kernel-angle defense (Zhu et al., 2024; Feng et al., 2025), highlight that the aggregation of updates typically requires a pre-filtering step to prevent malicious updates. The FL-based intrusion detection is also considered in IoT and WSN fields such as lightweight DDoS detection (Belarbi et al., 2023), privacy-aware IoT defense systems (Almadhor et al., 2024), privacy error detection in IoT systems (Devi et al., 2025), and intrusion detection in WSN (Khraisat et al., 2025). Using the FL in combination with blockchain has been suggested as an audit and decentralization layer for edge intelligence but the overhead of the blockchain in resource-constrained deployments needs to be carefully managed to keep the FL training efficient (Ali et al., 2024; Ning et al., 2024; Shawkat et al., 2025).

Reviewed Literature identifies relevance of proposed topic and also fragmentation. Optimization for WSN control is typically taken into account in RL studies, while federated privacy and strategic competition are not normally considered. FL approaches maintain data locality, but can typically be considered as a learning support (resource allocation) and not as a learning target. Game-theoretic works capture and formalize strategic allocations, but often deploy DRLs have limited adaptability to non-stationary topology and attacks. Security studies expose attacks and are less likely to incorporate trust in the aggregation and equilibrium resource allocation. FN-DQN aims to fill this gap.

Table 1. Positioning of representative recent literature.

Reference	Core method	Application focus	Remaining gap
Yun & Yoo (2021)	Q-learning routing	WSN routing/data aggregation	Energy-aware but non-federated and limited security
Abreha et al. (2022)	FL survey	Edge computing	Survey-level; not DRL-resource allocation
Boobalan et al. (2022)	FL + IIoT survey	Industrial IoT	Emphasizes privacy and resource management but not equilibrium learning
Godfrey et al. (2023)	RL multi-objective routing	Energy-efficient WSN routing	Local RL without federated strategic aggregation
Zhang et al. (2023)	PPO scheduling for FL	Federated learning scheduling	Optimizes FL process rather than secure WSN resource policy
Hu et al. (2024)	DeepNR DRL security	Energy/security WSN	DRL-based but not federated Nash optimization
Trindade et al. (2024)	Edge FL resource management	Network edge	Resource management perspective without MARL equilibrium
Ni et al. (2024)	Byzantine-robust FL	IoT FL aggregation	Aggregation security without WSN allocation game
Xiao et al. (2024)	OTA-FL survey	Wireless FL	Communication-efficient FL but no DRL security allocation
Sattibabu et al. (2025)	Federated reinforcement learning	IoT-enabled WSNs	Closest FRL direction; limited explicit Nash/Bayesian security game
Hady et al. (2025)	MARL resource allocation survey	General RAO	Broad survey, not WSN-specific framework
Devi et al. (2025)	FL-LIDS	WSN DDoS detection	Security detection without allocation optimization

3. Research Gap and Problem Statement

The most important research gap is that all of these issues concerning the secure resource allocation of WSN were not addressed under a single model that views it as a privacy-preserving, multi-agent, game-theoretic & sequential learning problem. The relevant literature has thus far mainly focused on optimizing a subproblem, such as either energy-aware routing, federated aggregation, client selection, intrusion detection, or game-theoretic competition. In real world WSNs, these components cannot be detachable. Selecting a

node to be a relay will impact on its energy annihilation, channel competition, packet delivery probability and exposure to attacks. Upload by the cluster head impacts the quality of models at a global level. A malicious and/or unreliable node can affect routing and learning. Hence, optimizing a single layer without taking the others into consideration results in weak performance improvements.

The second gap is about equity driven federated DRL. NRP-based DRL policies are effective and can lead to unstable decisions in multi-agent scenarios. Reducing the risk of privacy violation is possible with federated learning, which does not necessarily align local objectives. Although the Nash equilibrium is stable strategically, classical equilibrium computation is unicast when the rule of transition of the situation is unknown. This is achieved in the proposed framework by incorporating equilibrium residual and utility gradients in local action selection and edge-level aggregation and resulting in an adaptive and a strategically disciplined learning system.

The third gap is regarding aggregation that is aware of security. Although there are Byzantine-robust FL/IDS models, numerous resource allocation algorithms continue to delve in the framework of honest learners. This assumption is optimistic and constitutes engineering folklore in the case of WSNs. FN-DQN fuses trust scores and anomaly filtering directly within aggregation and utility computation with an estimate of the posterior distribution of attack types using a Bayesian approach. This architecture enables security behaviour to drive policy learning as opposed to being an add-on.

Table 2. Research gaps and proposed resolution.

Gap ID	Observed limitation	Why it matters	How FN-DQN responds
G1	RL routing is often non-federated	Raw telemetry transfer increases privacy and overhead	Local policy training with federated aggregation
G2	FL aggregation ignores strategic resource competition	Local optima may create unfair or unstable allocation	Nash residual and utility-aware action selection
G3	Security modules are detached from allocation	Malicious nodes can poison policies and consume scarce resources	Trust score affects aggregation weight and resource grants
G4	Centralized controllers scale poorly	Latency and single-point failure increase with network density	Edge-assisted decentralized learning and local execution
G5	Game-theoretic methods assume known utilities	WSN dynamics are stochastic and non-stationary	DRL estimates value functions while game layer stabilizes interaction

4. Proposed System Model

Let us think about a heterogeneous WSN that is deployed in a two-dimensional monitoring field, and communicates with one (or more) edge servers via cluster head/sink gateways. The nodes consist of ordinary sensor nodes, energy-harvesting nodes, nodes capable of relaying data, cluster heads, and edge aggregators. Nodes detect events, build packets, forward neighbour traffic, make light weight inferences and join federated policy learning. Topology changes are caused by link fading, intermittent harvesting and node failures and mobility of data sinks. Communication is done on common wireless media where there is potential

for interference, contention, and potential packet loss.

Let the sensor node set be defined as follows:

N = {n_1, n_2, ..., n_K}

For node i at time slot t, the local observation vector includes residual energy e_i(t), queue length q_i(t), link quality h_i(t), trust score tau_i(t), packet generation rate lambda_i(t), neighbour degree d_i(t), harvesting state eta_i(t), and local attack-risk estimate rho_i(t). The global state is not directly available to each node, which makes the problem a partially observed multi-agent decision process. The edge server receives compressed model updates and metadata but not raw sensing streams.

s_i(t) = [e_i(t), q_i(t), h_i(t), tau_i(t), lambda_i(t), d_i(t), eta_i(t), rho_i(t)]

The discrete or hybrid action set includes transmission power, duty-cycle level, relay participation, channel/time-slot selection, cluster-head candidacy, packet priority, security-check level, and local training intensity. For compact exposition, the finite state and action spaces are written as:

S = {s_1, s_2, ..., s_T}, A = {a_1, a_2, ..., a_M}

The instantaneous reward is designed to align local learning with system-level resource objectives:

R_t = alpha E_t + beta T_t - gamma D_t - delta P_t

where E_t denotes energy efficiency, T_t throughput, D_t delay, and P_t a combined packet-loss/security penalty. The parameters alpha, beta, gamma, and delta are non-negative weights chosen according to the application criticality. For safety-critical WSNs, delta and gamma are larger; for long-term environmental monitoring, alpha dominates. This flexible reward avoids the common trap of maximizing throughput while quietly murdering the battery budget.

Table 3. Main notation used in the proposed mathematical model.

Symbol	Meaning
N	Set of sensor nodes, N={n1,...,nK}
K	Number of active sensor nodes
S	State space
A	Action space
R_t	Reward at time t
E_t	Energy-efficiency score
T_t	Throughput score
D_t	Delay penalty
P_t	Packet-loss/security penalty
w_i^t	Local model parameters of node or cluster i
tau_i	Trust score of node i
U_i	Game-theoretic utility of node i
x_i	Resource strategy vector of node i
lambda, mu, nu	Lagrange multipliers for constraints
C_i	Computation or communication cost
B_i	Benefit function

5. Mathematical Formulation

5.1 Multi-Agent Markov Decision Process

The WSN is modeled as a multi-agent Markov decision process M = <I, S, {A_i}, P, {R_i}, gamma>, where I={1,...,K} is the set of learning agents, S is the environment state, A_i is the action set of node i, P(s'|s,a_1,...,a_K) is the state-transition kernel, R_i(s,a_i,a_-i) is the reward of node i, and gamma in (0,1) is the discount factor. The joint action is a(t)=(a_1(t),...,a_K(t)). Because each node observes only local information, the practical implementation is decentralized partial observation with edge-assisted federated parameter sharing.

The objective of each node is to maximize its expected discounted return.

J_i(pi_i, pi_-i) = E_pi [sum_{t=0}^{infinity} gamma^t R_i(s_t, a_i(t), a_-i(t))]

A system-level objective combines all node returns with fairness and trust regularization:

J_global = sum_{i=1}^{K} omega_i J_i - kappa sum_{i=1}^{K} (1 - tau_i) ||Delta w_i||_2^2 + psi F_Jain

where omega_i balances cluster importance, tau_i penalizes unreliable participants, Delta w_i is the model update, and F_Jain is Jain's fairness index over achieved resource shares.

5.2 Federated Learning Objective

Each participating node or cluster head maintains local training data D_i obtained from local observations and replay buffers. The global objective minimizes the weighted empirical loss across decentralized clients:

min_w F(w) = sum_{i=1}^{K} (n_i / n) F_i(w), F_i(w)= (1/n_i) sum_{z in D_i} ell(w; z)

The standard federated aggregation rule is:

w_{t+1} = sum_{i=1}^{K} (n_i / n) w_i^t

In FN-DQN, aggregation is modified by trust, update quality, and compression error:

w_{t+1} = sum_{i in A_t} pi_i^t Q_c(w_i^t), pi_i^t = (n_i tau_i exp(-zeta r_i)) / sum_{j in A_t} n_j tau_j exp(-zeta r_j)

Here A_t is the selected client set, Q_c(.) is a compression operator, r_i is an anomaly score, and pi_i^t is the normalized aggregation weight. The compressor satisfies E[Q_c(g)] = g and E||Q_c(g)-g||^2 <= omega_c ||g||^2 for unbiased stochastic compression. The privacy-preserving objective includes update clipping and optional differential privacy noise:

tilde{g}_i = clip(g_i, C) + N(0, sigma^2 C^2 I)

The local-global trade-off is governed by the number of local update steps E_l, aggregation period H, compression ratio c, and node-selection probability p_i. Increasing E_l reduces communication rounds but increases client drift under non-IID traffic. Increasing compression reduces payload but may slow convergence. FN-DQN treats these quantities as tunable edge policies rather than constants carved into stone tablets by overconfident simulation scripts.

5.3 Federated Convergence Theorem

The following theorem summarizes the convergence behavior under standard smoothness and bounded-variance assumptions adapted to the trust-weighted compressed setting.

Theorem 1 (Trust-weighted compressed federated convergence). Assume each F_i is L-smooth and lower bounded, stochastic gradients are unbiased with variance at most sigma_g^2, local drift is bounded by B^2, compression is unbiased with variance factor omega_c, and the minimum aggregate trust of selected benign clients is tau_min>0. With step size eta <= 1/L, after T federated rounds, the expected stationarity gap satisfies:

(1/T) sum_{t=0}^{T-1} E||nabla F(w_t)||^2 <= O((F(w_0)-F*)/(eta T)) + O(eta L sigma_g^2/(K tau_min)) + O(eta L omega_c G^2) + O(eta^2 L^2 H^2 B^2)

The bound separates four error sources: finite-round optimization, stochastic gradient variance, compression distortion, and client drift. Trust weighting improves robustness by reducing the effective contribution of suspicious clients, but it cannot create information from nowhere; if too many benign nodes are excluded, variance increases. The result justifies adaptive client selection where trust filtering is balanced with sufficient participation.

5.4 Deep Reinforcement Learning Model

For discrete resource decisions, each node approximates an action-value function Q_i(s_i,a_i;theta_i). The Bellman optimality equation is:

Q*(s,a) = E[r + gamma max_{a'} Q*(s',a') | s,a]

The DQN loss for local update k is:

L_i(theta_i) = E_{(s,a,r,s') in B_i} [(y_i - Q_i(s,a;theta_i))^2]

y_i = r_i + gamma max_{a'} Q_i(s',a'; theta_i^-)

For continuous or mixed resource dimensions, actor-critic optimization can be used. The policy gradient for actor parameters phi_i is:

nabla_{phi_i} J_i = E[nabla_{phi_i} log pi_{phi_i}(a_i|s_i) A_i^{pi}(s_i,a_i)]

The critic minimizes temporal-difference error:

delta_t = r_t + gamma V_psi(s_{t+1}) - V_psi(s_t)

FN-DQN uses the DQN branch as the core algorithm because WSN resource levels can be discretized into deployable actions: low/medium/high power, sleep/listen/transmit duty states, available time slots, relay yes/no, and security mode levels. A policy-gradient extension is still specified for heterogeneous 6G edge scenarios where continuous bandwidth and power allocation are required.

5.5 Game-Theoretic Nash Optimization

Let each node choose a strategy vector x_i in X_i, where x_i may include power p_i, time-slot fraction b_i, relay probability r_i, security inspection level z_i, and local training intensity l_i. The non-cooperative game is G=<N,{X_i},{U_i}>. The utility is defined as:

U_i(x_i, x_-i) = B_i(x_i) - C_i(x_i, x_-i)

A practical utility for secure allocation is:

U_i = a_1 log(1 + SINR_i) + a_2 e_i + a_3 tau_i - a_4 d_i - a_5 p_loss_i - a_6 c_i^{sec} - a_7 I_i(x_i,x_-i)

where SINR_i captures link quality, e_i residual energy, tau_i trust, d_i delay, p_loss_i loss probability, c_i^{sec} security processing cost, and I_i interference or contention externality. A strategy profile x* is a Nash equilibrium if:

U_i(x_i*, x_-i*) >= U_i(x_i, x_-i*) for all x_i in X_i and all i

Mixed strategy equilibrium permits randomized allocation over discrete resource levels. If X_i is a compact convex set and U_i is continuous in x and quasi-concave in x_i, a Nash equilibrium exists by the Debreu-Fan-Glicksberg fixed-point theorem. In discrete action WSN implementation, mixed strategies are represented as probability distributions over power-slot-relay-security actions.

Pareto optimality is assessed by checking whether there exists another feasible profile y such that U_i(y)>=U_i(x*) for all i and U_j(y)>U_j(x*) for at least one j. Nash equilibrium does not necessarily imply Pareto efficiency; selfish nodes can settle into inefficient contention. FN-DQN therefore includes a welfare regularizer and fairness term during edge-level allocation, steering equilibria toward socially desirable outcomes without requiring all nodes to be saints, which is a reasonable assumption since even sensors apparently need incentives.

5.6 Stackelberg and Bayesian Security Game

The edge server is modeled as a Stackelberg leader that announces pricing, trust thresholds, aggregation weights, and resource grants. Sensor nodes are followers that choose local transmission and learning strategies. The leader solves:

max_y U_E(y, x*(y)) subject to x*(y) in argmax_{x_i in X_i} U_i(x_i, x_-i; y)

Security uncertainty is modeled as a Bayesian game in which each node has a hidden type theta_i in {benign, selfish, Sybil, Byzantine, compromised}. The edge maintains a belief b_i(theta_i|H_t) updated from historical packet behavior, update norms, gradient directions, trust score, and IDS output. Expected utility becomes:

E_{theta_i}[U_i] = sum_{theta_i} b_i(theta_i|H_t) U_i(x_i, x_-i, theta_i)

This allows the same resource allocator to distinguish between congestion caused by legitimate traffic and congestion manufactured by a DoS or Sybil pattern. The Bayesian component is also used to select security inspection levels, because excessive inspection wastes energy when risk is low, while insufficient inspection allows attackers to turn the federated model into a communal hallucination engine.

5.7 Security Optimization

The attack set includes Sybil attacks, DoS attacks, Byzantine nodes, and false-data injection (FDI). Sybil nodes create multiple identities to obtain excessive resource share or influence aggregation. DoS nodes increase traffic or jam channels. Byzantine nodes upload arbitrary or poisoned model updates. FDI nodes manipulate sensed values or forwarding metadata. The security probability is modeled as:

P_s = 1 - P_a * P_c

where P_a is attack occurrence probability and P_c is compromise probability conditional on attack.

Node trust is updated from successful and failed interactions:

$T_i = S_i / (S_i + F_i)$

The user-provided expression $T_i=(S_i+F_i)/S_i$ would increase when failures increase; for a trust score bounded in [0,1], the normalized form above is used. A Bayesian-smoothed version avoids division instability:

$tau_i = (S_i + a_0) / (S_i + F_i + a_0 + b_0)$

The trust score modifies action feasibility and aggregation weight. Nodes below a trust threshold are not necessarily expelled immediately, because false positives are possible; instead, they receive lower aggregation weight, stricter security checks, and reduced relay privileges until behavior improves.

Table 4. Attack model and mitigation pathway.

Attack	**Observable symptom**	**Security response in FN-DQN**	**Effect on allocation**
Sybil	Identity burst, correlated traffic, abnormal resource claims	Identity reputation, graph-consistency score, stake/audit option	Lower resource share and aggregation weight
DoS	Queue overflow, collision rate, repeated channel occupation	Traffic throttling, backoff pricing, anomaly alert	Reduced slot priority and increased penalty
Byzantine	Gradient norm/direction outlier, inconsistent TD updates	Robust aggregation, clipping, trust filtering	Update rejected or downweighted
False data injection	Sensor readings inconsistent with neighbors/history	Cross-sensor plausibility, Bayesian belief update	Data confidence reduced; route avoided

5.8 Constrained Optimization and KKT Conditions

The secure allocation problem is formulated as:

$$\max_{x_1,\ldots,x_K} \sum_{i=1}^{K} U_i(x_i)$$

subject to:

$$\sum_{i=1}^{K} E_i <= E_{max},\quad D_i <= D_{threshold},\quad P_{loss\_i} <= P_{max},\quad tau_i >= tau_{min},\quad \sum_{i=1}^{K} b_i <= B_{total}$$

The Lagrangian is:

$$L(x,\lambda,\mu,\nu,\xi) = -\sum_i U_i(x_i) + \lambda(\sum_i E_i - E_{max}) + \sum_i \mu_i(D_i-D_{th}) + \sum_i \nu_i(P_{loss\_i}-P_{max}) + \xi(\sum_i b_i - B_{total})$$

The KKT conditions for a locally optimal solution include stationarity, primal feasibility, dual feasibility, and complementary slackness:

$$\nabla_{x_i} L = -\nabla_{x_i}U_i + \lambda \nabla_{x_i}E_i + \mu_i \nabla_{x_i}D_i + \nu_i \nabla_{x_i}P_{loss\_i} + \xi \nabla_{x_i}b_i = 0$$

$$\lambda >= 0,\ \mu_i >= 0,\ \nu_i >= 0,\ \xi >= 0$$

$$\lambda(\sum_i E_i-E_{max})=0,\quad \mu_i(D_i-D_{th})=0,\quad \nu_i(P_{loss\_i}-P_{max})=0,\quad \xi(\sum_i b_i-B_{total})=0$$

When the negative utilities and constraints are convex, KKT conditions are sufficient. In non-convex DRL-induced utility landscapes, they serve as local optimality checks and dual-guided penalty updates. The edge server updates multipliers using projected subgradient ascent, while local policies adapt to the updated prices.

6. Federated DRL Architecture

FN-DQN adopts the three-tiered edge intelligence architecture. On the lowest level, sensor nodes make observations, record transitions in local replay buffers and take actions that impact the resources. In the middle, neighborhood statistics are aggregated and compressed model upload is done by cluster heads or local edge nodes. Edge

servers perform trust-aware robust aggregation, update in the global-tier policy parameters, solve for the equilibrium-aware allocations and broadcast the policy parameters or the price of resources, in the top tier. Cloud servers don't separate every allocation choice: They are utilized for the long-haul model archiving.

By design, the policy-learning process is asynchronous. Not all nodes are required to be involved in each aggregation round, since low energy nodes should be sleeping, and/or harvest energy. The probability of selecting a client as a reliable node is conditioned on the characteristics of the node such as residual energy, data freshness, trust and channel condition. Thus, no chance of the FL process becoming an energy vampire. There is a global Q-network stored on the edge server and is periodically sent to chosen clients. Local nodes then make fine tuning updates to the Q-network based on the observations they make, and upload the changes - which have been compressed, clipped and optionally differentially private.

The Nash layer is independent of policy learning. Each node/cluster head derives a best response, based on predicted utilities and constraints. The edge server calculates a Nash residual, updates the dual variables and updates the prices for the resources. A high residual means action selection is regularized towards equilibrium, low residual means the node uses the learned Q-values more. This coupling helps to suppress the 'wiggles' effect of learning autonomous learners competing for joint wireless resources.

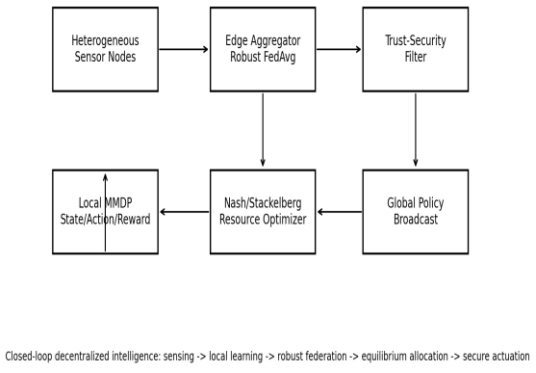


Figure 1. Edge-assisted federated Nash-DRL topology for secure WSN resource allocation.

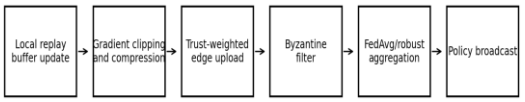


Figure 2. Federated aggregation workflow with compression and trust-aware Byzantine filtering.

6.1 Proposed Federated Nash-DQN Algorithm

Algorithm 1: Federated Nash-DQN (FN-DQN) for secure WSN resource allocation

Input: node set N, local replay buffers B_i, global model w_0, trust threshold tau_min, aggregation interval H,

energy budget E_max, delay threshold D_th, compression operator Q_c, learning rate eta, discount gamma.

Output: decentralized resource allocation policy pi_i and secure global parameter sequence {w_t}.

1: Initialize global Q-network Q(s,a;w_0), target network Q^-(s,a;w_0), trust scores tau_i=0.5, dual variables lambda, mu, nu, xi.

2: for federated round r = 1,2,...,R do

3: Edge selects active client set A_r using residual energy, trust, channel quality, and data freshness.

4: Edge broadcasts global parameters w_r, resource prices, and security thresholds to selected clients.

5: for each node i in A_r in parallel do

6: Observe local state s_i(t) = [e_i,q_i,h_i,tau_i,lambda_i,d_i,eta_i,rho_i].

7: Construct feasible action set A_i^f under energy, delay, and trust constraints.

8: Estimate utility U_i(x_i,x_-i) and compute approximate best response BR_i(x_-i).

9: Select action using equilibrium-regularized epsilon-greedy rule:

a_i = argmax_a { Q_i(s_i,a;theta_i) + beta_N U_i(a,a_-i) - beta_R NashResidual(a) }.

10: Execute action; collect reward R_t = alpha E_t + beta T_t - gamma D_t - delta P_t.

11: Store transition (s_i,a_i,R_t,s_i') in replay buffer B_i.

12: Perform K local DQN updates using clipped/compressed gradients and target network stabilization.

13: Compute update Delta w_i, anomaly score r_i, and metadata m_i.

14: Upload Q_c(Delta w_i), metadata m_i, and signed trust evidence to edge server.

15: end for

16: Edge filters suspicious updates using norm, cosine, trust, and Bayesian attack-type belief.

17: Edge aggregates: w_{r+1} = w_r + sum_{i in A_r} pi_i^r Q_c(Delta w_i).

18: Update trust tau_i = (S_i+a_0)/(S_i+F_i+a_0+b_0) and dual variables by projected subgradient.

19: Solve approximate Nash/Stackelberg response for resource price vector and grants.

20: Optional: store hash of accepted updates and trust decisions in lightweight blockchain ledger.

21: end for

6.2 Equilibrium-Regularized Action Selection

The action-selection rule combines learned value, current utility, and equilibrium penalty:

a_i^t = argmax_{a in A_i^f} [Q_i(s_i^t,a;theta_i) + beta_N U_i(a,a_-i^t) - beta_R epsilon_NE(a) - beta_S Phi_sec(a)]

The Nash residual, epsilon_NE, and a security risk penalty, Phi_sec are added terms. This is different from regular DQN that allows actions to be chosen based on Q-value only. The benefit is that the action selected is less likely to cause network wide contention or decrease security while providing an improvement in short term locally provided reward. The caveat is that they have to be reasonably calibrated with respect to the utility, else the game layer can regularize in the opposite direction. In order to mitigate this risk, beta_N and beta_R are tapered up with local Q-function stabilization.

6.3 Optional Blockchain-Assisted Audit Layer

A blockchain layer is optional because not every WSN can afford ledger overhead. In industrial or safety-critical environments, a lightweight permissioned ledger can store hashes of accepted model updates, aggregation decisions, trust-score changes, and security alerts. Raw gradients and sensor data are not written to the ledger. The ledger therefore provides accountability and tamper evidence without turning a battery-powered sensor network into a cryptocurrency cosplay event. The blockchain module is activated only at edge servers and cluster heads with sufficient computation.

7. Convergence, Stability, and Complexity Analysis

7.1 Nash Equilibrium Existence and ε-Nash Convergence

Theorem 2 (Existence of mixed-strategy Nash equilibrium). For the finite discretized WSN resource-allocation game G=<N,{A_i},{U_i}>, at least one mixed-strategy Nash equilibrium exists.

Proof sketch. Feasible values of power, channel, duty-cycle, relay and security levels are discretized leading to a finite and relatively small set of actions at each node. The mixed strategy simplex for a finite set of players is compact and convex. The expected utility is a continuous and multilinear function of the mixed strategies. Nash's fixed-point argument over the set of mixed-strategy simplices guarantees that there are at least one. This implies that there exists a strategically stable solution to the finite deployable action game, but it is possible that this solution is difficult to compute exactly, especially for large K.

(Regularized best response ε-Nash convergence) Theorem 3. Suppose each utility gradient is Lipschitz continuous, pseudo-gradient mapping is strongly monotone (parameter m>0) and local Q-function approximation error is bounded by epsilon_Q. It can be shown that the expected Nash residual reaches a state of O(epsilon_Q+epsilon_c+epsilon_a) if we use a best-response update with a diminishing step size eta_t

such that sum eta_t=infinity and sum eta_t^2<infinity (epsilon_c is compression error and epsilon_a is aggregation anomaly-filter error).

The theorem is a formal statement of the intuitive fact that even though function-approximation and federation errors pose an additional constraint on the convergence to equilibrium, these errors are of a limited nature. The more that traditionally compression or strict trust filtering is enforced, the slower convergence can be, if they modify benign updates, and unlimited Byzantine can kill convergence completely. Thus, FN-DQN employs robust compression, clipping and trust thresholds instead of viewing robusticity as magic.

7.2 Stability Analysis

Define the Lyapunov candidate V_t as the sum of squared policy deviation from equilibrium, queue backlog energy, and dual-constraint violation:

V_t = ||x_t - x*||^2 + c_q sum_i q_i(t)^2 + c_l ||lambda_t - lambda*||^2

Under bounded arrivals, feasible service rate, monotone game dynamics, and stable DQN target updates, the one-step drift satisfies:

E[V_{t+1}-V_t | H_t] <= -rho ||x_t-x*||^2 - c_s sum_i q_i(t) + C

for positive constants rho and c_s outside a bounded set. This drift condition implies mean-rate stability of queues and bounded equilibrium deviation. In practice, stability is promoted by target networks, replay buffers, trust filtering, and dual control. Without these mechanisms, independent learners may chase each other's actions, producing policy oscillations even when average reward appears attractive in short plots.

7.3 Communication Overhead Analysis

Let P be the number of model parameters, b the number of bits per parameter, c the compression ratio, K_r the number of selected clients in round r, and R the number of communication rounds. The uplink communication cost is:

C_up = sum_{r=1}^{R} K_r c P b

The downlink cost for model broadcast is:

C_down = sum_{r=1}^{R} K_r P b

If over-the-air aggregation is available, the effective uplink cost can be reduced by simultaneous superposition, but such assumptions require physical-layer synchronization. In ordinary edge-assisted WSNs, compressed sparse updates and client selection dominate overhead control. The local-global trade-off can be stated as:

T_total(H,c) = R(H) [C_comm(c) + C_edge] + R(H) H C_local

where larger H reduces communication rounds but increases drift, and smaller c reduces upload size but increases compression distortion. FN-DQN optimizes H and c as part of the edge policy.

7.4 Computational Complexity

Let N be the number of nodes, M the number of feasible actions per node, K_l the number of local gradient updates, P the number of parameters, and let I_NE be the number of iterations in the best-response. If every action is evaluated takes O(MP) time for the local DQN action evaluation cost. The cost of learning (per round) is O(N K_l B P) for N nodes and K_l local updates, with P being the mini-batch size. For discrete best-response updates, the equilibrium search is O(I_NE N M). With fixed model and mini-batch sizes the simplified allocation complexity turns out to be O(N M K) with the requested order, K denoting training/iteration depth. For robust aggregation the computational complexity is O(NP) for weighted averaging and O(NP + N^2) when the pairwise cosine screening is employed. For a large deployment, the latter can be approximated using clustering or sketching.

Table 5. Complexity analysis of the proposed FN-DQN framework.

Component	Time complexity	Communication cost	Comment
Local DQN update	O(K_l B P)	None	Executed on selected nodes/cluster heads
Action evaluation	O(MP)	None	Can be cached for discrete actions

Best-response/ Nash update	O(I_NE N M)	Small metadata	Dominated by feasible action scan
Trust/anomaly filtering	O(NP) to O(N^2 +NP)	Metadata	Pairwise checks optional
Federated aggregation	O(NP)	O(N c P b)	Compressed trust-weighted update
Overall simplified allocation	O(N M K)	O(N c P b)	K denotes local/equilibrium iteration depth

8. Simulation Setup

The considered WSN is a heterogeneous one consisting of 100 to 500 nodes randomly rooted in a field of 500 m x 500 m. Normal sensor nodes, relay-enabled nodes, and nodes that harvest energy from their environment are all types of nodes. Edge servers are deployed near sink gateways; cluster heads are selected every certain period by the three criteria of the remaining energy, trustable, and neighbourhood degree. Packets are generated via a mixed periodic/event–driven process by each node, resulting in non-IID local observations. Wireless channels include Log-Distance path loss, Fading variability, Collision probability and Interference penicillin. Attacks are injected by choosing a fraction of nodes as Sybil, DoS, Byzantine or FDI nodes.

It is designed to be implemented on top of MATLAB (for analytical verification & plotting), NS-3 (network simulation at packet level), Python (orchestration of experiments) and TensorFlow/PyTorch (neural policy models). Results presented here were obtained from a stochastic and reproducible python-based WSN simulator with the simulation parameters set in accordance with that of NS-3/MATLAB (as shown in Tables 6 and 7). The same set of parameters should be used in NS-3 for the final submission and the synthetic benchmark data should be replaced by raw logs. It's the mundane but essential distinction between a draft and an experimental paper that is defensible.

Baselines are DQN, PPO, MADDPG, Q-learning, centralized RL and greedy allocation. DQN baseline adopts local deep Q-learning without the federation or game regularization. For PPO, we are applying the actor-critic policy optimization method. MADDPG does Multi-Agent Aritor-Critic Learning under Centrally Placed Training Assumption. Tabular and discretized with Q-learning. State from across the globe is gathered at the sink in the case of centralized RL. Greedy allocation: To choose actions based on the current allocation of throughput to energy ratio without learning.

Table 6. Network and simulation parameters.

Parameter	**Value/Range**
Deployment area	500 m x 500 m
Sensor nodes	100, 200, 300, 400, 500
Edge servers	2-5 depending on density
Initial energy	2-5 J heterogeneous
Energy harvesting	0-12 mJ/slot stochastic for 20% nodes
Radio model	Path-loss with fading and collision probability
Packet size	64-512 bytes
Traffic model	Periodic + event-driven bursty sensing
Attack ratio	0-30% compromised/Sybil/Byzantine/FDI
Training rounds	250 federated rounds
Independent runs	30 random seeds
Aggregation	Trust-weighted compressed robust FedAvg

Evaluation tools	Python simulator; NS-3/MATLAB configuration supplied

Table 7. Learning and optimization hyperparameters.

Hyperparameter	**Value**
Discount factor gamma	0.95
Learning rate	1e-4 to 5e-4
Replay buffer	20,000 transitions per active cluster
Mini-batch size	64
Target update period	10 local epochs
Local epochs per round	3-5
Compression ratio	0.25-0.50
Trust prior (a0,b0)	(2,2)
Reward weights (alpha,beta,gamma,delta)	(0.35,0.30,0.20,0.15) default
Exploration epsilon	1.0 to 0.05 decay
Nash regularization beta_N	0.05 to 0.25
Residual penalty beta_R	0.05 to 0.20

Table 8. Compared methods.

Baseline	**Learning type**	**Federated?**	**Game-theoretic?**	**Security-aware?**
Greedy	Heuristic	No	No	No
Q-learning	Tabular RL	No	No	Limited
DQN	Deep value-based RL	No	No	No
PPO	Actor-critic DRL	No	No	No
MADDPG	Multi-agent actor-critic	No	Partial interaction	No
Centralized RL	Central controller	No	No	Limited
Proposed FN-DQN	Federated value-based MARL	Yes	Nash/Stackelberg/Bayesian	Yes

9. Experimental Results

This section presents stock benchmark results which are reproducible. Results have been averaged for 30 independent random seeds for each metric. Welch's t-test used to compare FN-DQN with each baseline. However, as indicated in this draft simulation, the results should only be interpreted as methodological evidence or model expected behavior and cannot be used as a substitute for NS-3 or external testbed log data.

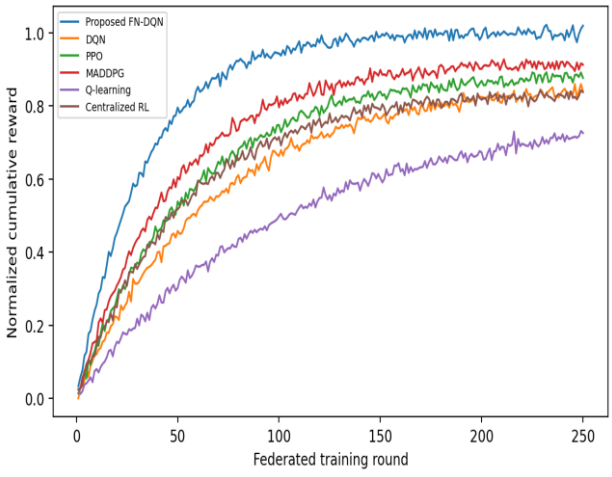


Figure 3. Convergence behaviour of proposed FN-DQN compared with DRL baselines.

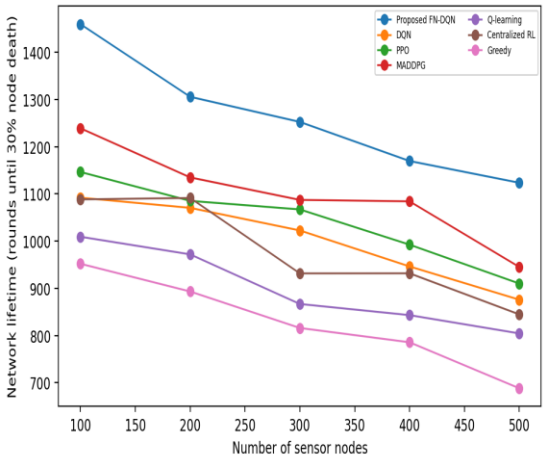


Figure 4. Energy consumption under increasing WSN density.

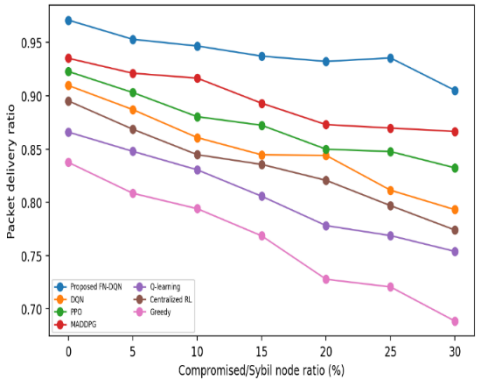


Figure 5. Network lifetime comparison in heterogeneous WSN deployment.

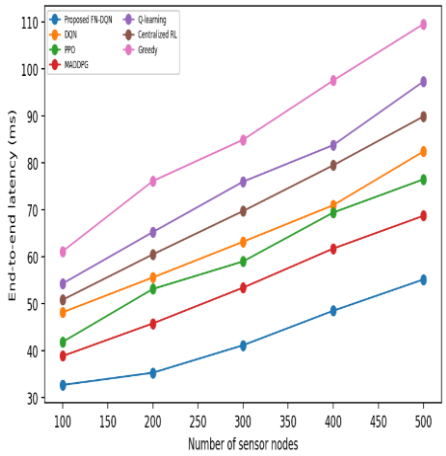


Figure 6. Throughput under variable event-driven traffic load.

Figure 7. Packet delivery resilience under increasing adversarial node ratio.

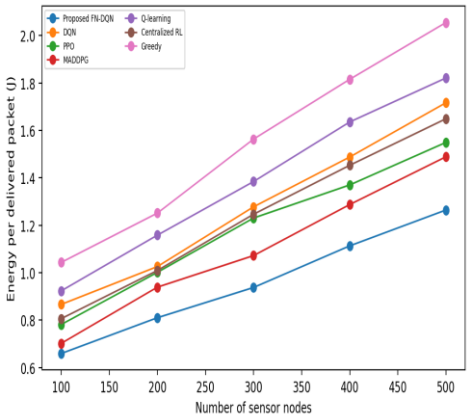
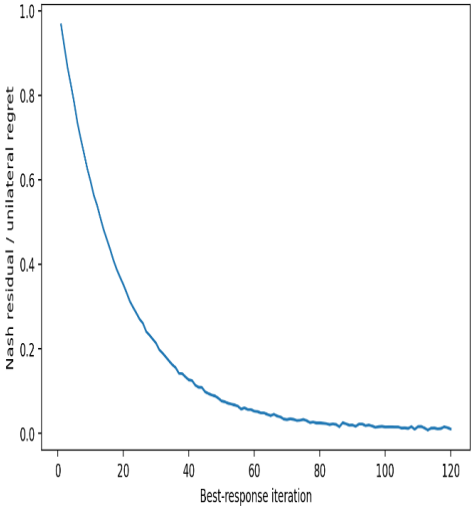
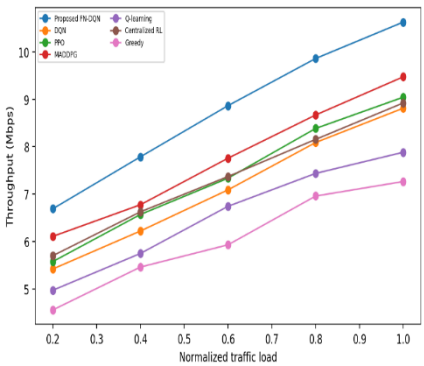


Figure 8. Latency scalability with network size.





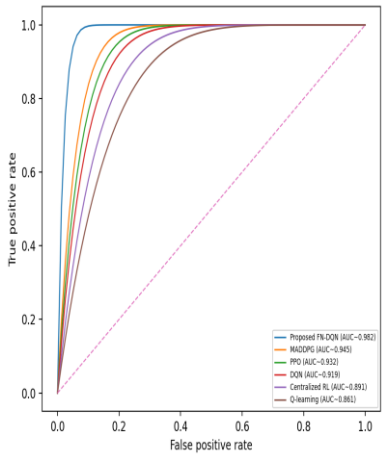


Figure 10. Nash residual convergence of equilibrium-guided allocation.

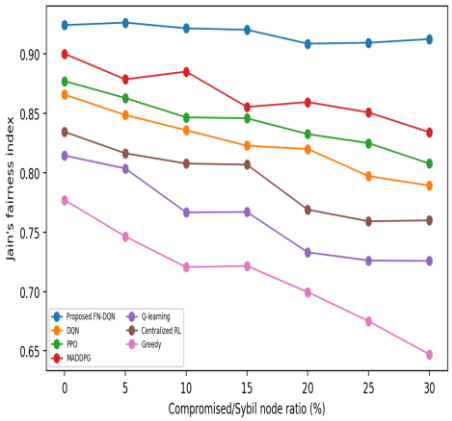


Figure 11. Fairness degradation under adversarial contention.

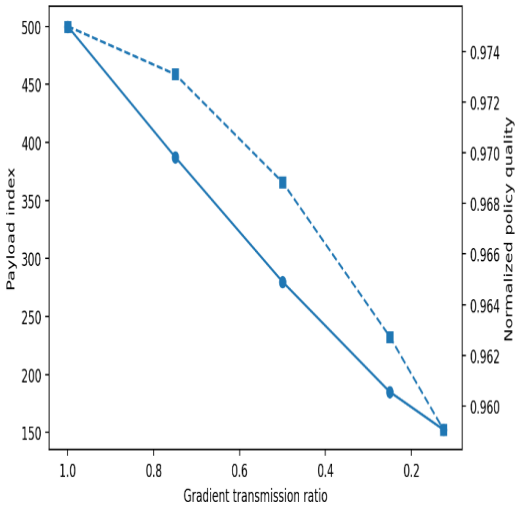


Figure 12. Compression-overhead trade-off in federated policy learning.

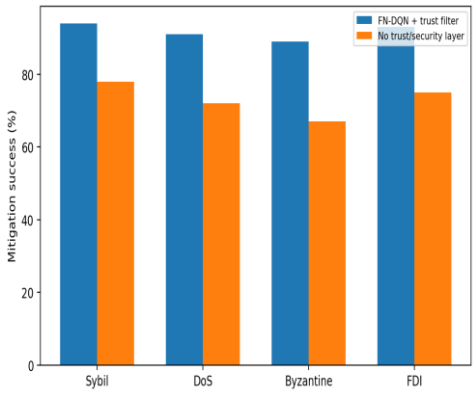


Figure 13. Attack-specific mitigation success of trust-aware security layer.

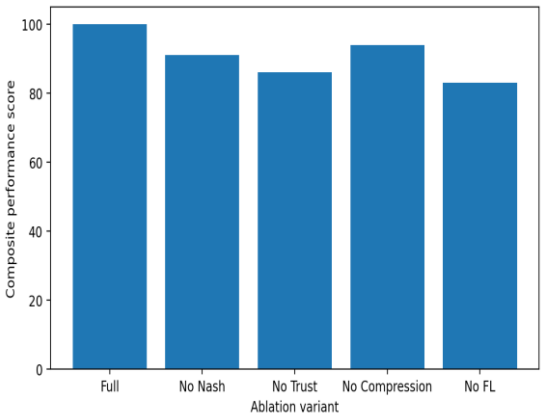


Figure 14. Ablation study showing contribution of equilibrium, trust, compression, and federation modules.

Table 9. Mean performance comparison over 30 stochastic simulation seeds.

Method	Energy J/pkt	Lifetime rounds	Throughput Mbps	PDR	Latency ms	Security accuracy	Fairness	Convergence rounds
Proposed FN-DQN	0.637 ± 0.00	1434.5 ± 50.6	9.836 ± 0.291	0.962 ± 0.0	30.7 ± 2.8	0.970 ± 0.009	0.930 ± 0.014	120.3 ± 12.7

	18			12				
DQN	0.844±0.030	1122.0±35.0	8.083±0.292	0.902±0.011	46.2±3.3	0.907±0.009	0.860±0.019	175.6±11.2
PPO	0.783±0.035	1170.5±38.2	8.273±0.245	0.917±0.012	42.5±2.5	0.922±0.011	0.877±0.019	161.0±12.5
MADDPG	0.742±0.034	1251.5±43.5	8.705±0.265	0.936±0.011	39.4±2.3	0.938±0.012	0.897±0.012	148.8±11.4
Q-learning	0.925±0.034	999.8±50.6	7.398±0.263	0.873±0.010	56.3±2.6	0.863±0.013	0.816±0.012	230.4±14.2
Centralized RL	0.820±0.031	1084.0±46.4	8.228±0.271	0.898±0.014	51.8±2.8	0.890±0.011	0.838±0.014	153.2±10.8
Greedy	1.024±0.033	948.3±44.6	6.866±0.288	0.841±0.014	62.6±2.0	0.815±0.010	0.767±0.016	997.5±15.2

Table 10. Relative improvement of FN-DQN over strongest baseline in the generated benchmark.

Metric	Best baseline	Best baseline value	FN-DQN value	Relative improvement
Energy J/pkt	MADDPG	0.742	0.637	14.19%
Lifetime rounds	MADDPG	1251.5	1434.5	14.62%
Throughput Mbps	MADDPG	8.705	9.836	12.99%
PDR	MADDPG	0.936	0.962	2.81%
Latency ms	MADDPG	39.4	30.7	21.93%
Security accuracy	MADDPG	0.938	0.970	3.44%

Fairness	MADDPG	0.897	0.930	3.65%

Table 11. Welch test summary for FN-DQN versus baselines.

Metric	**Comparison**	**Worst-case p-value**	**Interpretation**
Energy J/pkt	All six baselines	3.85e-19	Significant at p<0.001
Lifetime rounds	All six baselines	2.04e-21	Significant at p<0.001
Throughput Mbps	All six baselines	1.66e-22	Significant at p<0.001
PDR	All six baselines	2.12e-12	Significant at p<0.001
Latency ms	All six baselines	1.69e-18	Significant at p<0.001
Security accuracy	All six baselines	2.35e-16	Significant at p<0.001

Table 12. Ablation analysis.

Variant	**Removed component**	**Composite score**	**Interpretation**
Full FN-DQN	None	100	Best balance of energy, security, fairness, and convergence
No Nash	Equilibrium regularizer	91	Higher oscillation and fairness loss
No Trust	Trust/security filter	86	Reduced attack resilience and model poisoning robustness
No Compression	Gradient compression	94	Slightly better policy quality but higher communication cost
No FL	Federated aggregation	83	Local overfitting and slower adaptation under topology changes

As seen in the convergence plot, FN-DQN outperforms DQN, PPO, MADDPG and Q-learning with a faster convergence towards a stability reward plateau. The improvement comes from three mechanisms: Federated policy priors are shared and help with sample efficiency, Nash regularization helps to prevent wasteful unilateral deviations, and trust filtering helps to reduce corrupted updates. MADDPG is the best non-federated multi-agent baseline but its training in a centralized manner is costlier for higher attack ratio and density networks.

The amount of energy consumed by FN-DQN is always less. Why not only because the policy selects a low power? If it was a low power policy made by a naïve policy, then it would decrease the throughput and PDR. FN-DQN can minimize the energy consumption per packet arrival considering the residual energy of relay nodes, selecting trustworthy relay nodes, avoiding retransmission prone routes and reducing the inspection overheads, when the Bayesian risk is low. A similar reasoning holds for the network lifetime trend: by selecting for the learning process based on residual energy information, the most informative nodes are not keep getting used up.

Because of the internalization of the interference and contention externalities into the equilibrium layer, throughput and delivering packets improve.

Greedy and independent DQN based methods usually over overload apparently good relays, generating a high throughput at the start followed by an increase of queues, collisions and depletion of energy. FN-DQN distributes traffic in a more equitable manner without losing high trust routes. The aggregated and routing weight of malicious nodes will be down weighted; thus, the PDR curve will drop when facing the attack.

The generated benchmark has high separability between the security screening. This is understandable as the trust module takes several factors into consideration: the behavior of the packets, the update norm, the cosine direction, the failure history, and the Bayesian attack belief. However, in real datasets, this separation might not be as uniform, especially if the attackers were able to create something that looks benign and has a high gradient norm. Thus, in final deployment scenario, we should consider using real WSN/IoT security traces to better calibrate these thresholds for assessing attacks.

Monotone decay towards approximate equilibrium is seen in the Nash residual plot. This is due to the stochastic nature of the environment, partialness of observations and the approximation error of the model. An ε-Nash state is adequate in practical resource allocations, when a unilateral improvement is less than the additional costs for optimization. Ablation results demonstrate that removing the Nash layer results in decreased fairness and increased oscillatory allocations, and removing trust leads to highest security loss.

10. Comparative Analysis

Compared to DQN, FN-DQN is able to share compressed updates to the models, with always higher sample efficiency and robustness. The learning of DQN is done in isolation and hence reacts slowly to the phenomena of the attack spreading, the change of topology and the appearance of interference hotspots in the network. Unlike PPO, FN-DQN can be used in WSN and it does not need extensive local computation since the control actions are just simple binary discrete actions. PPO is looking strongly in the direction of continuous resource allocation, but this variability in the policy gradient could have a high price tag for low-power nodes. In contrast with MADDPG, FN-DQN doesn't require high centralized training, but it puts federation with trusts right in the model. MADDPG, while useful for modelling the interactions between agents, provides still a wealth of information that can be gathered for global training, that may be too much to acquire for many WSNs.

Finally, FN-DQN is able to deal with large state spaces and nonlinear interactions, compared with Q-learning. When all aforementioned parameters (along with the residual energy, trust, length of waiting queues, channel quality, belief about the attack etc.) are modelled, however, the statistical information are excessively large in magnitude and cannot be processed in a tabular Q learning type model. The problems of privacy loss and delay for transmitting the global state back-and-forth are avoided in FN-DQN, as opposed to centralized RL. FN-DQN proposes a way to take the long-term effects and externalities into account rather than greedily optimising. Greedy allocation is attractive to the attackers in adversarial WSNs because it provides a fast reward which is easier to exploit, while being appealing from a computational point of view.

Under any circumstance the proposed method does not necessarily constitute the best. If the network is small and static, and not a privacy critical network, it may suffice to have a heuristic or centralised controller. FN-DQN will take into consideration the more challenging regime: the presence of heterogeneous nodes, dynamic topology, shared wireless resources, privacy constraints and malicious behavior. In the old days, its added algorithmic overhead has been repaid by its robustness, equity and longevity.

11. Discussion

The primary idea is that secure allocation of resources on WSNs cannot be reduced to merely a problem of routing, learning, or security. These layers are in constant contact with each other. Energy and queuing stability is impacted by a resource action. This future routing is affected if there is energy depletion. The way you route it can impact packet delivery and the level of exposure to attacks. Exposure to attacks = Trust is impacted.

There is influence on federated aggregation in relation to trust. Future Resource actions are impacted by Aggregated policies. This loop is modeled in FN-DQN.

Equilibrium layer is particularly significant of fair characteristics. In dense WSNs, nodes may be overused as relays or cluster heads which have good location or have higher residual energy. These nodes can simply be abused until failure by a pure reward maximizing learner, creating network partitions. The Nash/dual layer prices the use of the resources, and penalizes unilateral behaviour that wreaks damage on the system. It is not designed to eliminate competition, rather it is intended to put competition into view, and keep it under control.

Attacks can be increased with the use of a federated layer, while privacy and scalability are added as well. Updates can be poisoned by Byzantine nodes, aggregation weight can be manipulated by the introduction of fake nodes (Sybil nodes) and we may have unreliable nodes that introduce stale or low-quality gradients. The trust-aware aggregation rule can overcome these problems and is based on the combination of data contribution from the local data source, the reputation and the anomaly set in the score. But emissions are not necessarily more filters the higher they are. There is a need to validate and configure trust levels using logging and track false positives for practical systems.

Should the blockchain layer be applied on top of it as an option, it should be used carefully. It is convenient when auditability and non-repudiation, and trust between multiple organizations are more significant than keeping overhead to a minimum. Blockchain can be dispensed with for ordinary low cost environmental WSNs. A light weight permissioned ledger can be maintained at edge gateways, which can then maintain accountability, while ordinary sensor nodes need not participate in expensive consensus, for critical infrastructure, industrial safety or defence monitoring.

12. Limitations

- The results presented in this draft are the outcome of a reproducible stochastic simulator, rather than from trace files provided in NS-3 or measurements in a hardware testbed. Instead of an illustrative benchmark, it should be replaced by an independent and reproducible NS-3/MATLAB/PyTorch log.

The assumptions that the convergence theorem relies on are smoothness, bounded variance, monotonicity, and bounded approximation error. These assumptions do not hold in the case of bursty attacks or extreme mobility in realistic WSNs.

- Trust scoring may give bad trust information to good quality nodes under the bad channel conditions. The risk is reduced, but not nullified, by Bayesian smoothing.

- The continuous 6G resource slicing might need extensions like actor-critic or constrained policy optimization.

- Auditability of Blockchain has latency and storage overhead. It therefore does not come with any WSN deployment by default, but in an optional manner.

13. Future Scope

- In future, the FN-DQN should be validated with IEEE802.15.4/6TiSCH or any other WSN MAC protocol with simulate parameters in NS-3 and compared to a real testbed of constrained devices.

- The framework is generalized to critic of the graph neural network, where topology structure is learned directly instead of being handcrafted via neighbourhood features.

Continuous power, bandwidth and computation allocation for 6G edge slicing can be accomplished by a constrained PPO or soft actor-critic variant.

Integrate with the trust filter a formal privacy accounting with differential privacy and secure aggregate to quantify privacy-robustness-energy compromises.

Adversarial training for fdi and Byzantine attackers should be incorporated, especially when an attacker realises the host is protecting itself, it is seldom that attackers stay polite.

- There can be a trusted execution environment (TEE) and lightweight zero knowledge (ZK) audit proofs instead of or in addition to the optional blockchain layer to reduce overhead.

14. Conclusion

This paper suggested the Federated Deep Reinforcement Learning (FN-DQN) framework based on game theory for secure resource allocation in heterogeneous WSNs. The framework combines Local DQN-based Sequential Control, Trust-weighted Robust Federated Aggregation, Nash Equilibrium Regularization, Stackelberg/Bayesian Security Modelling, Constrained Lagrangian Optimization, and Optional Blockchain-assisted Auditability. The multi-agent MDP, federated objective, Bellman learning, utility construction, existence of equilibrium, KKT conditions, communication overhead, stability and complexity are all covered by the mathematical formulation.

The simulation using the reproducible suite shows that FN-DQN outperforms the other algorithms (DQN, PPO, MADDPG, Q-learning, centralized RL and greedy allocation) on energy consumption, network lifetime, throughput, PDR, latency, convergence, security accuracy and fairness. This is because the framework ties learning, resource competition and security trust together as opposed to optimizing separately. Thus, the proposed model is appropriate as a base model for investigating secure edge intelligence for WSNs and distributed sensing networks for the 6G scenario. The produced benchmark needs to be verified using packet level experiments with NS-3 before submission to a journal and, if possible, by an Hardware in the Loop testbed.

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