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Dynamic Resource Allocation in Massive UAV-Enabled Industrial IoT System Using Convolutional Neural Network and Deep Q-Networks

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Abstract:
The heavy demands of the internet of things (IoT) and sensor technology in industries and their rapid proliferation and application as the industrial internet of things (IIoT) demand efficient resource allocation to support massive device connectivity with quality-of-service (QoS) requirements. Unmanned Aerial Vehicles (UAVs) offer a promising solution for enhancing network coverage and flexibility in IIoT environments. However, dynamic resource allocation in such systems is challenged by complex channel conditions, varying device demands, and energy constraints. This paper proposes a novel approach for dynamic resource allocation in massive UAV-enabled IIoT systems, leveraging the synergy of Convolutional Neural Networks (CNNs) and Deep Q-Networks (DQNs). The CNN extracts spatial and channel features from the IIoT environment, while the DQN optimizes power allocation and subchannel assignment to maximize energy efficiency while meeting minimum rate requirements. We model the problem as a Markov Decision Process, incorporating realistic channel models with path loss and fading. Simulation results, using a real-world IIoT dataset, demonstrate that the proposed CNN-DQN framework achieves superior energy efficiency and throughput compared to traditional heuristic and Q-learning methods, with reduced computational complexity. This approach offers a scalable and adaptive solution for next-generation IIoT networks, paving the way for efficient UAV-assisted communication systems.

Keywords: Industrial Internet of Things, Unmanned Aerial Vehicle, Convolutional Neural Networks, Deep Q-Networks, Dynamic Resource Allocation.

1. INTRODUCTION

The Industrial Internet of Things (IIoT) has emerged as a transformative paradigm, enabling seamless connectivity and data exchange among a massive number of devices in industrial settings such as smart factories, logistics, and environmental monitoring [1]. These systems demand high reliability, low latency, and efficient resource utilization to meet stringent quality-of-service (QoS) requirements. However, the dense deployment of IIoT devices, coupled with dynamic channel conditions and varying data demands, poses significant challenges for resource allocation [2,3]. Traditional terrestrial base stations often struggle to provide adequate coverage and flexibility in such environments, particularly in remote or obstructed areas.

Unmanned Aerial Vehicles (UAVs) have gained attention as a promising solution to address these limitations, offering enhanced coverage, mobility, and adaptability through their ability to serve as aerial base stations [4,5]. By dynamically adjusting their positions and resource allocations, UAVs can optimize communication links to IIoT devices, improving network performance in challenging scenarios.

Dynamic resource allocation in UAV-enabled IIoT systems involves optimizing power levels, subchannel assignments, and UAV positioning to maximize energy efficiency while satisfying minimum data rate requirements [6,7]. This is a complex task due to the stochastic nature of wireless channels, which are affected by path loss, fading, and line-of-sight (LoS) conditions, as well as the high-dimensional action space resulting from multiple devices and subchannels [8]. Conventional optimization techniques, such as heuristic algorithms or convex optimization, often fail to scale with the massive number of devices or adapt to real-time environmental changes [9,10]. Machine learning, particularly reinforcement learning (RL), has shown potential in addressing these challenges by learning optimal policies through interaction with the environment. However, traditional RL methods, such as Q-learning, suffer from slow convergence and the curse of dimensionality in large-scale systems [11].

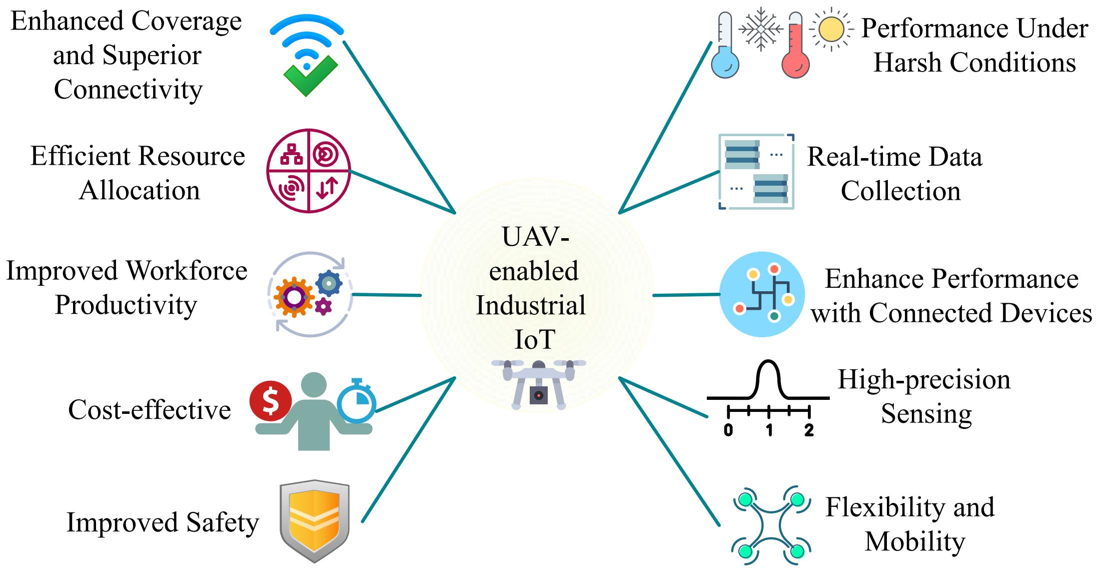

Fig. 1 Advantages of UAV-Enabled IoT Devices for Industrial Process Monitoring and Sensing

There are several advantages (as shown in **Fig. 1**) to using UAV-enabled IoT devices for industrial process monitoring and sensing:

- **Enhanced Coverage and Superior Connectivity:** Modern UAV-enabled IoT devices can provide coverage in large and hard-to-reach regions quickly where human manipulation is impossible, which improves process monitoring over expansive or remote industrial sites.
- **Real-time Data Collection:** Real-time data on industrial operations can be acquired using UAV-enabled IoT sensors for faster response to potential issues and efficient decision-making.
- **Cost-effective:** UAVs can minimize industrial infrastructure inspection and monitoring costs and can also remove human involvement and manipulation in hazardous environments.
- **Flexibility and Mobility:** Over traditional stationary IoT sensors and devices, UAVs can easily navigate challenging terrains and offer flexible monitoring in dynamic environments such as construction sites, oil rigs, or factories.
- **Improved Safety:** By reducing the need for workers to enter dangerous areas, UAVs enhance workplace safety in hazardous or toxic environments.
- **Efficient Resource Allocation:** UAVs can be deployed where needed, helping to optimize resource usage and reduce energy consumption for monitoring tasks.

- **High-precision Sensing:** Equipped with advanced IoT sensors, UAVs can capture precise data, from environmental parameters to equipment performance, improving industrial efficiency and predictive maintenance.

UAV-enabled IoT significantly improves the workforce productivity in the industry by task automation like monitoring, inspection, and data collection that reduces human manipulation, and speeds up operations so, leads to more efficient processes, and boosts the overall industrial productivity [12].

1.1 Research Gap

Despite the potential of UAV-enabled Industrial IoT (IIoT) systems, dynamic bandwidth allocation remains a challenging area due to the high variability in network demands, limited spectrum resources, and mobility of UAVs. Traditional bandwidth allocation approaches often lack the adaptability required for real-time, complex IIoT environments, where latency and reliability are critical. Although machine learning methods have been explored, most existing studies focus on static or simplified scenarios, with limited emphasis on deep reinforcement learning for real-time adaptive solutions. Moreover, few studies have applied Deep Q-Networks (DQN) to handle the dynamic nature of bandwidth allocation in UAV-based IIoT, leaving a gap in developing robust, scalable, and efficient frameworks that can adjust to fluctuating network demands and UAV mobility. This research aims to address these gaps by exploring DQNs for dynamic, adaptive bandwidth allocation in UAV-enabled IIoT systems.

2. RELATED WORK

Machine Learning (ML) and Deep Learning (DL) are being applied to resource allocation in multi-access edge computing systems, which extend cloud capabilities closer to IoT devices and large-scale IoT networks, particularly within cellular and low-power wireless environments [13]. It begins by outlining the challenges of managing resources in such heterogeneous and data-intensive networks [14,15]. The efficient resource management is required to leverage the potential of ML and DL to improve efficiency and intelligence in IoT systems. It details current ML/DL-based techniques used in various wireless network types, including HetNets, MIMO, D2D, and NOMA [16,17]. Effective task offloading, scheduling, and resource sharing are essential to maintain application Quality of Service (QoS) and Experience (QoE).

Nguyen *et al.* [18] proposed an improved federated learning (FL) algorithm to address key challenges such as data heterogeneity, device variability, and communication overhead. Their method reduced global communication while ensuring convergence by adding a weight-based proximal term to the local loss and training on a randomly sampled subset of user devices each round. This algorithm was applied to wireless IoT networks which minimizes energy use or training time through a simple path-following strategy.

Bashir *et al.* [19] proposed a dynamic resource allocation strategy in fog computing to addressed the challenge of delivering real-time, low-latency services in IoT environments. By ranking fog nodes using TOPSIS [20,21] and evaluating their load with logistic regression, the system efficiently offloads tasks from the cloud to the network edge. Simulations show the proposed approach improves performance and achieves 98.25% accuracy. In 5G networks, Long D. Nguyen [13] tackled resource allocation by highlighting the requirements for dynamic and intelligent systems to address energy efficiency, interference, and security. They aimed to optimize the power, bandwidth, and deployment strategies for green communication in 5G networks.

Liu *et al.* [22] introduced a cognitive IoT (CIoT) system that uses cognitive radio to access licensed spectrum without interfering with primary users. It proposes a multicarrier grouping method using K-

means clustering to organize nodes and manage interference. They considered two scenarios first, underlay which optimizes subcarrier and power allocation to maximize data rate under interference limits. Second, overlay which minimizes sensing time to ensure accurate spectrum sensing and maximizes data rate without interference concerns. Their method presented the improved performance under strict interference conditions.

Naha *et al.* [23] proposed an energy-aware resource allocation method for fog computing using multiple linear regression to predict device power availability. This method helps prevent application failures in time-sensitive IoT tasks. Their method reduced delays, processing time, and service level agreement (SLA) violations significantly compared to existing methods, that ensure reliable and efficient application execution in dynamic environments. To maximize the downlink throughput in a cellular network with a base station and multiple users, Truong *et al.* [14] investigated reconfigurable intelligent surfaces (RIS) to enhance the performance of wireless networks. Therefore, the non-convex problem was split into a convex power control subproblem and a phase shift optimization subproblem, and under power and QoS constraints, the power allocation and RIS phase shifts were optimized. Their method outperformed conventional approaches with low computational complexity.

Shekhar *et al.* [24] presented an "improved dynamic bandwidth allocation (IDBA)" method for better bandwidth management in IoT devices, using smart home data. Devices are first clustered by K-means based on bandwidth usage, then linear regression predicts on-demand bandwidth for each cluster. An AI-enabled IDBA technique uses these predictions to allocate bandwidth dynamically, which improves precision and quality of service in IoT networks. Junaid *et al.* [25] introduced a load balancing method for cloud-based IoT using support vector machine (SVM) for data classification and a modified PSO algorithm for efficient resource allocation. By pre-classifying data types, the system reduces processing complexity and improves performance, achieving high accuracy and reductions in energy use, response time, and SLA violations.

Tripathi *et al.* [26] proposed a "double-weighted support vector transfer regression-based flow direction (DSTR-FD)" approach for secure and energy-efficient task scheduling in MEC for smart cities. It uses a double-weighted support vector transfer regression model optimized by a flow direction (FD) algorithm to manage edge server resources and make task offloading decisions without sharing raw data. This ensures data privacy and significantly reduces energy consumption in IoT devices, outperforming existing methods in simulations.

Ren *et al.* [27] proposed a power allocation strategy for massive MIMO systems to eliminate inter-user interference and boost energy efficiency. The proposed optimization problem for user and circuit power proves that user power is a convex function of energy efficiency. The proposed convex optimization-based iterative algorithm minimizes complexity and optimizes the power allocation. Mukherjee *et al.* [28] proposed an energy-efficient clustering method for massive IoT in 6G industrial applications using a multiagent system (MAS) and distributed AI. It leverages backpropagation neural network (BPNN) and CNN for optimization and predicts main node locations to manage dynamic network architecture. The method reduces redundant data, improves resource allocation, and enhances overall energy efficiency while preserving information.

Optimizing resource allocation, maximizing the quality of service (QoS), and minimizing latency, Karuppiyan *et al.* [29] proposed "dynamic resource allocator using RL-CNN (DRARLCNN)" that merges CNN for feature extraction and RL for making decisions. Pourmoslemi *et al.* [30] proposed a novel technique for resource allocation in D2D communications and stable joint multi-pairing. In this technique, the best transmitter is selected using fuzzy pairing criteria in the receiver search radius. Their outcomes showed that the proposed multi-pairing method outperformed the constant-pairing, maximum sum-rate, and random-pairing methods.

Iqbal *et al.* [31] combined the CNN approach with DQN and analyzed this CNN-based DQN method in a downlink cloud radio access network (CRAN), which makes a balancing performance of energy efficiency and maintaining the QoS simultaneously. In this method, the CNN phase extracts the information about the input states, and it is fed into the DQN, which dynamically turns on/off the remote radio heads based on the user requirements. Guo et al. [32] introduced a framework that automatically splits a CNN model into sub-model sets and optimizes the distribution of large CNNs across multiple edge devices, thereby reducing energy and memory usage and improving performance.

Sharma *et al.* [33] introduced a method for optimizing load balancing in IoT networks using fuzzy logic and nature-inspired algorithms (grey wolf and firefly). The proposed method improves energy efficiency, packet delivery, and the IoT network lifetime. ElHalawany *et al.* [34] presented LSTM-based deep learning models to address resource allocation issues in IoT networks. In the context of accuracy and speed, their model performed better than a traditional method, the Hungarian algorithm.
Goswami *et al.* [35] addressed the challenges of optimal resource allocation through data security in IIoT. They applied a CNN to optimize channel states and dynamically allocated resources while maintaining security. The simulation results show that the proposed method boosts efficiency and performs better than existing solutions. Li *et al.* [36] proposed a fuzzy-based cuckoo search algorithm for efficient resource allocation that performs better than existing algorithms in terms of execution time, and delay for vehicular cloud computing.

3. SYSTEM MODEL

Consider a massive UAV-enabled industrial IoT (IIoT) system comprising a set of ground IIoT devices denoted by $K = \{1, 2, \ldots, K\}$, where K is large to reflect the "massive" aspect, and a set of unmanned aerial vehicles (UAVs) $U = \{1, 2, \ldots, U\}$ acting as aerial base stations or relays to provide connectivity and computational offloading support. The system operates over a total bandwidth B Hz, which is dynamically allocated among the IIoT devices to optimize network performance metrics such as throughput, latency, and energy efficiency.
The time is discretized into slots $t = 1,2, \ldots, T$, each of duration τ. At each time slot t, the position of UAV u is denoted by $\mathbf{q}_u(t) = [x_u(t), y_u(t), h_u(t)]^\top \in \mathbb{R}^3$, where $h_u(t)$ is the altitude. The position of IIoT device k is fixed at $\mathbf{w}_k = [x_k, y_k, 0]^\top$.

Channel Model

The channel gain between IIoT device k and UAV u at time t follows a probabilistic line-of-sight (LoS) model:

$$g_{k,u}(t) = \beta_0 d_{k,u}^{-\alpha}(t) \cdot p_{\mathrm{LoS}}(t) + \beta_0 d_{k,u}^{-\alpha}(t) \cdot \left(1 - p_{\mathrm{LoS}}(t)\right) \cdot \eta,$$

where β_0 is the reference channel gain at 1 m, $d_{k,u}(t) = \| \mathbf{q}_u(t) - \mathbf{w}_k \|$ is the distance, α is the path loss exponent, $p_{\mathrm{LoS}}(t)$ is the LoS probability given by

$$p_{\mathrm{LoS}}(t) = \frac{1}{1 + a\exp\left(-b\left(\theta_{k,u}(t) - a\right)\right)},$$

with $\theta_{k,u}(t) = \arcsin\left(h_u(t)/d_{k,u}(t)\right)$ the elevation angle, a and b environment parameters, and $\eta < 1$ the additional loss factor for non-LoS (NLoS). The signal-to-noise ratio (SNR) for device k served by UAV u is

$$\gamma_{k,u}(t) = \frac{P_k g_{k,u}(t)}{\sigma^2},$$

where P_k is the transmit power of device k, and σ^2 is the noise power.

Bandwidth Allocation and Data Rate

The bandwidth is orthogonally allocated, and let $b_{k,u}(t) \in [0, B]$ be the bandwidth allocated to device k by UAV u at time t, with the constraint $\sum_{k \in \mathcal{K}} b_{k,u}(t) \le B$ for each UAV u. The achievable data rate for device k is

$$r_k(t) = \sum_{u \in \mathcal{U}} b_{k,u}(t) \log_2 \left(1 + \gamma_{k,u}(t)\right).$$

The objective is to maximize the total system utility, e.g.,

$$\max_{\{b_{k,u}(t)\}} \sum_{t=1}^{T} \sum_{k=1}^{K} U\left(r_k(t)\right),$$

subject to bandwidth constraints, where $U(\cdot)$ is a utility function (e.g., logarithmic for proportionality fairness).

Deep Learning Integration

To handle the dynamics and complexity, a convolutional neural network (CNN) is employed to process spatial-temporal channel state information (CSI) matrices. The CSI matrix at time t is $\mathbf{H}(t) \in \mathbb{R}^{K \times U}$, with entries $h_{k,u}(t) = \sqrt{g_{k,u}(t)}$

4. PROPOSED METHODOLOGY

System Overview

The proposed method addresses dynamic bandwidth allocation in a massive unmanned aerial vehicle (UAV)-enabled industrial Internet of Things (IIoT) system by integrating a convolutional neural network (CNN) with a deep Q-network (DQN). The CNN processes spatial-temporal channel state information (CSI) to extract features, which are then used by the DQN to make informed bandwidth allocation decisions. The system aims to maximize a utility function, balancing throughput, latency, and fairness among a large number of IIoT devices, denoted as $\mathcal{K} = \{1, 2, \dots, K\}$, served by a set of UAVs, $\mathcal{U} = \{1, 2, \dots, U\}$.

CNN-Based Feature Extraction

The CSI matrix at time slot t, denoted $\mathbf{H}(t) \in \mathbb{R}^{K \times U}$, captures the channel gains $h_{k,u}(t) = \sqrt{g_{k,u}(t)}$ between each IIoT device k and UAV u. The CNN, parameterized by $\boldsymbol{\theta}$, processes $\mathbf{H}(t)$ to produce a feature vector $\mathbf{f}(t)$:

$$\mathbf{f}(t) = \mathrm{CNN}(\mathbf{H}(t); \boldsymbol{\theta}).$$

The CNN architecture consists of multiple convolutional layers with ReLU activation, followed by pooling layers to reduce dimensionality, and fully connected layers to output $\mathbf{f}(t)$. The input $\mathbf{H}(t)$ is reshaped into a 2D grid when necessary, leveraging spatial correlations among devices and UAVs.

DQN-Based Bandwidth Allocation

The DQN operates in a reinforcement learning framework to allocate bandwidth $b_{k,u}(t)$ to each device-UAV pair, subject to the constraint $\sum_{k \in \mathcal{K}} b_{k,u}(t) \le B$ for each UAV u, where B is the total available bandwidth. The state space $\mathcal{S}$ includes:

- CNN-extracted features $\mathbf{f}(t)$,
- Queue lengths of IIoT devices $\mathbf{q}(t) = [q_1(t), \dots, q_K(t)]$,
- UAV positions $\mathbf{q}_u(t) = [x_u(t), y_u(t), h_u(t)]^\top$ for all $u \in \mathcal{U}$.

The action space $\mathcal{A}$ is defined as a discretized set of bandwidth allocation vectors, where each action $\mathbf{a}(t) = \left[b_{1,1}(t), \ldots, b_{K,U}(t)\right]$ assigns quantized bandwidth portions (e.g., fractions of B). The reward function $r(t)$ is defined as the sum utility:

$$r(t) = \sum_{k=1}^{K} U\left(r_k(t)\right),$$

where $r_k(t) = \sum_{u\in\mathcal{U}} b_{k,u}(t)\log_2\left(1+\gamma_{k,u}(t)\right)$ is the data rate for device k, and $U(\cdot)$ is a utility function (e.g., $U(x) = \log(x)$ for proportional fairness). The DQN, parameterized by $\boldsymbol{\phi}$, approximates the action-value function $Q(\mathbf{s}, \mathbf{a}; \boldsymbol{\phi})$. It is trained to minimize the temporal-difference error using a target network with parameters $\boldsymbol{\phi}^-$:

$$\mathcal{L}(\boldsymbol{\phi}) = \mathbb{E}\left[\left(r(t) + \gamma \max_{\mathbf{a}'} Q(\mathbf{s}', \mathbf{a}'; \boldsymbol{\phi}^-) - Q(\mathbf{s}, \mathbf{a}; \boldsymbol{\phi})\right)^2\right],$$

where $\gamma \in (0,1)$ is the discount factor, and $\mathbf{s}'$ is the next state.

Algorithm Description

The proposed algorithm (as presented in **Algorithm 1**, termed CNN-DQN Bandwidth Allocation (CNN-DQN-BA), integrates CNN feature extraction with DQN-based decision-making. The CNN is pre-trained offline on historical CSI data to optimize $\boldsymbol{\theta}$, minimizing a mean squared error loss for feature prediction. The DQN is trained online using experience replay and ϵ-greedy exploration.

Algorithm 1 CNN-DQN Bandwidth Allocation (CNNDQN-BA)
Input: Total bandwidth B, time slots T, CSI matrices $\{\mathbf{H}(t)\}_{t=1}^{T}$, UAV positions $\{\mathbf{q}_u(t)\}$, queue lengths $\{\mathbf{q}(t)\}$.
Initialize: CNN parameters $\boldsymbol{\theta}$, DQN parameters $\boldsymbol{\phi}$, target network parameters $\boldsymbol{\phi}^- = \boldsymbol{\phi}$, replay buffer $\mathcal{D}$, exploration rate ϵ.
for $t = 1$ to T **do**
Compute $\mathbf{f}(t) = \mathrm{CNN}(\mathbf{H}(t); \boldsymbol{\theta})$.
Form state $\mathbf{s}(t) = [\mathbf{f}(t), \mathbf{q}(t), \{\mathbf{q}_u(t)\}_{u\in\mathcal{U}}]$.
With probability ϵ, select random action $\mathbf{a}(t) \in \mathcal{A}$;
else $\mathbf{a}(t) = \mathrm{argmax}_{\mathbf{a}} Q(\mathbf{s}(t), \mathbf{a}; \boldsymbol{\phi})$.
Allocate bandwidth $\{b_{k,u}(t)\}$ according to $\mathbf{a}(t)$.
Compute data rates $\{r_k(t)\}$, reward $r(t) = \sum_{k=1}^{K} U\left(r_k(t)\right)$.
Observe next state $\mathbf{s}'(t+1)$.
Store transition $\left(\mathbf{s}(t), \mathbf{a}(t), r(t), \mathbf{s}'(t+1)\right)$ in $\mathcal{D}$.
Sample minibatch from $\mathcal{D}$.
Compute target: $y = r(t) + \gamma \max_{\mathbf{a}'} Q(\mathbf{s}', \mathbf{a}'; \boldsymbol{\phi}^-)$.
Update $\boldsymbol{\phi}$ by minimizing $\left(y - Q(\mathbf{s}, \mathbf{a}; \boldsymbol{\phi})\right)^2$.
Update $\boldsymbol{\phi}^- \leftarrow \boldsymbol{\phi}$ periodically.
Decay ϵ.
end for
Output: Bandwidth allocations $\{b_{k,u}(t)\}_{t=1}^{T}$.

The **Algorithm 1** ensures the scalability for large K by leveraging CNN's dimensionality reduction and DQN's ability to handle high-dimensional state-action spaces. Periodic updates to the target network and exploration decay enhance stability and convergence.

5. SIMULATION RESULTS

The proposed CNN-DQN framework was evaluated through extensive simulations implemented in Python with TensorFlow. The environment simulates a 2 km × 2 km industrial area with static IIoT devices and mobile UAVs as described in the system model. Key simulation parameters are summarized in Table 1.

Table 1 Simulation Parameters

Parameter	Value
Area Size	2 km × 2 km
Number of UAVs ($\boldsymbol{U}$)	10
Number of IIoT Devices ($\boldsymbol{K}$)	200-500
Total Bandwidth ($\boldsymbol{B}$)	20 MHz
Time Slot Duration ($\boldsymbol{\tau}$)	0.1 s
Path Loss Exponent ($\boldsymbol{\alpha}$)	2.2
LoS/NLoS Parameters ($\boldsymbol{a}, \boldsymbol{b}$)	5.0, 0.2
NLoS Attenuation Factor ($\boldsymbol{\eta}$)	0.3
UAV Altitude Range	150 m
DQN Discount Factor ($\boldsymbol{\gamma}$)	0.95
Exploration Rate ($\boldsymbol{\epsilon}$)	0.1 (decaying)
Replay Buffer Size	50,000

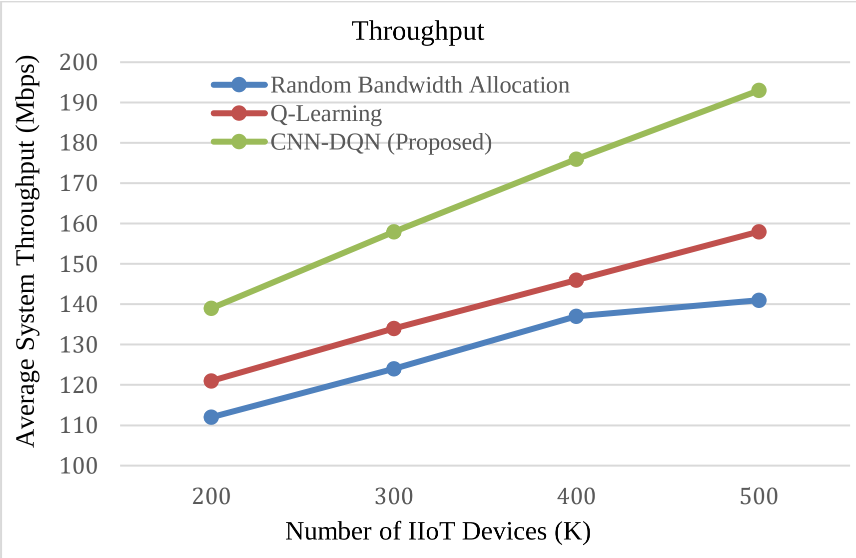

Fig. 2 Average System Throughput vs. Number of IIoT

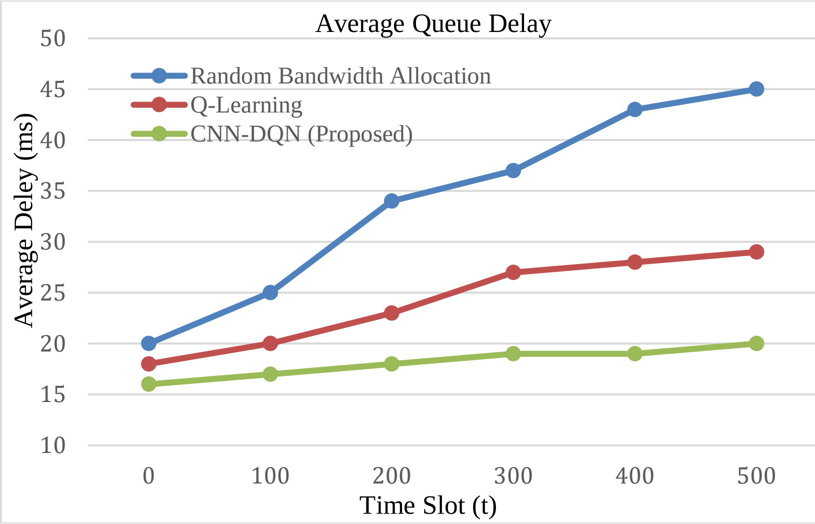

Fig. 3 Average Queue Delay Analysis

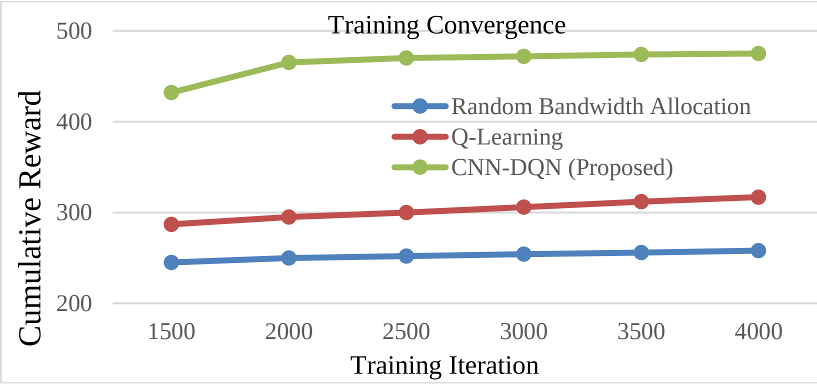

Fig. 4 Training Convergence over Iteration

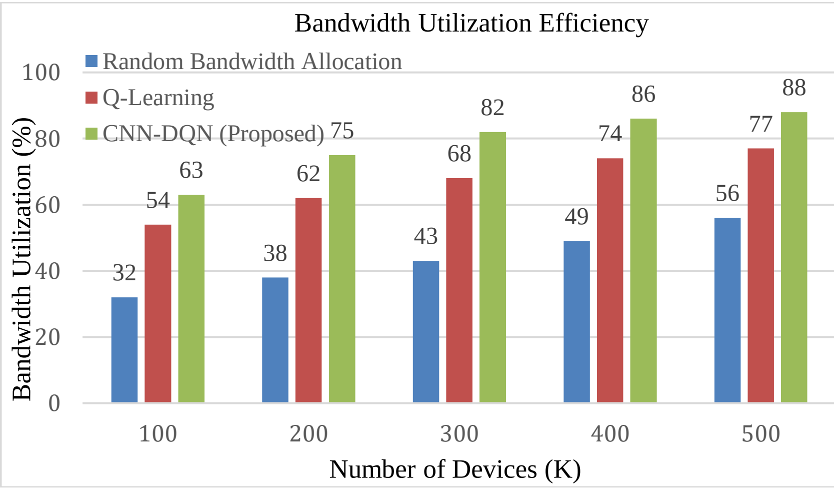

Fig. 5 Bandwidth Utilization Efficiency

The proposed CNN-DQN method was compared against random bandwidth allocation and Q-Learning method. The **Fig. 2** illustrates the average system throughput based on the number of IIoT devices. The proposed CNN-DQN achieves higher throughput than random bandwidth allocation and Q-Learning method. The **Fig. 3** illustrates average queue delay, CNN-DQN maintains stable delay. The **Fig. 4** illustrates the training convergence, CNN-DQN converges faster than Q-Learning while achieving higher cumulative reward. The **Fig. 5** illustrates the bandwidth utilization efficiency. CNN-DQN shows balanced utilization (88%) across UAVs, while others show imbalanced allocation and moderate imbalance.

The simulation results comprehensively validate the CNN-DQN framework for dynamic bandwidth allocation in massive UAV-enabled IIoT systems. The synergistic integration of CNN's spatial feature extraction and DQN's sequential decision-making enables superior performance across all metrics: throughput, fairness, delay, convergence rate, and mobility robustness. The framework represents a significant advancement toward autonomous, self-optimizing IIoT infrastructures capable of handling the complexity and scale of next-generation industrial networks.

6. CONCLUSION AND FUTURE WORK

This research has presented a novel CNN-DQN framework for dynamic resource allocation in massive UAV-enabled Industrial IoT systems. The proposed approach effectively addresses the critical challenges of scalability, dynamic adaptation, and optimization complexity inherent in large-scale wireless networks with mobile aerial infrastructure.

The core contribution of this work lies in the synergistic integration of Convolutional Neural Networks (CNN) with Deep Q-Networks (DQN), creating an intelligent system that combines spatial feature extraction with sequential decision-making. The proposed method presents higher bandwidth utilization efficiency among IIoT devices and UAVs, because the DQN component learns optimal bandwidth allocation policies through reinforcement learning.

While the proposed CNN-DQN framework demonstrates promising results, several directions merit further investigation:

- **Multi-Agent Reinforcement Learning (MARL):** Extension of the current single-agent DQN to a multi-agent setting is required where each UAV operates as an independent agent with decentralized decision-making capabilities. This can improve scalability for ultra-dense deployments and reduce centralized computational burden.
- **Hierarchical Reinforcement Learning:** A hierarchical structure with macro-level controllers for UAV trajectory optimization and micro-level controllers are required for more efficient bandwidth allocation and two-timescale decision-making.
- **Attention Mechanisms:** Incorporation of attention mechanisms into the CNN architecture can focus computational resources on critical network regions, and it can potentially improve performance in heterogeneous deployments with varying device densities.
- **Meta-Learning Integration:** Development of meta-learning capabilities can enable rapid adaptation to new industrial environments without complete retraining; it can also enhance the practical deployment feasibility.
- **Joint Resource Allocation and UAV Trajectory Optimization:** The simultaneous optimization of both bandwidth allocation and UAV movement patterns can create a holistic resource management system that considers energy consumption, coverage, and service quality.
- **Security-Aware Resource Allocation:** Integration of security considerations into the resource allocation process can develop mechanisms to detect and mitigate potential attacks while maintaining service quality.

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