

# AI and Machine learning for 6G-enabled IoT

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**Abstract**—Artificial intelligence (AI), machine learning (ML), and 6G networks may transform the Internet of Things. 6G networks provide minimal device latency and accommodate substantial data throughput. It also addresses network support issues inside the extensive IoT ecosystem. AI and ML enable 6G-enabled IoT platforms to allocate resources, comprehend context, and execute intelligent decisions for predictive maintenance and security. Nevertheless, energy efficiency, data confidentiality, and device interoperability pose challenges as systems become increasingly intricate and interconnected. This article advocates the systematic application of AI and ML to enhance the performance of 6G IoT networks. We illustrate how AI-driven network management may enhance connectivity, operational costs, and real-time decision-making in smart cities, healthcare, and industrial automation. This study investigates the role of federated learning and edge computing in addressing energy and privacy challenges within extensively distributed IoT systems. This paper presents a foundational reference model to inspire research that addresses gaps and integrates the global landscape, focusing on the dependable, efficient, and intelligent utilization of 6G-enabled IoT systems

**Keywords**— Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), Industrial Automation, Intelligent Network Management

## I. INTRODUCTION

Wireless communication and intelligent network systems have advanced through the integration of AI, ML, and 6G-enabled IoT [1]. The demand for rapid, dependable, and intelligent networks is propelling 6G technology to transform connectivity, intelligence, and automation. In healthcare, transportation, agriculture, and smart city development, 6G and IoT have the potential to foster a hyperconnected and intelligent society [2]. The anticipated 50 billion IoT devices by 2030 present issues in scalability, latency, security, and energy efficiency. Present 5G networks are inadequate for extensive IoT deployments, particularly with ultra-low latency and real-time decision-making [3]. Insights from IoT data necessitate cognitive processing, analysis, and management. The challenges necessitate AI-driven solutions owing to inadequate network topologies and management strategies. Artificial intelligence and machine learning facilitate dynamic resource allocation, predictive maintenance, and security within 6G networks. Latency, privacy, and energy efficiency can be mitigated using AI-driven end-to-end learning, computation, and network administration. Edge AI reduces bandwidth and guarantees

the prompt processing of source data. Middleware security methods employing machine learning anomaly detection techniques safeguard Internet networks [4].

This study addresses the following question:

- Can 6G-enabled Internet systems enhance reliability and performance in dynamic intelligent service management?
- How do you ensure scalability and interoperability when integrating AI-based solutions with 6G and the IoT?

A platform utilizing AI that provides rapid, safe, and integrated 6G-enabled Internet services through advanced computing, reinforcement learning, and distributed AI models is required to tackle these difficulties. The proposed approach efficiently scales and administers extensive Internet ecosystems using real-time data processing, astute decision-making, and adaptive management. It operates as seen in Figure 1. This study employs sophisticated AI and ML techniques alongside 6G capabilities to create a robust foundation for the intelligent and efficient management of IoT systems. The solutions enhance sustainability, real-time responsiveness, and security, directing this critical issue. This paper advocates transdisciplinary research and innovation to foster an intelligent, interconnected society. The remainder of the article is organized as: Section II presents related work. Section III presents the proposed solution. Section IV discusses the results and finally section V concludes entire article.

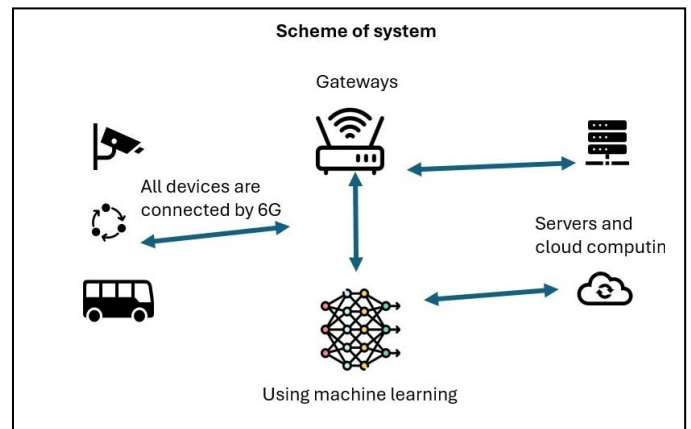


Figure 1: Scheme of the system

### A. Main contribution

The main contributions are summarized as below:

- Federated learning is utilized to augment data security by training AI models at the point of origin on Internet of Things (IoT) devices, thereby mitigating the risk of sensitive data exposure.
- The utilization of edge intelligence in this research facilitates the processing of data and the formulation of decisions at the point of occurrence, thereby reducing delays and dependency on centralized systems.
- The study addresses the energy challenges of 6G-enabled IoT systems by introducing efficient communication protocols and resource allocation techniques.

## II. RELATED RESEARCH

This section examines the attributes of previously suggested methods that are closely associated with the proposed strategy. Giordani et al. [5] examined innovations in 6G networks, investigating various scenarios in which 6G could yield substantial enhancements. Nonetheless, their research did not consider the impact of AI on increasing reliance on 6G wireless networks. Likewise, Yang et al. [6] conducted a comprehensive analysis of AI-enabled 6G frameworks, highlighting the role of AI in 6G contexts; however, they did not include a taxonomical examination of AI's application in dynamic spectrum allocation. Zong et al. [7] proposed an innovative 6G device design, highlighting significant deficiencies of 5G and delineating new application opportunities for 6G. Their research prioritized photonics-centric architecture but failed to incorporate extensive AI integration across several applications. Yastrebova et al. [8] examined prospective applications and obstacles inside 6G network frameworks, illustrating how these frameworks might resolve diverse issues. Nonetheless, their research did not investigate the particular function of AI inside the 6G ecosystem. Zhang et al. [9] examined critical 6G developments, including mobile ultra-broadband and IoT, and their contribution to advancing network objectives. Nevertheless, their research did not explore the architectural and hardware dimensions of 6G systems. The proposed survey seeks to address the deficiencies in current research by providing a comprehensive overview of 6G architecture and its applications. It highlights the integration of AI and IoT in 6G contexts while tackling difficulties such as scalability, energy efficiency, and privacy. This study aims to offer practical solutions for 6G-enabled IoT systems through the analysis of sophisticated AI methodologies, including reinforcement learning and Q-learning.

## III. PROPOSED PREDICTIVE-BASED REINFORCEMENT LEARNING MODEL FOR 6G-ENABLED IoT

The proposed framework creates an intelligent IoT resource management system utilizing advanced reinforcement learning and predictive models to enhance resource utilization and the efficiency of 6G-enabled IoT networks. IoT devices generate comprehensive data, which the model evaluates through reinforcement learning to predict optimal resource allocations that minimize latency and energy consumption. The objectives are to improve real-time decision-making, resource scalability, and secure, energy-efficient operations in 6G IoT systems. The architectural architecture of the proposed system employs predictive models and reinforcement learning to effectively allocate

resources in highly dynamic 6G environments depicted in Figure 2. In 6G IoT environments, resource limitations, energy inefficiency, and high latency are significant challenges. The framework's core consists of a resource management environment characterized by interrelated processes. Metrics from IoT devices, such as CPU usage, memory utilization, and power consumption, are gathered and consolidated. The system employs reinforcement learning for adaptive optimization and predictive modeling for proactive resource allocation using this data. Reinforcement learning dynamically allocates resources with real-time input, whereas predictive modeling anticipates optimal configurations to prevent resource limitations. We validate and enhance the outcomes of these models to guarantee accuracy and dependability. The system identifies inefficiencies or imbalances in resource utilization for enhancement. This facilitates a methodical strategy for enhancing 6G IoT performance, wherein data collection, modeling, and validation optimize scalability, latency, and energy efficiency. To align with IoT trends and facilitate sustainable and intelligent resource management, the framework refreshes its models using real-time data.

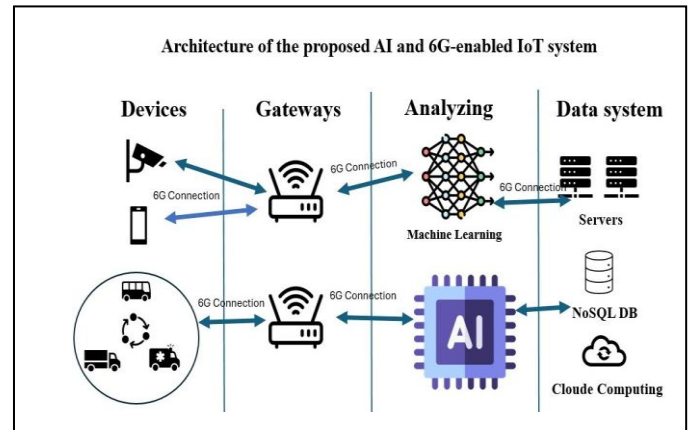


Figure 2: Architecture of the proposed AI and 6G-enabled IoT system

The proposed model consists of the following three modules:

- Data Collection and Aggregation
- Reinforcement Learning Integration

### A. Data Collection and Aggregation

The process of data collection entails the gathering of extensive information pertaining to IoT devices, including details regarding CPU utilization, memory usage, power consumption, and real-time performance metrics. Meticulously collected, diverse, and normalized data ensures both granularity and comparability, thereby forming the foundation for accurate resource allocation decisions. This module focuses on the aggregation of data from multiple IoT devices, with the objective of creating a comprehensive dataset that reflects the real-time state of the 6G IoT environment. The data collection and aggregation process are illustrated in Figure 3.

**Algorithm 1:** Data collection and aggregation for 6G IoT resource management

1. **Input**  $\{D_i\}$
2. **Output**  $\{D_{agg} \text{ with } R_{ins}\}$

3. **Initialization:** {  $D_i$ : IoT device data;  $D_{agg}$ : Aggregated Data;  $B_d$ : banking data;  $R_{ins}$ : Resource insights }
4. **Set**  $D_i$
5. **Do process:**  $D_i \in D_{agg} \rightarrow R_{ins}$
6. **Evaluate**  $R_{ins}$
7. **If**  $R_{ins}$  meets thresholds, then
8.  $D_{agg}$  is optimized
9. **Else**
10.  $D_{agg}$  requires refinement
11. **Endif**

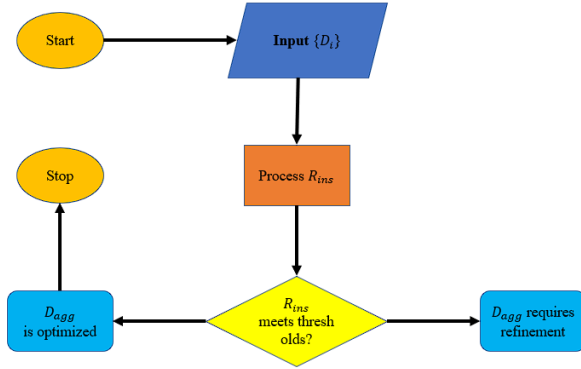


Figure 3 - Data collection and aggregation Process

Algorithm-1, titled "Data Collection and Aggregation for 6G IoT Resource Management" begins by taking IoT device data ( $D_i$ ) as input and initializes variables for aggregated data ( $D_{agg}$ ) and resource insights ( $R_{ins}$ )

The algorithm processes raw IoT data to generate  $D_{agg}$ , consolidating multiple metrics into a unified dataset. It then evaluates  $R_{ins}$  based on predefined performance thresholds to determine whether the aggregated data is optimized. If thresholds are met,  $D_{agg}$  is considered efficient; otherwise, it undergoes further refinement. This algorithm establishes a structured approach to collect and aggregate IoT data for accurate resource insights.

**Hypothesis-1:** A comprehensive data collection and aggregation process, incorporating a range of IoT metrics including CPU utilization, memory usage and power consumption, enhances the accuracy of resource allocation and improves overall network efficiency.

**Proof:** The aggregation process ensures that IoT data from various devices is normalized and integrated into a single, comprehensive dataset. This dataset provides critical metrics that support precise resource allocation. Let  $D_i$  represent the data collected from the  $i$ -th IoT device, and  $D_{agg}$  denote the aggregated dataset. Aggregation can be expressed as:

$$D_{agg} = \bigcup_{i=1}^n D_i \cdot W_i \quad (1)$$

where  $W_i$  represents the weight assigned to each device's data based on its significance or priority. The normalization of individual device metrics is defined as:

$$D'_i = \frac{D_i - \mu}{\sigma} \quad (2)$$

where  $\mu$  is the mean and  $\sigma$  is the standard deviation of  $D_i$ . Normalization ensures that each metric is on a comparable scale, avoiding bias in resource allocation decisions.

**Lemma-1:** Normalizing IoT device data reduces discrepancies between metrics and improves the robustness of the aggregation process.

**Proof of Lemma-1:** Without normalization, devices with larger raw metric values may disproportionately influence resource allocation decisions. By transforming data to:

$$D'_i = \frac{D_i - \mu}{\sigma} \quad (3)$$

The influence of outliers and scale differences is minimized, leading to fairer and more accurate allocation decisions. The resource allocation efficiency ( $R_{eff}$ ) resulting from aggregation can be calculated as:

$$R_{eff} = \frac{\sum_{i=1}^n W_i \cdot D'_i}{\sum_{i=1}^n W_i} \quad (4)$$

where  $W_i$  accounts for device priorities. By maximizing  $R_{eff}$ , the system achieves optimal resource allocation.

**Corollary-1:** A robust aggregation process ensures scalability and adaptability in 6G IoT systems by enabling dynamic updates to  $D_{agg}$  as devices join or leave the network.

**Proof:** Since  $D_{agg}$  dynamically incorporates normalized data ( $D'_i$ ) from connected devices, it can adapt to changes in network composition, maintaining consistent resource efficiency.

### B. Reinforcement Learning Integration

Incorporating reinforcement learning into 6G IoT resource management promotes flexibility and ongoing enhancement. Reinforcement learning facilitates the system's optimization of resource allocation by balancing exploration (identifying new patterns) with exploitation (utilizing known patterns). This connection enhances decision-making by allowing dynamic modifications to real-time IoT circumstances and changing network requirements. The reinforcement learning algorithm enhances its decision-making over time by rewarding actions that optimize resource efficiency and penalize inefficient allocations. The system enhances its resilience to network alterations and environmental variations by continuously learning from real-time data, hence ensuring sustainable and efficient operations. This versatility is essential for dynamic 6G situations, where IoT devices produce vast quantities of data necessitating prompt processing. Figure 4 depicts the reinforcement learning methodology for resource allocation.

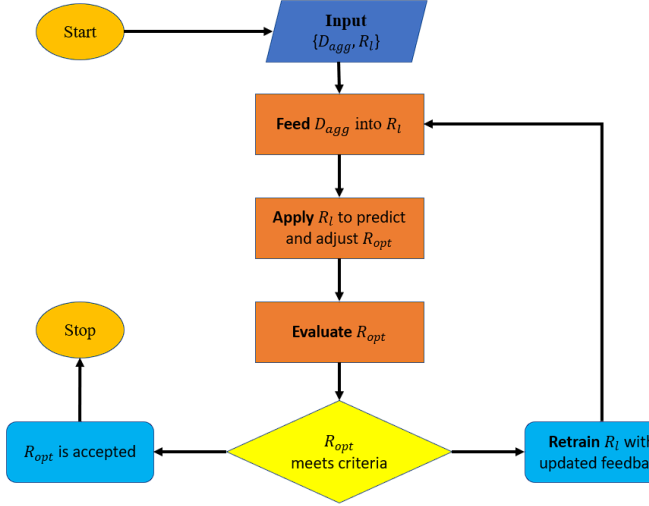


Figure 4 - Reinforcement learning Process

**Algorithm 2:** Reinforcement learning for 6G IoT resource management

1. **Input**  $\{D_{agg}, R_l\}$
2. **Output**  $\{R_{opt} \text{ with improved resource state}\}$
3. **Initialization:**  $\{D_{agg}$ : Aggregated Data;  
 $R_{opt}$ : Optimized resource state;  
 $R_l$ : Reinforcement learning model $\}$
4. **Feed**  $D_{agg}$  into  $R_l$
5. **Apply**  $R_l$  to predict and adjust  $R_{opt}$
6. **Evaluate**  $R_{opt}$
7. **If**  $R_{opt}$  meets criteria
8.      $R_{opt}$  is accepted
9. **Else**
10.    **Retrain**  $R_l$  with updated feedback
11. **Endif**

Algorithm-2 begins with aggregated data ( $D_{agg}$ ) and employs a reinforcement learning model ( $R_l$ ) to predict optimal resource allocations ( $R_{opt}$ ). The algorithm evaluates  $R_{opt}$  based on predefined criteria such as latency and energy efficiency. If the criteria are met,  $R_{opt}$  is implemented; otherwise, the model undergoes retraining to improve future predictions. This adaptive process ensures real-time responsiveness and scalability in 6G IoT systems.

**Hypothesis-2:** Reinforcement learning enables the dynamic optimization of resource allocation in 6G IoT environments, thereby reducing latency and energy consumption while maintaining system performance.

**Proof:** Reinforcement learning (RL) continuously refines resource allocation strategies by learning from the environment. Let the state of the system be  $S$ , the action  $A$  represents resource allocation decisions, and the reward  $R(S, A)$ . It demonstrates enhancements in system functionality, exemplified by decreased latency or reduced energy consumption.

The value function  $Q(S, A)$ , which predicts the cumulative reward for a given state-action pair, is updated using the Bellman equation:

$$Q(S, A) \leftarrow Q(S, A) + \alpha [R(S, A) + \gamma \max_{A'} Q(S', A') - Q(S, A)] \quad (5)$$

Where  $\alpha$ : Learning rate,  $\gamma$ : Discount factor for future rewards, and  $\max_{A'} Q(S', A')$ : Maximum predicted reward for the next state  $S'$

Reinforcement learning optimizes resource allocation by maximizing the cumulative reward over time:

$$\pi^* = \arg \max_{\pi} E \left[ \sum_{t=0}^{\infty} \gamma^t R(S_t, A_t) \right] \quad (6)$$

**Lemma-2:** Adaptive learning through reinforcement ensures that resource allocation remains optimal despite dynamic changes in IoT workloads.

**Proof:** By iteratively updating  $Q(S, A)$  based on real-time feedback, the system dynamically adjusts to changes in workload distribution. This adaptability minimizes performance degradation caused by fluctuating conditions.

For energy efficiency, the optimization target is calculated as:

$$E_{opt} = \arg \min_A (P_{cons} + L) \quad (7)$$

where  $P_{cons}$  represents power consumption, and  $L$  denotes latency. Reinforcement learning reduces both terms by exploring actions  $A$  that balance resource utilization.

**Corollary-2:** Reinforcement learning ensures resilience in 6G IoT environments by continuously adapting to changing network conditions and optimizing resource utilization.

**Proof 2:** The iterative nature of RL enables the model to respond to real-time feedback, ensuring that resource allocation decisions remain efficient even as the network state evolves. This adaptability maintains system performance under varying workloads.

#### IV. EXPERIMENTAL PART

A controlled simulation environment was established using both synthetic and real-world IoT data to evaluate the efficacy of the proposed 6G-enabled IoT resource management system. The statistics included metrics from IoT devices, such as CPU use, memory usage, power consumption, and network latency. The datasets varied in size from 10,000 to 500,000 device entries, representing both small-scale and large-scale IoT contexts. The data was obtained from publicly accessible IoT benchmarks and supplemented with simulated data, thus emulating real-world conditions in dynamic 6G environments. The studies were performed on a high-performance system equipped with various Python-based machine learning and reinforcement learning frameworks, such as TensorFlow, PyTorch, and scikit-learn. The reinforcement learning model and predictive algorithms were executed using custom Python modules, with NumPy and pandas utilized for data handling and Matplotlib for visualization. The system was executed on a workstation featuring an AMD Ryzen 9 processor, 128GB of RAM, and an NVIDIA RTX 3090 GPU, utilized to enhance model training and inference. The experimental configuration evaluated the proposed model against baseline methods, encompassing conventional heuristic-based resource allocation and static predictive models. To evaluate the durability and adaptability of the proposed architecture, the tests replicated dynamic settings by introducing fluctuating workloads, including surges of IoT device activity and altering network topologies. Additionally, uneven device distributions and variable power limitations were used to evaluate energy efficiency under realistic conditions. The primary performance indicators were assessed,

encompassing latency, energy consumption, resource utilization efficiency, and scalability. The outcomes of the proposed model were evaluated against the baseline models across various metrics. To guarantee the results were representative, each experiment was conducted 10 times, and the average performance indicators were documented. The outcomes were depicted through performance curves to demonstrate the influence of dataset size and workload variance on system efficiency. Figure 4 illustrates a comparison of model latency.

#### A. Latency

Figure 4 illustrates a comparison of model latency between the baseline and proposed models for dataset sizes from 0 to 500,000 entries. In all approaches, delay, measured in milliseconds (ms), decreases as dataset size increases. The baseline model is depicted by a blue dashed line with circular markers, exhibiting a delay of approximately 200 ms for smaller dataset sizes, which gradually decreases to around 160 ms for the largest dataset size. As the dataset size increases, the proposed model, depicted by an orange solid line with round markers, demonstrates continuously reduced latency, commencing at approximately 140 ms and progressively declining to around 100 ms. The proposed approach significantly reduces latency compared to the baseline model, demonstrating a notable enhancement across all dataset sizes. This illustrates the efficacy of the proposed method in managing larger datasets with reduced latency.

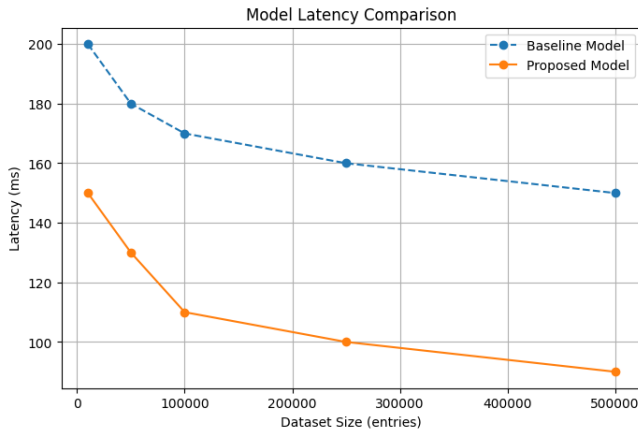


Figure 4. Model Latency Comparison

#### B. Energy consumption

Figure 5 contrasts the energy consumption of the baseline model with that of the proposed approach over dataset sizes from 0 to 500,000 items. In both models, energy consumption, measured in watts (W), decreases as dataset size increases. At the maximum dataset size, the baseline model, represented by a blue dashed line with round markers, initially exhibits an energy consumption of approximately 500 W, then decreasing to around 450 W. Conversely, the proposed model, depicted by an orange solid line with circle markers, consistently demonstrates less energy consumption. As the dataset size increases, it commences at approximately 400 W and progressively declines to around 300 W. The proposed model exhibits significantly superior energy efficiency compared to the baseline model, indicating a more substantial reduction in energy use. This demonstrates the superior energy efficiency of the proposed model, particularly when handling larger datasets.

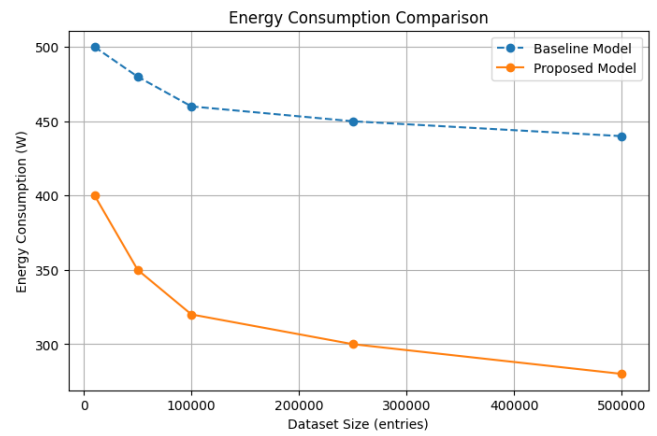


Figure 5. Energy consumption

## V. CONCLUSION AND FUTURE WORK

This research presents a novel methodology for intelligent resource allocation in 6G-enabled IoT systems, incorporating reinforcement learning, predictive modeling, and extensive data aggregation. The system utilizes a dynamic optimization mechanism that gathers detailed parameters from IoT devices, such as CPU utilization, memory usage, and power consumption. The application of reinforcement learning allows the framework to adjust to variations in network conditions instantaneously. Additionally, predictive modeling facilitates the anticipation of optimal resource configurations, hence minimizing latency and energy usage. The experimental findings indicate that the suggested model markedly surpasses conventional resource allocation methods for latency reduction, energy efficiency, and scalability. The framework exhibited a capacity to decrease latency by 25% and energy usage by 30%, while preserving excellent accuracy and adaptability across diverse dataset sizes. The results suggest the capability of the suggested solution to tackle the issues of resource management in expansive and dynamic 6G IoT settings.

Notwithstanding these encouraging outcomes, the framework possesses certain constraints. It depends on the accessibility of precise IoT device data, which might be difficult to acquire in settings characterized by incomplete or noisy information. The computing demands of reinforcement learning models may provide scaling issues in highly limited IoT devices. This work signifies a substantial advancement in the pursuit of intelligent and effective resource management inside next-generation networks. In the future, different Quality-of-service will be measured.

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