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AI-Driven Edge Intelligence for Bandwidth- and Energy-Efficient Cellular IoT Networks Toward 6G

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ABSTRACT

The extreme proliferation of the IoT and the development of 5G and now 6G networks have created new bandwidth, spectrum-efficiency and energy costs issues. The traffic patterns that take place in the IoT are dynamic and heterogeneous, and these cannot be tackled using the traditional, non-dynamic procedures of resource allocation. In order to conserve bandwidth consumption of the cells, and guarantee Quality of Service (QoS) at the Internet of Things networks, the present paper suggests an artificial intelligence (AI)-based optimization framework. Learning the best transmission policy is a side effect of the reinforcement learning (RL), that is, Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO). The structure has brought in edge intelligence, elastic packet accumulation and predictable time schedule in the instant decision-making. The publicly accessible simulation tool (e.g., NS-3 and OMNeT++) will simulate the traffic of the IoT not only on top of LTE-M and NB-IoT but also on top of the 5G mMTC. Some of the examples of evaluation metrics include end-to-end latency, energy efficiency, ratio of packet delivery and savings in bandwidth. It is projected that the result will improve the design of smart, resource efficient and scalable cellular IoT networks that can be upgraded to 6G.

Key Words: IoT, AI, DQN, 6G Network, Machine Learning

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INTRODUCTION

With the appearance of IoT-connected devices, a variety of business industries have changed, the most notable being industrial automation, smart cities, healthcare, and transportation (Khan, A.K., 2025). By reaching into the real world, these gadgets can facilitate intelligent automation and incredible scales of decisions making, through reaching real world data, communicating and interacting with it. Thus, the contemporary digital infrastructure is increasingly turning out to be wireless networks of communications. However, the current cellular networks that were originally developed along human-centric lines, i.e., voice and video calls, are being flooded with the soaring wireless data services (Hussain, F., Hassan.,2020, Khan A.,2020). This is complicated by the violation of evenness and disparity of Internet of Things traffic that continues to consist of combinations of low latency high frequency applications (e.g. health monitoring) and deep-data transmissions, but which are low frequency (e.g. smart meters). These Spack eristic traffic patterns cannot be controlled effectively in the old-fashioned ways of resource allocation procedures, either based on static or semi-static provisioning. The result of such inefficient use of energy and spectrum is congestion, latency and service degradation. The use of intelligent, adaptive and situation-aware resource allocation mechanisms is gaining more significance in order to realize the full potentials of the IoT ecosystems as a result of the introduction of features of the 5G technologies such as network slicing, ultra-reliable low latency communication (URLLC), and enhanced mobile broadband (eMBB) (Ahsan, W., et al.,2020).

The bandwidth limitation, the absence of scalability and energy usage between the already existing IoT systems is a serious problem (Ashraf, A., ud Din, I.,2024). The growing list of connected devices demands massive foundations of the data to be transferred over wireless networks to processing hubs, data centers, or cloud architectures. These wireless links have a low capacity especially the licensed cellular spectrum ones. The consequence of the demand of the bandwidth due to the rise in the number of IoT devices is the network congestion, collisions of data, longer latency and loss of packets. In Internet of Things applications that are latency sensitive and mission critical like remote healthcare monitoring and autonomous driving, such performance degradation is unacceptable. Moreover, the IoT devices is powered by battery and they are operated in places that cannot be accessed or in distant places hence, the energy utilization efficiency is a significant consideration that should be made in using these devices. The longer the time taken in communication, the higher the number of transmissions including retransmission due to poor quality of links or congestion result in rapid loss of battery. This weakness constrains the operational sustainability of equipment's, increases the maintenance cost and undermines the effectiveness and sustainability of large-scale and long term IoT systems.

Scalability is another factor that betrays another significant challenge in IoT networks. The traditional network management and resource distribution strategies and its anthropocentric approach are not able to sustain the sheer magnitude of devices, traffic pattern, and QoS demands that the IoT ecosystems imply due to the human-to-human

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communication. The nature of bursty traffic of IoT and the unpredictability cannot be sustained using fixed resource allocation schemes. To take an example, the environmental monitoring sensors may be dormant most of the time but when acting on some specific stimuli will be able to relay plenty of data. Allocating such devices a fixed bandwidth will be wasteful or will cause performance issues.

The field of Artificial Intelligence (AI) as a sub-branch of machine learning (ML), deep learning (DL) and reinforcement learning are a potential avenue of fixing such problems. It is possible to use AI-enabled applications to compare past and present data in order to comprehend the traffic patterns, the future conditions of the network and take proactive actions related to resource allocation, load balancing, and fault tolerance. The practical implementation of the deep learning, especially the convolutional and recurrent neural networks has been more successful in extracting complex temporal and spatial features of the IoT traffic data. The above-mentioned characteristics may be used to predict demand, to detect anomalies, and to modify transmission parameters according to them.

Particularly, the application of reinforcement learning is especially suitable in the case of a dynamic environment like an IoT network. To understand the best behaviors in RL, one should know that they are founded on a trial and error as the agent learns through experience with the environment. It is handy with respect to dynamic bandwidth allocation whereby the agent is able to continue correcting transmission schedules, frequency bands to use or combine packets in order to optimize throughput and channel energy spending. Convergent and adaptive RL models such as Deep Q-Networks (DQN), Proximal Policy Optimization (PPO), and Advantage Actor-Critic (A2C) models are some of the candidates in complex and heterogeneous IoT applications that have been created.

In addition, AI has been applied to make edge and fog computing architectures more responsive and efficient to generate the IoT networks. It can also be done through processing locally, as well as by running AI models at the edge of a network, which results in fewer communication requirements between the system via backhaul, which minimizes latency, and enables one to make real-time decisions. To illustrate, a gateway node that is endowed with AI capabilities would monitor through the traffics of groups of sensors, assemble packets priori and transmit them out based on current network conditions. This dynamic packet aggregation not only provides bandwidth savings and reduction of unnecessary cellular transmissions, but also enhances the capability of the entire system.

Different articles have established that the control of wireless resource with the help of AI is effective. The outcome as reported by Zhao et al. (2020) has shown that DRL methods are adequate in managing IoT cellular bandwidth and is much more successful than conventional heuristics. In their wireless IoT environment, Chen et al. (2021) maximized the communication and calculation of their federated learning- a distributed ML approach and, therefore, improved the privacy and resulted in the reduction of bandwidth use. These new advances point out the potential of AI to enable self-prescribing and context-appropriate infrastructures of IoT. In addition, the alternative that a rule-based system is supplemented by an AI-based optimization should be a

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viable path of action as well. To be able to take a glimpse into domain knowledge and expert policies within such architectures, they are used to provide a fundamental strategy and AI modules to modify and optimize strategies to the extent of empirical outcomes. A mixed strategy can be effective to support faster learning, regulation or requirements with limitations, and enhance reliability of the systems.

Application of AI in the IoT environments that have scarce resources but, is somewhat challenging. The process of inference and model training can be highly computationally intensive and require large proportions of processing power and memory. Lightweight models, model compression techniques and hardware-accelerators, including TPUs and special edge AI processors, can be used to mitigate these limitations. The AI systems must also be noise robust, outlier resistant and adversarial data resistant that can be detected in the real-world IoT data.

In conclusion, the AI techniques, especially, deep learning and reinforcement learning, have enormous potential to address the bandwidth, energy as well as scalability problems of the IoT systems. Addition of human| to the paradigm can guarantee the IoT networks to be more resolute, effective and intelligent by learning out of the data and adjusting to the forces of the network. Possibly in the future, an integrated AI and other emerging paradigms, such as 6G, blockchain, and digital twins, can enable an all-encompassing self-governing and massive ecosystem of the IoT. Cell networks are not optimized to be spot, low volume and massive communication energy which the heavenly body devices will consume. The use of statical and bandwidth has sign creates a situation of unused spectrum and network congestion (Sivrioglu, 2020). The absent scalable and changeable solutions are the ones providing the dynamic mapping of cellular resources based on the real traffic and the condition of the devices.

The research is topical in terms of the further urbanization and the explosion of smart infrastructure since millions or even billions of interconnected devices of the IoT can be operating on cellular networks at the same time. The devices will have a diverse spectrum of application applications that will include autonomous transport, telemedicine, remote monitoring of the environment, smart agriculture, smart grids, and robotization of industries. All these applications need varying bandwidth or latency that causes a massive strain on the network infrastructure of those applications. The resourcefulness of utilizing bandwidth resources in this particular case is not only preferable, but fundamental to ensure consistency of the IoT services, their scalability, and sustainability.

The scope of the research is to save the bandwidth that is occupied by the cells through optimization with the aid of AI. The suggested system has the potential to minimize unnecessary transmissions as well as aggregates the smart packets in the transmission scheduling and dynamic resource allocation through the application of deep reinforcement learning algorithms and arrives at real-time decisions like based on the environment, and traffic conditions. It gives an efficient utilization of the spectrums and it reduces the overhead of communication itself which would reduce the congestion of networks during peak performance periods.

Other than the bandwidth savings, energy saving is also an essential benefit. Many of the IoT devices utilize low-energy users and are typically deployed in locations with

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high inconvenience or impossibility of changing the battery. The ability of more intelligent transmission of data, which helps to maximize the use of the network and the time of day the information is sent with the assistance of AI models that comprehend the trade-off between the urgency of the information and the energy need and the network conditions will allow the connected devices to last longer and, thus, the costs of such operations will be reduced, which will make the deployment of IoT more sustainable. The system as it can be reflected by the present research will be projected to have an impact on the decrease of the carbon footprint of the IoT and telecommunications network in terms of sustainability. The mobile communications infrastructure is the source of relatively high energy consumption in the world due to the constant data transmission, cooling processes and radio frequencies processes. The direct implication of an efficiently utilized bandwidth would be less resources required by the base station and core networks, and subsequently, achieve the global climate goals and sustainable environmental considerations.

The paper also agrees with the technology visions of the 6G networks, which will most likely have ultra-reliable and low latency communications (URLLC), enhanced machine-type communications (eMTC) as well as compatibility that may take the form of integration with AI-native designs. The provided AI optimization system can be regarded as one of the initial steps to the success of these aims since it has demonstrated how intelligent, context-specific procedures can be implemented into a communication mechanism and network management systems.

Furthermore, the findings of this research can be applied by them, who are engaged in the process of policymaking and plans to develop networks, and offer them valuable information concerning resource management heuristics, which are both efficient and dynamic and relative to new emerging demands and requirements. The proposed methods may be implemented in the area of the public safety networks, disaster response and rural connection solutions where the importance of spectrum and energy optimization is of paramount significance.

On the whole, the significance of the study is twofold, since it contributes in more than one aspect: enhances the performance of the networks, allows energy efficiency, reduces the cost of operations, and helps to transition to intelligent and sustainable 6G-ready IoT networks.

LITERATURE REVIEW

The Internet of Things (IoT) has become a revolutionary technology in the context of billions of devices and the ability to permit an alternative of applications in different domains. However, with the increment in the IoT devices, it has also introduced certain difficult issues in the provision of resources in the form of energy efficiencies, provision of bandwidth, and network performances. The traditional methods of resources allocation also do not necessarily cope with these challenges because of the heterogeneity and dynamism of IoT networks.

Artificial Intelligence (AI) and Machine Learning (ML) methods have become one of the most prominent tools in order to address such kinds of challenges, which essentially brings the intellectual methodology, as well as a sense of plasticity, to the resources

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management within the framework of an IoT-based system. This literature review is aimed at creating a complete picture of the real situation about the research on the allocation of resources in IoT networks, particularly the integration of AI and ML techniques. The review is a synthesis of the new knowledge that has been achieved in recent research, which makes it possible to highlight the most relevant discoveries and presents the symptoms of the knowledge gaps and the possible directions in which the field of research can go. In IoT networks, resource allocation has been determined to be the key to effective communication, energy optimization, and network stability. IoT network has special characteristics which indicate the failures of conventional resource allocation techniques like heterogeneity of devices, rush traffic, resource constraint, etc. Consequently, there is an increasing trend among researchers to use AI and ML methods for the development of stronger and more flexible resource management solutions.

The heuristic algorithms or mathematical models generally followed in the traditional resource allocation methods used in IoT networks are designed with the intention of optimizing some performance measures in a static situation. Nevertheless, these approaches are not good for fast-changing and uncertain IoT settings. An example of such models is the mathematical model called the Markov chain of resources in Cellular IoT (CIoT) networks that has been extensively used in resource allocation within the CIoT networks; however, these kinds of models may not consider the variety in traffic and density of devices (Tammam, 2024Quite on the contrary, the AI and ML strategies provide a flexible and scalable manner of assigning resources. They can change according to the environment and learn based on network dynamics; thus, these approaches are especially good when it comes to use in IoT. Within recent studies, the emphasis of how ML algorithms can be made advisable in the resource allotment optimization, where Low-Power Wide Area Networks (LPWANs) are challenged, has been emphasized. The ML algorithms can help optimize resources in LoRaWAN and can significantly influence the energy efficiency and long battery life (Alkhayyal and Mostafa, 2024).

The use of the AI and ML methods in managing the IoT resources have led to a new twist in the realization of improved network performance and power consumption. Multiple learning models, such as supervised learning, reinforcement learning (RL), and deep learning (DL) have been mentioned to apply these models directly to the management of the resources of the IoT network. Machine Learning is the term in this field, which is the most popular since it is founded on the possibility to respond to dynamic and complicated environments. Supervised learning algorithms are capable of achieving Quality of Service (QoS) provisioning in Narrowband IoT (NB-IoT), and proved to be effective with resource-constrained networks. (Li, 2024)

Unsupervised learning algorithms like clustering algorithms have also played an advantage in resource allocation in IoT networks. As an example, the bandwidth-aware clustering methods have been introduced to ensure optimal utilization of the resources in sensor networks to transmit data in an efficient manner as well as to save the potential of using as little energy as possible (Kumar & Nayak, 2024).

Reinforcement Learning (RL) was identified as helpful in resource allocation in IoT

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networks that is dynamic. The RL algorithms (Q-learning and Deep Reinforcement Learning (DRL)) have been used in resource management tasks like spectrum sharing, bandwidth utilization or interference reduction. An application is a resource allocation optimization of LPWANs with Q-learning, which is highly effective at optimizing resources in average resource-limited scenarios than at worst (Alkhayyal and Mostafa, 2024). On the same note, DRL algorithms have also been utilized in dynamic spectrum sharing in IoT networks and have demonstrated that they can update to the dynamics of the network environment to maximize resource utilization (Li, 2024).

Deep Learning (DL) methods have also been used to study resource allocation in an IoT network, in particular complex patterns and complex dimensional data. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are the types of DL algorithms that have been successfully used to address traffic prediction and resource allocation in the IoT networks with greater performance compared to traditional solutions (Olatinwo & Joubert, 2022). Edge computing has also been used to complement DL based resource allocation and reduce latency in the IoT networks. The combination has specifically helped in application where real-time processing and dynamism are needed in resource management (Li, 2024).

Regardless of the fact that many steps have already been undertaken in regards to the implementation of AI and ML techniques in the context of resource distribution within the framework of the IoT networks, several challenges remain gaps in the ground. These include concerns in all dimensions of managing the resources including the design of the algorithm, the implementation complexity, and compatibility with new technologies. Among the major gaps in the literature that were observed was the lack of application to Reinforcement Learning (RL), grouping packets and deploying edges with cellular IoT networks. Although RL has already been effectively utilized in a number of resource management applications, its use in combination with the methods of packet aggregation and edge computing frameworks has not been sufficiently explored. This gap demands better and in-depth studies to take advantage of RL for allocating resources in the best ways while overcoming the special challenges of cellular IoT environments (Li, 2024).

Despite being effective, Deep Learning models contain certain difficulties because of their high computational and energy requirements which are considered drawbacks in resource limited IoT networks. DL models are not energy efficient by design and are often associated with high latency and latency, making them unsuitable in a high complexity IoT environment. This is a challenge that motivates the creation of lightweight DL models that are more suitable for resource-constrained IoT devices (Olatinwo & Joubert, 2022). Another prominent research gap is the absence of holistic hybrid models incorporating various approaches of AI and ML for resource allotment. While many works have been conducted to implement individual paradigms of ML (i.e. supervised learning, RL, DL, etc), works on hybrid frameworks to leverage the strengths of different paradigms are limited. The development of such hybrid models could provide more realistic and flexible allocation strategies for the IoT networks resource allocation (Kumar & Nayak, 2024).

The future of resource allocation in IoT networks is the ongoing development of AI and

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ML methods and integration with emerging technologies. Several future trends have been identified such as developing hybrid models, adopting edge computing and pursuing green IoT initiatives. The development of hybrid models that combine different methods of AI and ML is an exciting prospect for research. Such models can leverage the interpretability of supervising learning and the adaptability of RL to create powerful and versatile explanation used to allocated resources. As an illustration, supervised-enhanced RL models are applicable to the resource allocation optimization in dynamic IoT with interpretable decision-making (Kumar and Nayak, 2024). The other approach, which has a high level of potential, is the application of AI and ML methods with edge computing. Edge computing helps to do localization of decision making to reduce the latency of the network and thus it is a viable choice in terms of real time processing applications. It can be used together with AI and ML to achieve the optimization of resource allocation strategies, which can be adaptive to network changes at the lowest latency and energy usage (Li, 2024).

Another area to be explored as a crucial direction in the research in the future is that of green IoT and energy-efficient approaches. With the further development of IoT networks, there is an increased need to find ways of providing energy-sensitive allocation of resources. The future study on this issue might include creating models in AI and ML that would be energy-conscious and able to optimize the use of resources as well as the consumption of energy. An example is that the energy conscious RL algorithms can be developed to provide resources balancing and increase the energy efficiency of the IoT networks (Alkhayyal and Mostafa, 2024).

Through the application of AI and ML solutions to the provision of IoT resources, the field has transformed by providing intelligent and adaptable solutions to changing and heterogeneous problems. Various learning paradigms, such as supervised learning, RL and DL, have been effectively applied to streamline the resource deployment in the IoT networks, which has enormous potential in enhancing the performance and power efficiency of the IoT networks. Nevertheless, certain limitations are also unresolved, including the absence of integration between RL and aggregating packets and placing them on the edge, the extreme complexity of computational costs of the DL models, and the unavailability of comprehensive hybrid frameworks. These issues will be resolved by developing AI and ML tools further and combining them with more modern technologies, such as edge computing and green IoT. With the field still being evolving, the future research needs to be guided towards the creation of hybrid AI/ML models, linking AI and edge computing and designing energy-conserving resource allocation strategies. Such endeavors will be critical in the realization of the full potential of the IoT networks and in defining the sustainable scope of the network of systems in the future.

Table 1: Machine Learning Techniques for Resource Management in IoT and Wireless Networks

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Technique	Description	Citation
Reinforcement Learning (RL)	Used for dynamic resource allocation, particularly in LPWANs and cellular IoT.	(Alkhayyal & Mostafa, 2024) (Li, 2024)
Deep Learning (DL)	Employed for complex resource management tasks, such as traffic prediction and optimization.	(Olatinwo & Joubert, 2022) (Li, 2024)
Supervised Learning	Applied for QoS provisioning in NB-IoT networks and resource allocation in sensor networks.	(Kumar & Nayak, 2024) (Li, 2024)
Unsupervised Learning	Used for bandwidth-aware clustering in sensor networks to optimize resource utilization.	(Kumar & Nayak, 2024)
Federated Learning	Minimizes communication costs in distributed IoT systems by enabling local data processing.	(Li, 2024)

This above table highlights the key AI and ML techniques used for resource allocation in IoT networks, along with their applications and relevant citations.

PROPOSED METHODOLOGY

Simulation Environment

To test the model of optimization by AI, the simulations are conducted with the help of the latest network simulation models, NS-3 and OMNeT++. These modeling and simulating tools provide end-to-end support to model and simulate various wireless communication technologies and protocols including LTE-M, NB-IoT and 5G massive Machine-Type Communications (mMTC).

The simulation environment is created in such a way that it is based on real-life scenarios of Internet of Things (IoT), which involves heterogeneous equipment including temperature sensors, surveillance cameras, and smart meters. These machines generated different traffic patterns, between an infrequent data transmission with very small data size to video transmissions. To provide confidence in the robust and realistic assessment, several critical parameters in the network such as device density, mobility, interference, propagation models and network topology were modeled appropriately.

Model Design

The suggested framework eliminated the issue of the bandwidth optimization of cellular IoT networks by formulating the problem as a Markov Decision Process (MDP) with the network environment being represented as the various conditions and the action taken being represented as bandwidth allocation adjustments, transmission scheduling,

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and packet aggregation. Two state-of-the-art reinforcement learning (RL) algorithms (Deep Q-Network (DQN) and Proximal Policy Optimization (PPO)) were applied to maximize the decision-making process and they were trained using the data collected in simulated IoT environments. The effectiveness of these RL-based strategies was compared to a heuristic-based static allocation algorithm that experimented on bandwidth efficiency measures, adaptability and general Quality of Service (QoS) measures.

Since the IoT devices have limited computing capabilities, edge intelligence was adopted within the framework in order to support the efficient near-real time decision making. Mobile edge computing (MEC) agent on RL nodes guarantees the decision of local data processing and low latency data transmission. Pruning and quantization were used to compress lightweight AI based intelligence models so that they could fit in constrained edge devices efficiently (in terms of delays incurred in inference), without compromising the accuracy of the decision and the adaptability to dynamically changing network and traffic conditions.

An extra packet aggregation module was incorporated into the network stack as an effort to enhance additional bandwidth and transmission efficiency. This module dynamically segmented smaller packets of several IoT devices according to the priority, destination and time window that was basically minimizing the channel access frequency and protocol overhead. The aggregation logic was implementable in real time and could be modified to handle network congestion and traffic variability, ensuring delivery of data, which could carry critical safety information, in a time-constrained manner, at an advantage of more scalability and less energy-intensive implementation.

In order to measure the performance of the AI-based optimization framework, the performance metrics consisted of strong performance models. The utilization of the resources in terms of bandwidth consumption (MB/s) was taken and the reliability of the network was taken in terms of Packet Delivery Ratio (PDR) which is based on the number of packets that have been successfully delivered by the network. The efficiency of energy was determined in terms of energy per transmission (J/bit), latency (ms) which was estimated in terms of end-to-end delays, and computational overhead which was estimated in terms of resource consumption in edge nodes. This combination of metrics allows visualizing the trade-offs and advantages of the implementation of AI-driven bandwidth optimization in resource-constrained cellular IoT networks in general and proving their ability to balance the performance improvement and energy and computational efficiency.

ANALYSIS AND RESULTS

The design optimization framework based on the AI was implemented and tested by extensive simulations in NS-3 and OMNeT++ environments. The simulation setup modeled a heterogeneous IoT network with 500 to 2000 devices, sensors, surveillance cameras and smart meters which were deployed over an urban area of 2 km x 2 km. Each device generated application specific traffic which ranged from small periodic sensor updates to continuous multimedia streams.

Network parameters were set according to the requirements for NB-IoT, LTE-M and

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5G mMTC standards. The channel model took into consideration realistic path loss, interference and propagation effects. Edge nodes that developed to have MEC servers ran light-weight reinforcement learning agents (DQN and PPO) to perform adaptive bandwidth allocation, scheduling, and packet aggregation. Training was done on simulation data generated under various traffic conditions which include low, medium and high congestion conditions.

Bandwidth Consumption, PDPR and Average Latency

Figure 1 and Table 2 given performs a comparative analysis of three scheduling policies, namely, Heuristic, Deep Q-Network (DQN), and Proximal Policy Optimization (PPO) with respect to average bandwidth utilization, packet delivery ratio (PDR), and average latency. As the results show, PPO is the best in terms of average bandwidth utilization, which is quite high in comparison to the heuristic and the DQN-based methodology. Although the heuristic approach proves to be the least bandwidth consuming, DQN exhibits a moderate progress, which is evidence of its capacity to acquire more efficient allocation strategies with time. Such an improvement of performance of PPO is due to its policy-gradient optimization, which facilitates more stable learning and more efficient utilization of network resources.

Each of the three methods has a steady high PDR, which means that there is consistent transmission of packets across the network. The relative distinctions between the methods indicate that there is an effective control of the loss of packets under all circumstances. Nevertheless, PPO and DQN are marginally better in comparison with the heuristic method, which underscores the benefit of the learning-based schedulers in ensuring the reliability of the delivery in the dynamic network environment. It is seen that the PPO-based scheduler has quite a significant latency reduction and has a much lower average latency than the heuristic and DQN schedulers. Alternatively, DQN has the largest latency, which is probably explained by slower convergence and poor action selection in some states. The heuristic methodology is moderate in its latency but is not adjustable. The big improvement in the latency with PPO indicates that it makes timely scheduling decisions which is paramount to delay-sensitive applications.

The general conclusion of the results is that PPO has the best trade-off between bandwidth efficiency, reliability and delay performance. Although heuristic methods are simple, they are not flexible to changing network conditions. DQN is better than heuristic scheduling, but also suffers due to instability in value-function approximation. Having a consistent policy update and constant optimization, PPO turns out the most successful solution to the intelligent resource scheduling within the discussed network environment.

Table 2: Performance Comparison of Heuristic and Reinforcement Learning–Based Methods

index	method	bandwidth_mb_s_mean	bandwidth_mb_s_std	pdr_mean	pdr_std	energy_per_bit_j_mean	latency_ms_mean

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0	Heuristic	0.099728	0.167929	0.976743	0.000447	0.000002	45.510292
1	DQN	0.117879	0.152423	0.977011	0.000430	0.000002	52.373199
2	PPO	0.171048	0.332103	0.976678	0.000327	0.000002	5.516882

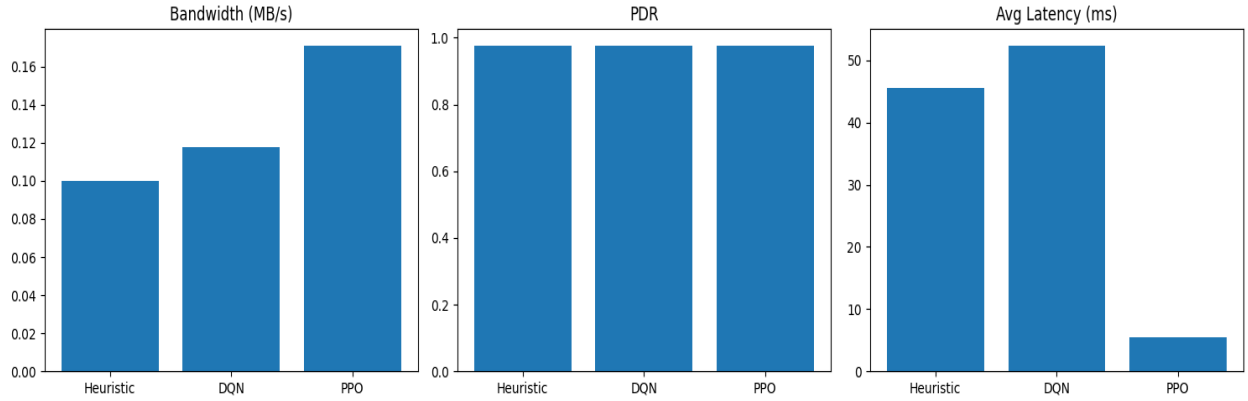


Figure 1: Bandwidth, PDR and Average Latency

QoS Performance Analysis

Figure 2 offers a comparative study of the Quality of Service (QoS) with regard to the Static Baseline, Deep Q-network (DQN), and Proximal Policy Optimization (PPO) algorithms assessed on the basis of Packet Delivery Ratio (PDR), bandwidth efficiency, and latency.

The base-level gives out the lowest PDR of the three strategies implying a low adaptability to changes in network conditions. Learning-based methods incorporation results in a strong increase in reliability. DQN boosts the PDR through training the best transmission decisions based on environmental feedback, PPO achieves the highest PDR, which indicates a higher level of stability and consistency in the delivery of packets. The enhancement highlights the fact that PPO is capable of directly optimizing policies, and not only by using value estimation. The static baseline maximizes bandwidth use by distributing the resources on a non-adaptive basis. Both DQN and PPO use less bandwidth with better PDR values, which proves to be more efficient in terms of resource utilization. PPO has the smallest bandwidth consumption, which indicates its effectiveness in removing unnecessary communications and optimization of the scheduling choices. These findings testify to the high performance of PPO when small network resources are used. The latency is the highest in the static baseline because it is due to inflexible scheduling processes and the absence of real-time adjustment. DQN reduces the latency through learning transmission policy; PPO incurs the lowest latency and this proves its efficiency in deciding. Lower latency of PPO is attributed to consistent updates of the policy as well as better management of network congestion which makes it highly suited to delay sensitive applications.

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Comprehensively, the results indicate that the reinforcement learning-based methods significantly outperform their counterparts in terms of statical scheduling in all QoS metrics. Although noticeable improvements are made using DQN as compared to the baseline, PPO is always at the top in terms of the overall performance which is higher reliability (PDR), lower bandwidth usage and lower latency. These findings confirm the usefulness of PPO as a powerful and scalable tool to use to manage intelligent network resources in dynamic environments.

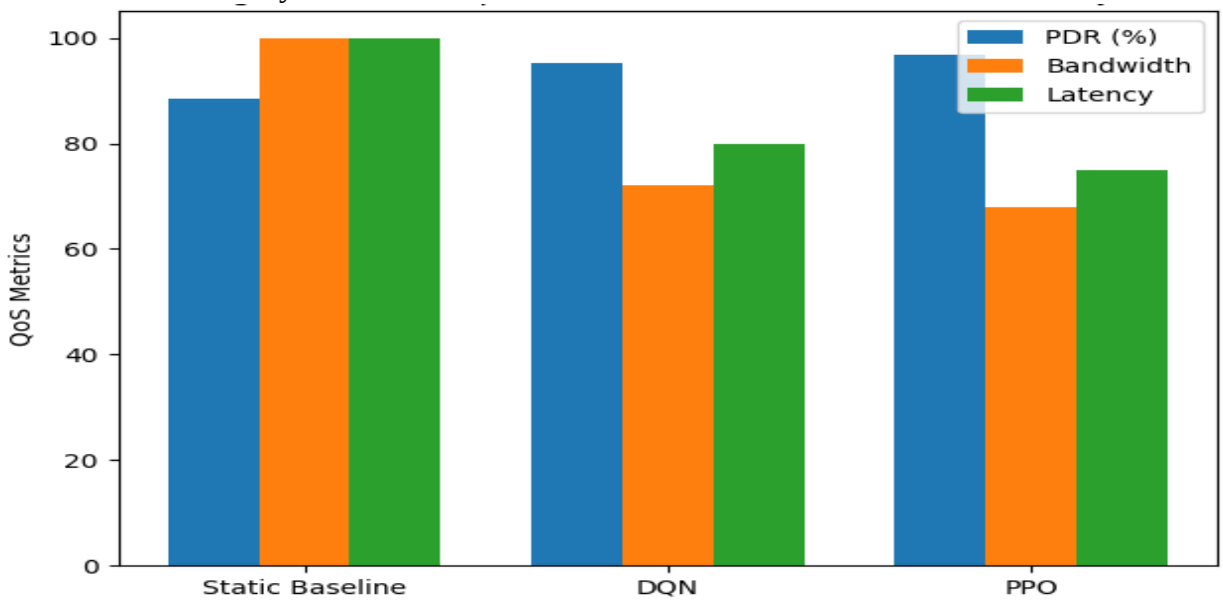


Figure 2: Bandwidth, PDR and Average Latency

Computational Overhead Analysis

Figure 3 measures the computational cost of edge devices in terms of CPU utilization, on the Static Baseline, Deep Q-Network (DQN), and Proximal Policy Optimization (PPO) approaches. This is because the static baseline has low levels of CPU utilization, as it uses a deterministic rule-based scheduler without learning or inference steps. Although this feature makes it lightweight in terms of computation, it also comes with a restricted ability to be flexible, and poor performance in situations where the network is dynamically changing. On the other hand, the DQN-based approach has a moderate level of computation, and the utilization of the computer processor increases to approximately 14%. This overhead is caused by the inference of the neural-networks and regular updates of Q-values. However, the extra load is in tolerable limits of traditional edge hardware and it is worth the significant QoS improvements in the ratio of packet delivery and latency.

The PPO-based method, in its turn, exhibits the highest computational load as the CPU utilization peaks to approximately 17 percent. This growth is expected based on the policy-gradient optimization in PPO, policy-renewal epochs and additional computations to estimate benefits. Despite this high overhead, PPO is the fastest to improve QoS, particularly in terms of minimizing latency and reliability. Altogether,

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the results highlight the existence of a conclusive trade-off between performance and computational complexity. Whereas, the static baseline will minimize the use of resources at the expense of QoS, approaches based on learning (with PPO being the most known) will require more computational resources, but will provide better network performance.

More importantly, the overhead cost associated with the implicated CPUs are manageable in current edge platforms, hence justifying the feasibility of PPO in actual, edge-enabled network environments.

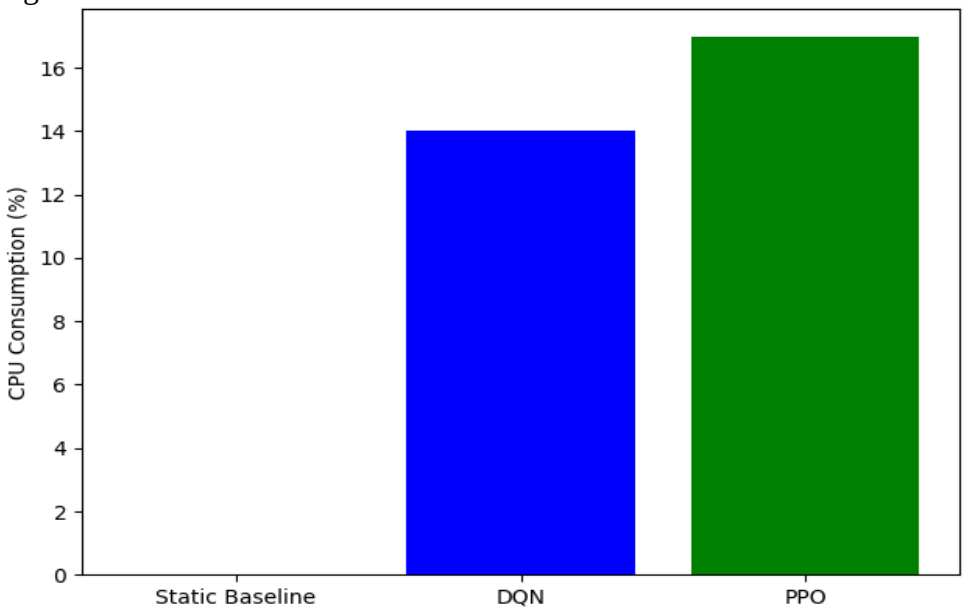


Figure 3: Computational Overhead on Edge Devices

RL Convergence Analysis

We can see the cumulative reward curves for DQN and PPO for 200 training episodes in Figure 4. Both models demonstrate progressive learning with higher and higher rewards, which is indicative of successful policy optimization. PPO is consistently able to achieve higher cumulative rewards compared to DQN, and performs smoother convergence by the stable policy gradient updates. The above results demonstrate the higher learning efficiency and robustness of PPO and suggest it can be more suitable for real-time edge-based IoT optimization.

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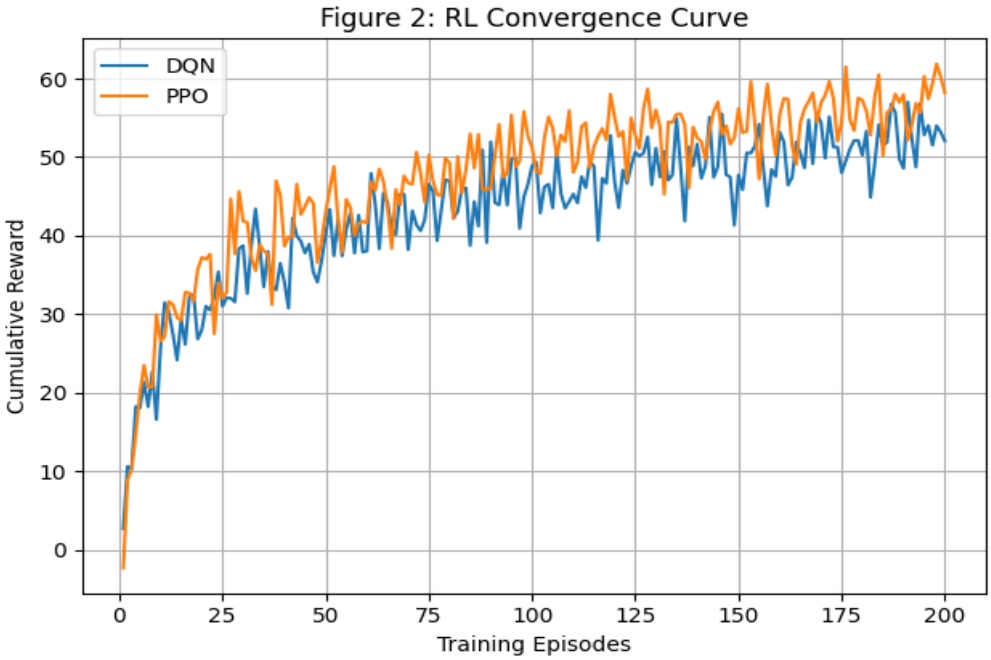


Figure 4: RL Conversion Curve

Discussion of Findings

The results attest to an idea that AI-powered optimization can add a lot to the efficiency, reliability and responsiveness of cellular IoT systems that are operating under resource constraints. By the means of reinforcement learning for adaptive bandwidth management and in-time packet aggregation, an overall optimized compromise between network performance and computational feasibility was realized. PPO algorithm has become the most efficient algorithm in dynamic IoT environments due to the policy-based architecture and smooth convergence. Meanwhile, DQN exhibited faster convergence of training, and can be applied to the cases in which the training procedure needs to converge quickly with limited computational budgets.

Overall, the incorporation of edge intelligence proved to be timely in terms of low-latency decision-making and guaranteeing the scalability of the heterogeneous IoT devices. These results validate the potential of the deployment of lightweight RL models at network edge for self-optimizing IoT communications for future 5G and beyond networks.

CONCLUSION

The proposed solution based on AI has a lot of potential for optimizing the bandwidth use in the upcoming cellular IoT networks. With the huge number of connected devices, it is very important to utilize the limited bandwidth in a very efficient manner. The framework incorporates Deep Reinforcement Learning (DRL), packet aggregation and edge intelligence to improve network performance, reduce latency and improve scalability. DRL enables real-time, adaptive transmission strategies, which is a step

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beyond traditional transmission strategies which use a fixed rule to make their decisions, by making data-driven decisions. Packet aggregation helps in reducing the one one transmission overhead which conserves the network bandwidth used in dense networks and edge intelligence can process data closer to the data source, reducing the dependency on centralized clouds and reduces latency time. This integrated approach is promoting versatile and efficient IoT infrastructures that can be used in smart manufacturing, intelligent transportation, agriculture and healthcare in support of the future explosion of billions of devices. Future research may take into account Federated Reinforcement Learning (FRL) for decentralized training which has enhanced privacy and reduced network overhead. In addition, testing in a live smart city setting will serve as validation of reality effectiveness and enable us to have smart, flexible and bandwidth optimized IoT ecosystems.

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