AI-Powered Dynamic Optimization of Mobile IoT Networks for Smart Cities and Industrial Applications

Muhammad Mursaleen Akbar[*], Ahmad Khan[†], Muhammad Adnan[‡], Muhammad Mubashir Yasin[§], Amir Khan[**]

Abstract

The development of the Internet of Things (IoT) technology enhanced communication through mobile gadgets to a great extent. Mobile IoT networks were however faced with the challenges of limited bandwidth, energy, and increasing demands of real-time processing. The problems in this area were solved by this study by providing improved networks using an AI-based solution in addition to packet aggregation and multiplexing. The dynamic framework proposed was made to be responsive to the mobile IoT systems where the devices were constantly moving between different zones and access points were changing resulting in handovers and fluctuating network conditions. The AI-based techniques monitored the activity of the network and dynamically adjusted the aggregation sizes and multiplexing procedures on the fly. The evaluation of the mobile IoT scenarios was throughput, latency, and energy consumption analysis. The experiments revealed that bandwidth overhead reduction, multiplexing, and real-time decision-making were facilitated by the use of AI systems because of packet aggregation. Typically, the solution has improved the efficiency of transmission, reduced energy usage and supported the performance enhancement of mobile IoT solutions. The project contributed to developing self-learning IoT applications, which will support the management of smart cities in the future, healthcare monitoring, and automation in industries.

Keywords: Internet of Things, Artificial Intelligence, Aggregation, 5G, Multiplexing, LoRaWAN, Sigfox.

Introduction

Internet of Things (IoT) network is a system that connects physical equipment to the internet so as to communicate and share data. (Kamal et al., 2021) Sensors, actuators, software, and communication technologies are usually installed on the devices. The main purpose of IoT network is to collect actual world data and use it to transform systems into

[*]Faculty of Computer Science & Information Technology, The Superior University Lahore, Lahore 53700, Pakistan, drmursaleen136@gmail.com

[†]Corresponding Author: Faculty of Computer Science & Information Technology, The Superior University Lahore, Lahore 53700, Pakistan, ahmad.khan.fsd@superior.edu.pk

[‡]Faculty of Computer Science & Information Technology, The University of Malakand, Chakdara 23050, Pakistan, adnanthana@gmail.com

[§]Faculty of Computer Science & Information Technology, The Superior University Lahore, Lahore 53700, Pakistan, info.optimalsolutions@gmail.com

[**]Faculty of Computer Science & Information Technology, The Superior University Lahore, Lahore 53700, Pakistan, raiamir541@gmail.com

smarter and more efficient. For example, Figure 1 below demonstrates that, through an IoT network (Almusaed et al., 2023), a smart home can be networked so that lights, fans, and security cameras among others automatically conduct daily tasks.

Figure 1: Smart Home System (Almusaed et al., 2023).

The IoT network typically incorporates a number of layers: Perception layer, Network layer, and Application layer as illustrated in Figure 2. The gateways are intermediaries that collect the data of devices and send them to the cloud without compromising the security of such messages (Almutairi & Sheldon, 2025). IoT networks are characterized by communication based on such technologies as Wi-Fi, Bluetooth, Zigbee, LoRa WAN, Sigfox and 5G. They have various technologies applied based on the requirements of their range, power usage, and speed Bluetooth and Zigbee are used to connect on a short distance whereas 5G and LoRaWAN are used on a long-distance basis (Asadullah & Ullah, 2017).

The key parameter that could be useful is that of automation and machines can perform without the intervention of humans. IoT networks in agriculture help farmers to check the moisture level of the soil, and they also help automatic control of the irrigation systems. Wearable IoT has potential applications in the medical industry to keep track of the heart rate or oxygen levels or even alert the doctor in the case of an emergency (Marwat, 2020). Smart cities have IoT networks to control garbage collection, streetlights and traffic lights (Wu et al., 2024). The industrial IoT networks provides greater efficiency of the manufacturing processes by monitoring the equipment and predicting failures.

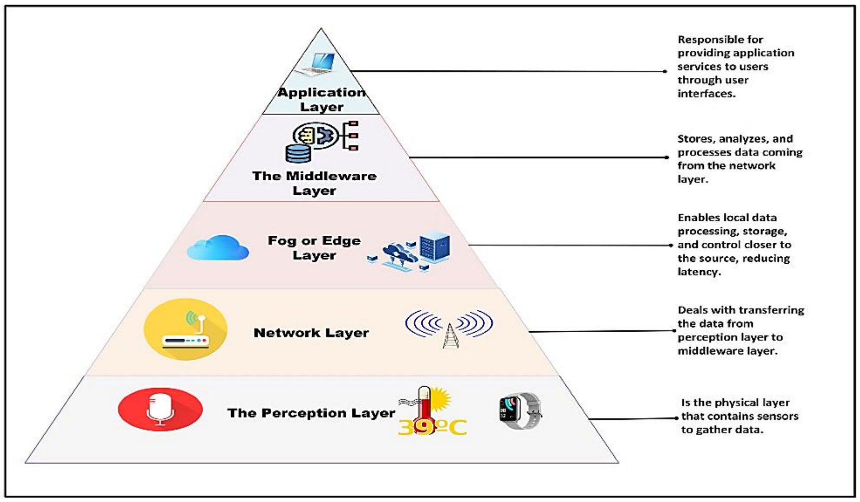

Figure 2: Smart Home System (Almutairi, & Sheldon, 2025).

IoT networks are also scalable and hence, they can accommodate millions of devices that are operating at the same time. However, it also introduces the issue of data privacy and data security as the connectivity is this broad. Attempts by the hackers can be made to have access to the devices and use personal or industrial data. To evade this, the IoT networks are encrypted, run using secure protocols or at times block chains. The second issue is the power consumption since the majority of IoT devices have small batteries and need the implementation of energy-saving communication solutions and energy-grabbing technologies (Atadoga et al., 2024).

Edge computing is also used to implement IoT networks by reducing delays by processing data close to the source. Artificial Intelligence (AI) in recognition and prediction of IOT and MioT is being deployed increasingly (Irfan et al., 2023. This kind of combination makes systems become smarter over time and makes it possible to take decisions in real-time.

To conclude, IoT networks are expanding the gap between industries, households and cities since they are rendering them smarter. In conclusion, IoT network is the foundation of the modern digitalized world where all the things are connected, and all the objects communicate. Mobile Internet Things (IoT) are dynamic environments that continuously change the networks of devices (Agiwal et al., 2021). Mobile IoT networks contrast with traditional IoT systems because they analyze dynamic actions of the system network in real-time and over different domains of the system. Such type of working environment frees devices of any form of restrictive infrastructure as they can move freely between one point and another. The mobile devices never cease to travel across network areas and access points. The network conditions are extremely unpredictable with mobile devices which are not supposed to be stationary because the movement of the devices influences the signal power levels, latency, and alters bandwidth resources and topological structures of the network (Al-Fuqaha et al., 2015). Mobile devices that can be connected to more than one access point result in handovers and variation of signals that create network traffic management problems.

With the current dynamic IoT networks, the fixed network conditions cannot be easily controlled when adapting the customary forms of the networks. Reliable network management systems have predetermined inflexible structures, which include single administration structure and low routing structures. The traditional networks are inefficient because they are required to meet the characteristics of the mobile IoT system including the dynamic topological structure, dynamic traffic pattern, and dynamic quality of services. The areas in which the operational issues can set in whenever the performance of the network is impaired include high packet loss and increased delivery time, low resource use and unsatisfied end-users (Nguyen et al., 2021; Saeed et al., 2019).

The current network system is also failing to meet the traffic capacity because of the increasing IoT devices and the demand of real time critical applications like self-driving cars, smart health monitoring systems, augmented reality systems and industrial automation systems. Real time applications entail the flow of information and information processing in real time and simultaneously as delay is always a rate buster. Network resources management and data flow interruption cause instability in the operational capacity and systems breakouts. There is an urgent need to seek solutions to the Mobile IoT to control the network resources and data flow within the environment (Shi et al., 2016; Cong et al., 2021).

The mobile IoT network employs a number of strategies that enhance both the performance and the reliability simultaneously. Artificial intelligence in network management combined with a mixture of packet aggregation and multiplexed network is the best solution that could be handled in the situation at hand. These optimization tools work concurrently in the performance areas of the respective performances, to stock up the overall competencies in the betterment of the efficiency of the mobile IoT system, and promote its reliability (Alsheikh et al., 2014; Hussain et al., 2020).

Packetizing, also known as the use of packet aggregation, is a process of sending a larger amount of data in form of a single large packet following a combination of a smaller amount of data in smaller packets (Khan, 2025). This will reduce the overhead cost of the packet headers of messages, the need of a frequent acknowledgements of the messages and enhance the performance of the transmission process. Lower frequencies can also be done with the networks by sending multiple packets in one unit of transmission and hence yet another power consumption reduction is achieved in addition to a bandwidth- this is an essential feature that battery-powered IoT devices require. Moreover, it works well in those networks where congestion is minimized by aggregation since the number of transmission lines is reduced and accordingly, as well as channel congestion. Besides this, multiplexing also enables streams of data of multiple data streams to be sent concurrently with the help of a single communication medium. Some approaches that have been adopted to enable multiple streams of data to run at the same time without interference to enhance the data throughput are Time division Multiplexing (TDM), Frequency division Multiplexing (FDM), and Code division Multiplexing (CDM). Multiplexing is necessary in management of the communication in a restricted network space by assisting various forms of traffic and enhancing Quality of Service (QoS) (Alzahrani et al., 2024; Gupta & Jha, 2015).

This system has addressed two major issues in the IoT, which include energy-conservation and communication efficiency. The decrease in traffic load and optimization of the use of resources made devices longer-lived and a bit less harmful to the environment. The need to study the behavior of the network in dynamic conditions and the desire to inspire the development of the IoT in the future of healthcare, industrial automation, and smart cities were facilitated by simulations and theoretical analysis (Irfan et al., 2023). Its applications were in real-time patient monitoring, effectiveness of manufacturing systems, and improved urban management in regard to traffic flow, safety and environmental observation. Based on the use of intelligent algorithms of packet aggregation and multiplexing, a more effective solution to the imprecision of mobile IoT networking is created. It provides the initial IoT uses and allows the future uses by the self-managing system commence as per the current trend (Verma et al., 2017).

There are three main problems that are encountered during implementation of mobile IoT network and these include limited storage capacity of energy storage, network congestion and delay that have implications on the functionality of the network in general. Mobile networks cannot be handled with the same solutions that have been created in the past because they are dynamic and thus the strategy of constant transmission parameters cannot work. The traffic of the IoT networks is also difficult to predict as not all the connected devices are operating in the same way. Live operation systems must have sophisticated approaches of feedback issues, not to mention enhancement of data delivery and reduced network delays and energy consumption (Farhan et al., 2021; Guo et al., 2023).

The major ones are bandwidth constraint, the high consumption of energy, and the effective real-time operation of data. These difficulties require the creation of dynamic and smart optimization methods that will be able to self-reconfigure performance to changing network conditions to guarantee reliable, energy efficient and timely communication within mobile IoT systems (Ahmad et al., 2019; Jaradat et al., 2023).

Literature Review

It is assumed that the IoT networks represent the most important addition and improvement to the traditional architectures of the IoT since the networks allow supporting devices which can move between cellular towers and the wireless gateways, unlike the fixed IoT systems. These types of networks are applied in the mobile context, where devices experience changes in signal strength, connection mobility, and additional changes in the overall performance. The device mobility poses issues to the continuity of the data transmission, uninterrupted, especially in vertical applications that are critical, such as health care, transportation, and autonomous cars, where the performance is prerequisite by low latency and high reliability (Taleb et al., 2017). Therefore, mobile IoT infrastructure must also be able to handle a vast variety of devices, such as wearable health monitors to self-driving vehicles, and can vary its management of the traffic based on the change of user behaviors, locations and across various time zones. Aktas et al. (2025) argue that in this case, high mobility, maintained stable communication is still an issue being open since the traditional methods of managing resources and the routing methods fail to deliver relevant outcomes. This thus necessitates the adaptive intelligent solutions in order to support mobility, bandwidth needs, traffic density, constraints energy and priority of the data.

The current research indicates that there are various most effective performance improvement techniques: edge computing, machine learning, energy-aware scheduling, packet aggregation, and multiplexing. Driss (2023) points out that these techniques will aid in the improvement of performance. It is also established that learning to use packet aggregation is among the best methods of mobile IoT communication optimization (Khan, 2025). It minimizes the overhead of transmission and improves the use of bandwidth, therefore boosting throughput by combining the small sized packets into the larger sized packets. This is extremely relevant in the IoT networks where tiny packets are produced at an enormous rate. It has been observed that the aggregation increases the data rate and reduces contention in a wireless channel, retransmission, and consequently latency (Trigka & Dritsas 2025). Moreover, the aggregation method consumes a lot less energy, which is extremely crucial since in the IoT devices, batteries usually have short life cycles. Experiments conducted by Ferhi (2025) indicate that transmissions and switching to lower frequencies can be reduced, which enhances life of batteries in mobile environments. Adaptive packet aggregation offers better yet again improved performance by dynamically changing the packet size in respect to network conditions like load, delay sensitivity and buffer occupation. It was reported that adaptive aggregation has the potential to decrease average delay by up to 30 percent and ensure energy efficiency (Wu et al., 2025). Studies also affirm that it works well in reducing traffic congestions, enhancing dependability and increasing the life of devices (Hosseinian & Mirzahossein, 2024). The combination of AI increases the performance of packet aggregation based on prediction of traffic patterns and dynamic optimization of parameters, therefore, increasing the QoS of priority streams of data.

In addition to aggregation, multiplexing schemes, including TDM and FDM, are also critical to the maximization of bandwidth efficiency of mobile IoT networks. TDM allows devices to have a time slot assigned, which causes minimal interference and preserves a clean transfer of data, therefore, is ideal with low-power IoT devices such as sensors and utility meters. According to Ali (2025) in contrast, FDM divides the band into discrete frequency bands and can transmit at the same time with fixed connections with heavy data load like video surveillance, mobile healthcare, autonomous driving, etc. Thus, the self-reconfiguring multiplexing reduces the data losses and provides more stable and faster flows, which is applicable to smart transportation, too that traffic patterns and density of devices vary dynamically and rapidly. Also, they conserve power: TDM enables devices to turn off during idle slots and adaptive spectrum allocation lessens the amount of retransmission caused by interference.

Besides the aggregation, certain types of the multiplexing methods like TDM and FDM are important in ensuring that the bandwidth in the Mobile IoT Networks is maximized. TDM assigns devices time slots thereby eliminating interference and ensuring data transfer order, and is a good fit where power consumption is a significant constraint like in IoT sensor and utility meter devices. FDM splits the band into discrete frequency bands and allows simultaneous transmissions as well as fixed connections with heavy load data transmissions like video surveillance, mobile medical, and autonomous driving (Ali, 2025). The self-drive multiplexing reduces data losses, increases the speed and provides more stable connections in smart transportation, particularly where traffic patterns and density of the devices vary rapidly. According to Singh (2025), other such savings are of energy wherein TDM will enable devices to turn off during idle slots and adaptive spectrum allocation will minimize retransmissions due to interference.

This leads to the fact that convergence of AI, packet aggregation, and adaptive multiplexing makes available a technological basis that directly enhances the reliability, efficiency, and scalability of the next-generation mobile IoT networks in adapting to extremely dynamic conditions. Although many optimization techniques such as packet aggregation, multiplexing, and AI have been proposed for mobile IoT networks, most existing solutions address these methods separately and lack real-time adaptive integration. This results in limitations such as increased latency, inefficient bandwidth utilization, and higher energy consumption under dynamic network conditions. To address this gap, the proposed solution integrates AI-based traffic prediction with adaptive packet aggregation and multiplexing to dynamically optimize resource allocation, reduce transmission overhead, improve energy efficiency, and enhance the reliability and scalability of mobile IoT networks.

Methodology

The research methodology used in this case was aimed at systematizing the research of the effect of the integration of AI-based optimization with the use of packet aggregation and multiplexing to ensure an improvement of the mobile IoT network performance. The general structure of the research was four significant steps connected to the system design, simulation model, AI-based optimization, and performance evaluation.

System Design

The simulated structure was designed based on a mobile IoT scenario in the context of which the devices are dynamically moving around cellular areas and wireless gateways. The network environment simulates the heterogeneous IoT-based devices, such as the health monitors, mobile sensors, and intelligent vehicles, which have varying traffic loads and mobility profiles. Two important optimization methods applied in it are packet multiplexing and packet aggregation. Aggregation was used to combine multiple small packets into big packets with the aim of reducing the overheads involved in transmission. Multiplexing on the other hand- TDM and FDM- is a method, which ought to be employed in maximizing bandwidth utilization among multiple devices. The system implemented AI components to provide adaptive real-time decisions by monitoring the network parameters such as the throughput, the latency, the traffic density, and the power consumption.

Simulation Modeling

The simulations in NS-3 were used to simulate real-world mobile IoT conditions. A simulated network topology was taken into account with several access points and areas to represent mobility of the devices and the handover conditions. To simulate realistic application scenarios to the IoT, for example, healthcare monitoring, which produces periodic low-rate data; autonomous transportation, which demands data at a high rate in real-time; and smart city sensors, which produce event-based transmissions, devices cause traffic. Dynamic mobility models model the motion of devices within the coverage areas without considering the access point handovers. No optimization and optimized scenarios that included the aggregation and multiplexing of packets in the traffic were compared.

AI-Based Optimization

Our AI smart is not that bad- it will automatically adjust the size of packet aggregation and multiplexing strategies depending on the conditions in the network. We used Long Short-Term Memory (LSTM) model to perform supervised machine learning using the network traffic capturing the temporal dependencies. The data that was used to train this model is publicly accessible network traffic data of an IoT network that concentrated on such key input features as the rate of packet arrival, the occupancy of buffers, and the indicators of the link quality. We split the data (70/15/15) whereby one-third was used as training data, another-third was used as validation data, and the remaining third was used as the test data to measure the generalizability of the model. Our proposed LSTM can predict the optimal schedule of aggregation and channel assignment scheme under varying conditions.

In order to ensure that it becomes dynamic in real-time, we added the idea of reinforcement learning, which employed a Deep Q-Network architecture. State space has the present load in traffic, buffer levels, and delay statistics whereas the action space encompasses the choice of aggregation sizes and multiplexing modes. We established a reward function that would minimize the end-to-end latency and packet loss, and maximize the throughput and energy efficiency. When the traffic is large, the AI is more likely to choose smaller aggregation sizes and frequency-division multiplexing to make sure that it is real-time responsive. However, when there is low traffic, it makes the aggregation intervals larger, and it also chooses time-division multiplexing to have the most energy efficiency and throughput.

The experiments we undertook differed in the speed of mobility, densities of the devices and the traffic pattern. We experimented on four conditions: a) no optimization of mobile IoT networks, b) packet aggregation, c) multiplexing, and d) our combined AI-based adaptive framework. We applied statistical methods in order to make our findings reliable, showing the serious positive changes in each situation.

Validation and Analysis

We critically examined the outcomes of the experiment to ensure that our framework worked. We discovered that the use of packet aggregation reduces a lot of transmission overhead, and amplifies throughput, whereas multiplexing enhances channel efficiency.

Results and Discussions

The optimization framework is implemented in a simulated mobile IoT environment which comprises of sensors, actuators, mobile health monitoring devices and smart appliances. Several common mobility models are used to model a variety of realistic devices movements: Random Waypoint and Gauss-Markov. The variable network conditions such as fluctuation of loads of traffic, changes in access points, and congestion periods have been modeled to test the framework.

NS3 built the adaptive algorithms of packet aggregation and multiplexing, and AI-based optimization, and was tested with control models without AI. Some of the key performance indicators were throughput, latency, energy consumption and the packet loss rate. In this regard, statistical graphs and tables of the obtained results revealed that the proposed system was characterized by increased throughput and less latency and lower energy consumption and reduced packet loss as compared to other conventional approaches.

Throughput Evaluation

Figure 3 and additional results with various number of devices can be examined later on the exploration of many methods that can be used to optimize the qubit allocation. In the baseline case, the throughput rose almost linearly until 10,000 devices when the throughput was approximately 8 Mbps. This indicates that the throughput rises with the number of devices but it is an indication of wasting the resources since better performance is compromised in favor of increased network load. Throughout the use of packet aggregation, throughput rate rose to a little less than 1Mbps when there were 10,000 nodes. It shows that although aggregation of small packets causes a reduction in overhead, the advantages are defined with large deployments of devices and are not applicable in high-throughput IoT situations. The high throughput of 9 Mbps was maintained by Multiplexing, though, at all levels of devices. This stability testifies of the ability of multiplexing to control traffic and give it efficiency but its performance saturation demonstrates that it is not receptive to the network variations.

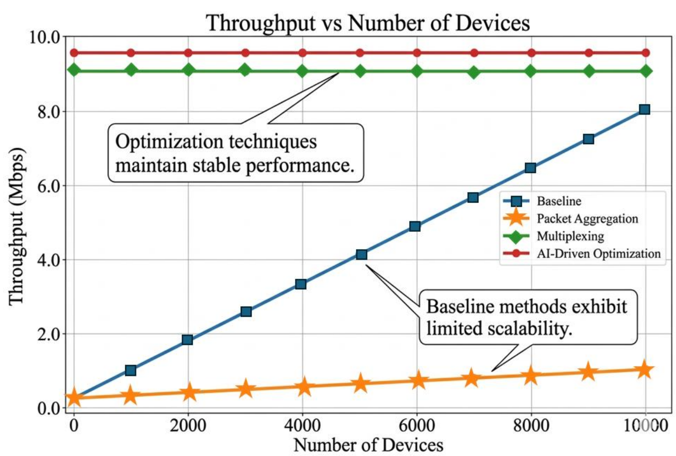

Figure 3: Throughput Evaluation.

The optimization scheme with AI made the optimal overall performance, with an average throughput of approximately 9.5 Mbps at all the numbers of devices. This confirms that AI-based adaptive mechanisms can intelligently utilize the resources and adjust communication to attain scalability and stability in an environment where the density of devices increases. All in all, the outcomes indicate that the packet aggregation and multiplexing have incremental benefits whereas the AI-based optimization can yield enhanced throughputs with the combination of responsiveness and resource utilization efficiency. It is thus more viable and viable to the future IoT and mobile networks.

Latency Evaluation

Figure 4 indicates the latency performance of the different methods of optimization. The highest latency was found to be always in the case of all the numbers of devices in the baseline case and this was approximately 100 ms. This means that without any option of optimization, the system is subjected to extreme delays which would ultimately hurt the time sensitive IoT applications.

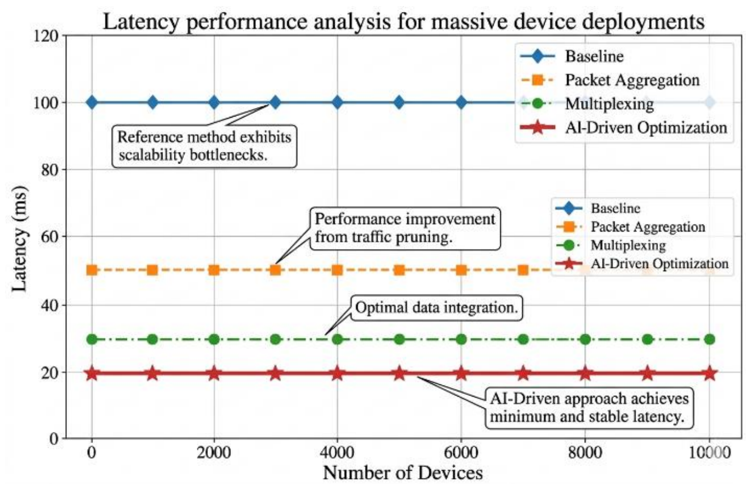

Figure 4: Latency Evaluation.

The latency was lowered to approximately 50 ms due to the use of packet aggregation, which is an improvement as compared to the baseline. The improvement in performance remains moderate as aggregation of packets can to a large extent eliminate the transmission overhead but cannot ameliorate congestion or scheduling delay in overcrowded networks.

The idea of multiplexing was then improved to ensure that the latency remained at a constant of about 30 ms irrespective of the number of devices. That would show how effective it can be in reducing the complexity in communication and eliminating the delays in queue albeit limited by fixed resource assignment.

The optimization technique was an AI-based one, which showed the lowest latency of approximately 20 ms, and it was consistently better than the other approaches. This proves the ability of AI-based dynamic approaches to control traffic intelligently, minimize queuing and scheduling delay and ensure a steady performance despite a high density of devices.

All in all, these results confirm that the reduction of latency by packet aggregation and multiplexing is better than the baseline, although the best and most scalable solution is provided by the AI-optimized one and is likely to be applied to the applications of latency-sensitive IoT and mobile communication.

Network Overhead

Figure 5 illustrates the impact of various optimizations to network overhead with the increase in devices. The maximum overhead of 16.7 percent in the base case implies that too many network resources are utilized in signaling, retransmission and control processes when not optimized. The overhead was cut down to the lowest possible level; it was limited to a maximum of 8%. This is just one short-term advantage of the idea of combining a couple of small packets into a bigger one and, in such a manner, minimizing the protocol overhead. Although this is still more efficient than the base case, the overhead is rather high in the case of large-scale IoT networks.

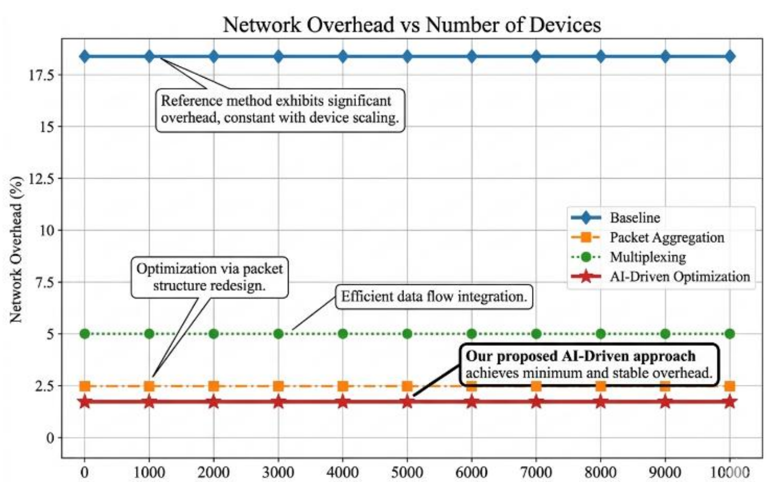

Figure 5: Network Overhead Evaluation.

Multiplexing produced a smaller result with reduction of network overhead of about 5% in all the cases with variation of the different numbers of devices. This outcome is indicative of the fact that multiplexing reduces the control signaling, and maximizes bandwidth usage, and thus it is more efficient than the packet aggregation. The lowest overhead of approximately 2% was obtained with AI-based optimization strategy since it was possible to maintain the same performance even with the increase of the number of devices up to 10,000. That way, intelligent resource assignment and responsive decision-making become effective towards reducing redundant signaling and streamlining communication events.

Overall, the findings confirm that optimization with AI can deflate the network overhead by a vast margin compared to traditional methods, and thus can provide an exceptionally efficient and scalable method of dealing with resource-constrained IoT networks management.

Energy Consumption Evaluation

As the graph given below in Figure 6 indicates, the number of devices and energy consumption is associated with the four alternative approaches, i.e., Baseline, Packet Aggregation, Multiplexing, and AI-Driven Optimization. It is quite clear that the rate of growth of the amount of energy consumed by any strategy is highly dissimilar with the number of devices but the rate varies widely depending on the method. The baseline scenario indicates massive power usage of nearly 50,000 mJ and 10,000 devices which could be seen as ineffective utilization of a system that has not been optimized. Packet Aggregation is more important, however, because it groups packets and results in less overhead of transmission and less power consumed of about 30,000 mJ per packet at the same number of users or about 40 percent of the base.

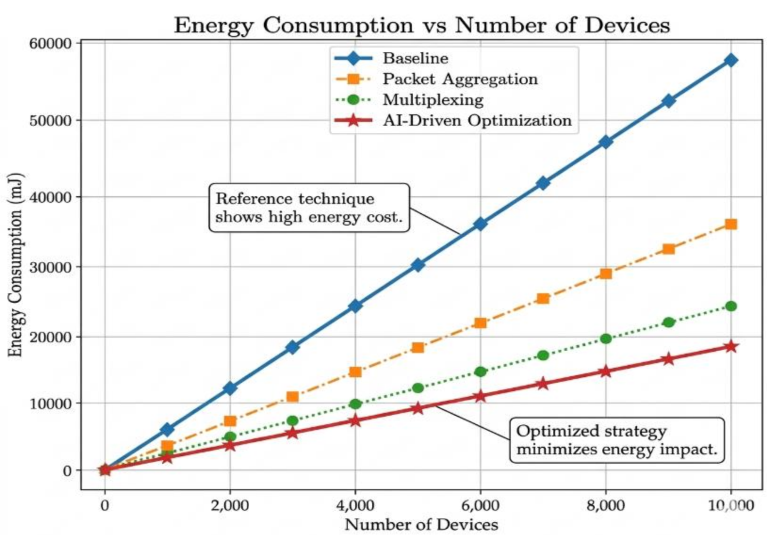

Figure 6: Energy Consumption Evaluation.

Multiplexing steps even further since it allows multiple signals to access the same channel and consequently, the power consumed is brought down to around 20,000 mJ, this is a phenomenal 60 percent. However, the most striking one is the AI-Driven Optimization. It is an ingenious resource usage plan and the inefficient energy usage is also brought down to the bare minimum of 15,000mJ to supply 10,000 devices- an astonishing 70 percent less of the energy usage as compared to the base.

In general, the results show that all optimization solutions may be employed to reduce the level of energy consumption, but the AI-Driven Optimization is the most beneficial and easily scaled-up one. The more devices are present, the more the difference in the performance of the baseline and optimized methods, which proves the fact that both methods can be particularly useful when it comes to the large-scale IoT and 6G networks where one of the factors is the energy-efficiency.

Comparison with Existing Systems

During both, high and low traffic conditions the proposed framework outperforms existing systems by delivering efficient adaptive control. While (Hussein & Ibnkahla, 2025) analyses show that through resource auto scaling edge slicing system achieved significant cost reduction and lacks the packet-level optimization. Similarly, to (Nassra et al., 2025) green architecture provides superior compression but without the dynamic traffic adaptability which is essential for smart cities. Unlike ONDS algorithm's selective node sampling (Abdellatif et al., 2024) or AdaptoFlow's which focus on inference decentralization (University of Cyprus Research Team, 2025). This framework employs a comprehensive packet aggregation strategy and minimizes the computational overhead seen in blockchain-based DRL approaches (Far et al., 2024). Finally, by integrating consistent adaptive control with AI-driven aggregation and multiplexing, the outputs of the proposed framework are resource utilization and significant performance gains that existing systems cannot match.

Conclusion and Future Work

This study showed that incorporating packet aggregation, multiplexing, and artificial intelligence really ramped up the efficiency of mobile IoT networks. By leveraging packet aggregation, we managed to cut down on protocol overhead and power consumption, which is a huge plus for those small data packets coming from health wearables and sensors. On the other hand, multiplexing made channel sharing smoother, enhancing bandwidth usage and minimizing interference. AI-driven models took it a step further by fine-tuning scheduling and resource allocation. They did this by anticipating network behavior and tweaking transmission methods in real time, ensuring low latency and high data rates, even in ever-changing environments. The research not only shed light on resource optimization from a theoretical standpoint but also had real-world applications in smart cities, healthcare, transportation, and industrial automation. All in all, this work tackled key communication challenges in mobile IoT and set the stage for energy-efficient, self-organizing systems for the upcoming 6G and edge intelligence networks.

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