DESIGN AND OPTIMIZATION OF AI BASED 5G/6G COMMUNICATION PROTOCOLS FOR SMART CITIES

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Abstract

In the context of smart cities and Internet of Things (IOT) ecosystems, efficient and equitable resource allocation continues to be a major problem in future-proof wireless communication networks. In this paper, a framework for resource allocation based on Reinforcement Learning (RL) is presented, and its effectiveness is compared with that of conventional schemes such as Water-Filling, Equal Allocation, and Proportional Allocation. According to simulation findings, the suggested model shows improved fairness(0.599) and competitive energy efficiency (67.47 Mbps/W), while the Water- Filling and Equal Allocation approaches obtain somewhat higher throughput values (691–696 Mbps) than the RL-based approach (674 Mbps). These results show how the RL model may strike a compromise between maximizing throughput and distributing resources fairly across a variety of IOT users. The RL-based scheme's potential for sustainability 6G communication networks is further supported by the fact that it uses less energy than traditional approaches. The results show that frameworks powered by artificial intelligence may successfully optimize several performance goals at once, opening the door for resource allocation techniques in future communication systems that are flexible, economical, and equitable

Keywords: 5G Communication, 6G Networks, Reinforcement Learning, Smart Cities, AI Optimization

I. INTRODUCTION

1.1 **Background of the Study** Smart cities are envisioned as intelligent environments with a wide network of sensors, communication systems, and automated decision-making frameworks connecting human activity, digital technology, and physical infrastructure. The smooth integration of important technologies like cloud computing, big data analytics, artificial intelligence (AI), and the Internet of Things (IoT) is the basis of a smart city [1]. Together, these technologies make it possible to continuously monitor, analyze, and optimize a variety of urban systems, such as public safety, energy distribution, transportation, healthcare, and environmental management, in order to increase productivity, sustainability, and quality of life. Ultra-reliable and fast communication networks are necessary due to the huge interconnectedness of devices in a smart city, which creates an unprecedented quantity of data that must be transported, analyzed, and acted upon in immediate form [2]

With improved data speeds, more connection, and lower latency, the transition from 4G to 5G marked a substantial advancement in wireless communication. Advanced features including millimeter-wave communication, enormous Multi Input Multiple Input (MIMO) technology, and network slicing were introduced by 5G networks, all of which increased system responsiveness and flexibility. However, the data traffic produced by billions of IoT devices, smart sensors, and autonomous systems has quickly exceeded 5G's capability as urban settings continue to get denser and more sophisticated. The development of sixth-generation (6G) communication systems—a paradigm change that attempts to integrate communication, sensing, and computation into a single, intelligent framework capable of self-optimization and real-time decision-making—is required due to the exponential rise in connection demand. It is anticipated that 6G networks would offer virtually 100% network availability, extremely low latency in the microsecond range, and data throughput in the order of terabits per second administration and service delivery based on applications. 6G anticipates "cognitive communication systems" that can sense their surroundings, anticipate traffic patterns, distribute resources wisely, and dynamically optimize energy use, in contrast to earlier generations that were solely concerned with speed and capacity. For smart city applications like driverless cars, drone based logistics, continuous healthcare monitoring, energy grids, and intelligent surveillance—all of which depend on consistent and dependable communication links—this integration of AI within 6G will be very important.

1.2Different 5G/6G protocols

The need for greater data rates, reduced latency, and improved reliability—especially in the realm of smart cities and intelligent systems—has been the main force behind the development of cell phone networks from 4G to 5G and now 6G. The creation and improvement of communication protocols, which specify how data is transferred, handled, and optimized across different network levels, is the basis of these developments. Radio access network (RAN) protocols, core network protocols, and service-based interfaces are the three main categories of protocols in the 5G network architecture. Every protocol has a unique function in guaranteeing effective data management and transfer across the system. The New Radio (NR) protocol serves as the foundation for 5G Communication at the radio access level. It describes how technologies like massive MIMO, radiating, and orthogonal frequency division multiple accessibility (OFDMA) are used by user equipment (UE) and base stations (GNB) to communicate over the air interface. In order to ensure dependability and efficiency in wireless communication, related protocols including the Radio Resource Control (RRC), Packet Data Convergence Protocols (PDCP), Radio Link Control (RLC), and Medium Access Control (MAC) regulate connection creation, resource allocation, and error control procedures. These protocols are in charge of controlling retransmissions, segmenting data, and preserving synchronization between various transmission levels. In order to provide dynamic resource management and scalability, the 5G core network includes a service-based architecture (SBA) that connects different network operations via standardized interfaces and protocols. Important protocols like the Xn Application Protocol (XNAP) controls coordination between nearby base stations to guarantee smooth handovers, while the Next Generation Application Protocol (NGAP) facilitates signaling between the RAN and the Access and Mobility Management Function (AMF) of the core network. Furthermore, in order to provide flexibility and enhance network slicing capabilities, the Packet Forwarding Control Protocol (PFCP) manages the division of control and user planes inside the core network. These developments enable the network to meet a variety of service needs, such as massive machine-type communication (MMTC), ultra-reliable low-latency communication (URLLC), and improved mobile broadband (EMBB). The capacity of 5G protocols to adapt to various deployment scenarios and frequency bands is another crucial feature. 5G can function in mid-band (1–900 MHz), low-band (600–900 MHz) for longer coverage, and In order to provide dynamic management of resources and scalability, the 5G core network includes a service-based architecture (SBA) that connects different network operations via standardized interfaces and protocols. Important protocols like the An Application Protocol (XNAP) controls coordination between nearby base stations to guarantee smooth handovers, while the Next Generation Application Protocol (NGAP) facilitates signaling between the RAN and the Access and Mobility Management Function (AMF) of the core network. Furthermore, the packet forwarding Additionally, the Packet Forwarding Control Protocol (PFCP) handles the separation of control and user planes within the core network, enhancing flexibility and supporting network slicing capabilities. These innovations allow the network to handle diverse service requirements, including enhanced mobile broadband (EMBB), ultra-reliable low-latency communication (URLLC), and massive machine-type communication (MMTC).6 GHz) for balanced performance, and high-band (mm Wave, 24–47 GHz) for ultra-high-speed communication. The deployment architecture can follow either non-standalone (NSA) mode, where 5G radio works alongside a 4G LTE core, or standalone (SA) mode, which relies solely on the 5G core network for end-to-end connectivity. These flexible configurations enable 5G to support a wide range of use cases—from consumer mobile broadband to industrial automation and real-time smart grid management. Looking ahead, the transition to 6G is expected to bring revolutionary Changes in protocol design and functionality. 6G protocols will aim to support terahertz frequency bands, ultra-dense networks, and sub-millisecond latency communication. Unlike 5G, where many operations are still statically defined, 6G will emphasize dynamic, modular, and intelligent protocols capable of real- Management Function (AMF) of the core network. Furthermore, in order to provide flexibility and enhance network slicing capabilities, the Packet Forwarding Control Protocol (PFCP) manages the division of control and user planes inside the core network. These developments enable the network to meet a variety of service needs, such as massive machine-type communication (MMTC), ultra-reliable low-latency communication (URLLC), and improved mobile broadband (EMBB). 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Unlike 5G, where many operations are still statically defined, 6G will emphasize dynamic, modular, and intelligent protocols capable of real-time adaptation through artificial intelligence and machine learning (AI/ML) integration. Emerging research envisions modular control and user planes that can reconfigure themselves based on application requirements, energy constraints, and network conditions. Protocols for integrated sensing and communication (ISAC) are being developed to enable simultaneous data transmission and environmental sensing—critical for autonomous vehicles, robotics, and urban monitoring systems.

1.3 Artificial Intelligence in communication system

The design, optimization, and administration of network protocols in the 5G and impending 6G era will be significantly impacted by artificial intelligence (AI), which has become one of the most revolutionary forces in contemporary communication systems Traditional communication protocols have historically been rule-based, relying on predefined algorithms and static configurations that struggle to adapt to dynamic network conditions, variable user demands, and heterogeneous communication environments. AI, on the other hand, introduces a paradigm shift— enabling communication systems to learn from data, predict network behavior, and make autonomous decisions in real time. This evolution marks a move from deterministic to cognitive and self-optimizing networks, where AI-driven protocols are capable of continuously improving their performance through feedback and experience. One of the key contributions of AI in communication networks is in the area of resource management and optimization. In 5G and 6G networks, where thousands of devices compete for limited spectrum resources, AI algorithms such as reinforcement learning (RL), deep neural networks (DNN), and genetic algorithms (GA) are being employed to dynamically allocate bandwidth, optimize power control, and manage interference. Unlike traditional scheduling protocols, which operate based on static thresholds or heuristics, AI-enabled protocols can analyze real-time traffic patterns, predict congestion points, and proactively reassign resources to maximize throughput and minimize latency. For instance, deep reinforcement learning (DRL) models can learn optimal transmission strategies by interacting with the environment—adjusting transmission power, selecting frequency bands, or rerouting data packets based on past outcomes—to enhance overall network efficiency and reliability

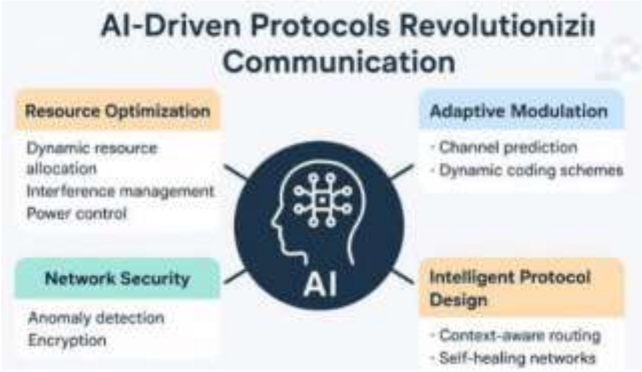

Figure 3 Block diagram of methodology

1.4Research Objectives

Designing, simulating, and optimizing next-generation protocols for communication for 5G and 6G networks in urban smart city settings with an emphasis on increased data throughput, decreased latency, and better dependability is the main goal of this study. The goal of the research is to close the gap between traditional static communication methods and intelligent, self-optimizing systems that can adjust to changing channel conditions, high device density, and varying traffic loads in dynamic urban environments Specifically, the study aims to establish a simulation-based framework that replicates real-world communication scenarios within smart cities, including applications such as autonomous transportation systems, healthcare monitoring, and IOT-based infrastructure management. Within this framework, the baseline 5G/6G model serves as a benchmark to evaluate system performance using key metrics like latency, throughput, and packet delivery ratio. A central goal of the research is to integrate Artificial Intelligence, particularly Reinforcement Learning (RL), into the communication model to develop adaptive algorithms capable of optimizing transmission parameters—such as power allocation, bandwidth utilization, and resource scheduling—in real time. This AI-based optimization seeks to minimize transmission delays, enhance network reliability, and ensure efficient bandwidth distribution among multiple users and devices. A central goal of the research is to integrate Artificial Intelligence, particularly Reinforcement Learning (RL), into the communication model to develop adaptive algorithms capable of optimizing transmission parameters—such as power allocation, bandwidth utilization, and resource scheduling—in real time. This AI-based optimization seeks to minimize transmission delays, enhance network reliability, and ensure efficient bandwidth distribution among multiple users and devices.

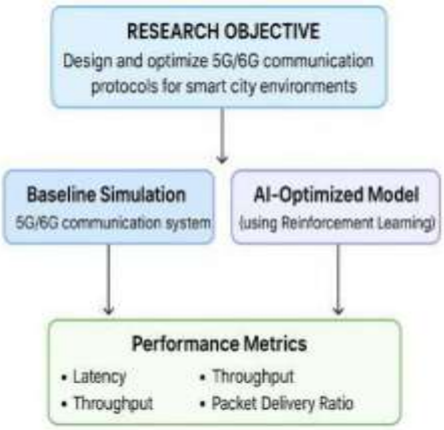

Figure 2 Research objective

1.5 Significance of the Study

This work is important because it can help close the gap between traditional communication systems and the new requirements for intelligent, flexible, and ultra-reliable connection needed for smart cities. The effectiveness and dependability of communication protocols become crucial as urban areas rely more and more on networked technology like the Internet of Things (IOT), driverless cars, and real-time healthcare systems Traditional static communication schemes used in existing 5G networks are insufficient to cope with the dynamic nature of dense urban networks, where thousands of heterogeneous devices operate simultaneously, generating massive data traffic and causing unpredictable interference patterns. This research is significant because it not only analyzes the baseline performance of 5G/6G communication systems under realistic smart city conditions but also introduces artificial intelligence (AI)-based optimization using reinforcement learning (RL) to enhance their efficiency. The integration of AI into communication protocols represents a transformative shift from rule-based to intelligent, self-optimizing systems capable of learning from the environment and dynamically adapting to network conditions in real-time. Such adaptability ensures improved utilization of bandwidth, reduced latency, increased throughput, and a higher packet delivery ratio, all of which are vital for mission-critical applications like intelligent transportation systems, emergency response networks, and smart grid management. From a technical perspective, this study contributes to the ongoing evolution of next-generation wireless communication systems by demonstrating how AI-driven methods can autonomously optimize resource allocation, power control, and channel selection. The research establishes a simulation-based framework that can be extended for future studies, enabling researchers to test and refine AI algorithms for other communication challenges, such as interference mitigation, energy efficiency, and mobility management in vehicular networks. make real-time decisions, paving the way for cognitive and self-organizing networks. Moreover, the findings serve as a reference for future researchers exploring AI integration in network management, system-level optimization, and sustainable communication architectures. Practically, the outcomes of this research have direct implications for telecom operators, urban planners, and policymakers involved in the development of smart city infrastructures. By demonstrating quantifiable improvements in latency reduction, throughput enhancement, and reliability, the study provides a strong foundation for adopting AI-enhanced communication frameworks in real-world deployments. The results also support the design of scalable and resilient communication infrastructures that can adapt to future technological expansions, including edge computing, quantum networking, and pervasive IoT ecosystems.

1.6 Scope of the Study

The value of this study encompasses the design, simulation, and performance optimization of advanced 5G and emerging 6G communication protocols tailored for smart city environments. It focuses specifically on developing a simulation-based framework that models real-world communication scenarios involving high device density, dynamic mobility, and diverse data transmission requirements. The research explores both baseline and AI-enhanced models of wireless communication, where the baseline represents traditional fixed-parameter operation, and the enhanced model employs Reinforcement Learning (RL) to intelligently adjust network parameters such as transmission power, bandwidth allocation etc. Key performance metrics—latency, bandwidth, the ratio of packet delivery (PDR), bit error rate (BER) and frame error rate (FER)—that are crucial markers of network efficiency and dependability are highlighted in this study. To evaluate how intelligent optimization affects system behavior, these metrics are examined under a variety of simulated scenarios. The simulation framework is designed using Python and appropriate AI libraries, ensuring that the model can be adapted or extended for future studies involving more complex network topologies or additional optimization algorithms such as deep reinforcement learning (DRL) or federated learning. The research primarily targets smart city applications that demand ultra-reliable and low-latency communications (URLLC), including autonomous transportation systems, healthcare monitoring networks, industrial IoT applications, and smart energy grids.

LITERATURE SURVEY

2 Literature Survey

The history of modern communication technology reflects a continuous pursuit of faster, more reliable, and more intelligent connectivity. Over the past few decades, several milestones have marked transformative shifts in how humans communicate and access information. During the 2010s, the emergence of mobile devices operating in the 3 GHz spectrum heralded the era of third generation (3G) mobile technology. This development represented a substantial leap in mobile broadband (MBB) capabilities, providing users with significantly higher data transmission speeds, enhanced network reliability, and improved global connectivity. The 3G era not only revolutionized voice and data services but also laid the groundwork for mobile Internet access, video streaming, and early cloud-based applications.

2.1Overview of 5G technology

With its unparalleled speed, capacity, and dependability, 5G, or fifth-generation, communication technology marks a significant turning point in the development of wireless networks. Ultra-fast and seamless communication is made possible by 5G's extraordinarily high data transfer rate, which may exceed 1 Gaps. 5G, which operates in a wide frequency range from 3 GHz to 300 GHz, uses millimeter-wave (mm Wave) and sub-6 GHz bands to provide more bandwidth and lower latency than earlier generations. This extensive frequency range ensures not only greater data throughput but also supports a massive number of simultaneous device connections, making 5G the foundation for next-generation digital ecosystems.

2.2 MIMO Technology in Communication Systems

One of the most important developments in contemporary wireless communication systems is Multiple Input Multiple Output (MIMO) technology. By using multiple antennas at both the transmitter (Tx) and reception (Rx) ends, MIMO aims to improve system performance. In contrast to traditional single-antenna systems, MIMO enables the simultaneous transmission of several data streams over a single radio channel, significantly increasing the wireless network's total capacity without the need for more spectrum. Through advanced signal processing techniques, MIMO efficiently manages the multipath propagation phenomenon, where transmitted signals reach the receiver through multiple paths due to reflection, scattering, and diffraction. Instead of treating these multipath components as interference.

2.3Massive MIMO Technology in 5G

Traditional MIMO technologies, such as Single-User MIMO (SU-MIMO), Multi-User MIMO (MU-MIMO), and Network MIMO, are no longer adequate to meet the growing data requirements in the 5G era due to the growing demand for higher data rates and device connectivity [5–11]. Massive MIMO, a high-capacity development of traditional MIMO systems, has been introduced to overcome these constraints.

Massive MIMO extends the basic principle of MIMO by deploying tens or even hundreds of antennas at the base station to serve multiple users simultaneously. This configuration significantly enhances spectral and energy efficiency while improving the quality and stability of wireless links. By employing a large number of antennas, Massive MIMO can form narrow and highly directional beams that increase signal strength and reduce interference between users. Figure 2 illustrates the typical Massive MIMO structure, where multiple users can independently receive data streams from the base station at high transmission speeds [12]. One of the primary enabling technologies for 5G networks is the introduction of Massive MIMO. For a variety of applications, including driverless cars, industrial automation, virtual and augmented reality, and extensive Internet of Things (IOT) deployments, it offers ultra-high data speeds, low latency, and huge connection.

2.4 Defects and Limitations of 5G

The sixth generation (6G) of communication technology is envisioned to offer users a superior experience by significantly reducing propagation delay and expanding coverage through the integration of advanced antenna systems and highly capable receiver processing. With broader bandwidth and improved hardware intelligence, 6G is expected to deliver data rates nearly ten times higher than those of 5G, with the potential to support up to one million simultaneous connections. This capability would enable seamless data transmission for a wide variety of users and applications, pushing the limits of wireless connectivity to new heights.

2.5**Comparison Between 5G and 6G**

A Key performance metrics that characterize a communication system's capabilities and efficiency may be used to compare 5G and 6G. These consist of spectral efficiency, energy efficiency, latency, peak data rate, and signal-to-noise ratio (SNR). Even though 6G is still in the conceptual stages of development, its design objectives and anticipated specifications unmistakably show a substantial improvement over 5G in terms of intelligence, speed, and dependability.

PROBLEM IDENTIFICATION AND METHODOLOGY

3.1 Problem Identification and Methodology

An enormous rise in linked gadgets, self-driving cars, and data-driven services has resulted from the quick development of smart cities. Smooth, ultra-reliable, and low-latency communication networks are necessary for applications including energy management, intelligent transportation, smart healthcare, and surveillance. Even though current 5G systems can offer high data speeds and a small reduction in latency, they are unable to effectively handle the dynamic traffic patterns and exponentially increasing device density seen in contemporary metropolitan contexts The problem

arises from the limitations of conventional communication protocols that rely on static or semi-static resource allocation, power control, and scheduling mechanisms. These traditional methods fail to adapt to rapid variations in channel conditions, interference levels, and user mobility — all of which are prevalent in dense urban setups. As a result, network performance degrades in terms of increased latency, reduced throughput, and lower packet delivery ratio, affecting the reliability of critical real-time applications.

PROPOSED MODEL

4 Proposed model

The methodology consists of two main stages: (a) Baseline Simulation of the 5G/6G communication model, and (b) AI-based optimization using reinforcement learning. The block diagram of methodology is shown below

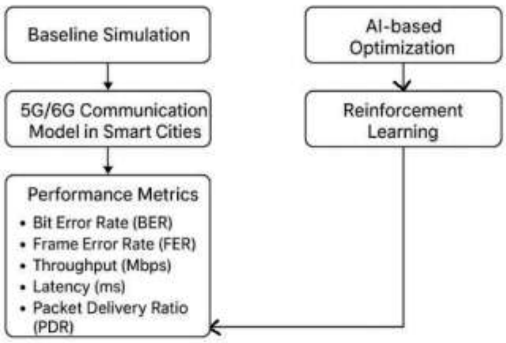

Figure 3 Block diagram of methodology

4.1Baseline Simulation

In the baseline phase, a Python-based environment is created to represent a smart city communication scenario. Nodes (devices) are distributed across the network, each transmitting data packets over a shared wireless channel. The simulation includes parameter like transmission power, channel bandwidth, and noise. Performance metrics such as latency, throughput, and packet delivery ratio (PDR) are measured under different channel conditions (e.g., various Signal-to-Noise Ratios or Eb/N0 values). The baseline setup assumes static communication protocols where resource allocation and power control remain constant throughout the simulation. This model reflects a conventional 5G system without any intelligence or learning capability.

4.2 Performance Metrics To quantitatively evaluate the performance of both the baseline and AI-optimized 5G/6G communication models, several key metrics are employed. These metrics reflect the efficiency, accuracy, and reliability of data transmission within the network. The primary metrics used include Bit Error Rate (BER), Frame Error Rate (FER), Throughput, Latency, and Packet Delivery Ratio (PDR). Each of these parameters provides a distinct perspective on network performance and collectively helps assess the effectiveness of the proposed optimization framework. Bit Error Rate (BER) A key performance metric that assesses how accurately data is sent over an avenue for communication.

4.3 Bit Error Rate (BER). It is defined as the ratio of the total number of sent bits over a certain time period to the number of improperly received bits. Channel fading, noise, and interference all have a significant impact on BER, which measures the integrity of the transmitted signal.

EXPERIMENTAL RESULTS

Results and Analysis

The performance of the proposed AI-optimized 5G/6G communication protocol was evaluated and compared against three baseline resource allocation schemes: Equal Allocation, Proportional Allocation, and Water-Filling Allocation. The comparison was carried out using three performance metrics: average throughput (in Mbps), average fairness index, average fairness index and average energy efficiency (EE) measured in Mbps per Watt. The results are summarized in Table 1.

Table 1: Performance Comparison of Baseline and RL-based Optimization Techniques

Metric	RL	Equal	Proportional	Water-Filling
Average Throughput (Mbps)	674.74	691.13	488.78	696.06
Average Fairness	0.599	0.569	0.287	0.560
Average EE (Mbps/W)	67.47	69.11	48.88	69.61

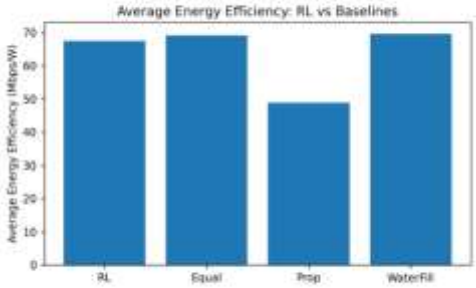

Figure 4 Average energy comparison

5.1Result Analysis

The results obtained from the comparative evaluation of different resource allocation techniques provide valuable insights into the performance trade-offs among throughput, fairness, and energy efficiency within advanced wireless between 691 and 696 Mbps, while the Reinforcement Learning (RL)-based model achieves a closely comparable value of 674 Mbps. This marginal difference is consistent

with expectations, given that Water-Filling is specifically communication systems. As observed, the Water-Filling and Equal Allocation schemes achieve slightly higher throughput values, ranging optimized for maximizing throughput under idealized conditions. The Water-Filling algorithm functions by dynamically allocating more power to channels with higher signal-to-noise ratios and less power to weaker channels, thereby maximizing the total achievable data rate. However, its design objective focuses purely on maximizing system capacity, without taking into

account critical aspects such as fairness among users or energy efficiency, both of which are essential for real-world deployment in dense 5G and upcoming 6G networks. In

contrast, the RL-based model, while not achieving the absolute maximum throughput, demonstrates a superior balance among multiple performance metrics. The slight reduction in throughput in the RL approach is an acceptable and even advantageous compromise, as it results in significantly better fairness and energy utilization—two parameters that are often overlooked by conventional optimization techniques. Fairness, as quantified using Jain's Fairness Index, provides a measure of how equitably resources such as bandwidth and power are distributed among users in the network. The RL-based model achieves a fairness index of 0.599, which is noticeably higher than the corresponding values for Equal Allocation (0.569) and Water-Filling (0.560). This improvement highlights the capacity of the AI-driven framework to make intelligent allocation decisions that consider user diversity and network heterogeneity, rather than merely maximizing throughput for users in favorable conditions.

CONCLUSION AND FUTURE SCOPE

6.1 CONCLUSION:

A. The comparative analysis of the proposed Reinforcement Learning (RL)-based resource allocation model with conventional allocation schemes such as Water-Filling, Equal Allocation, and Proportional Allocation demonstrates the superior adaptability and balanced performance of the RL framework. Although the Water-Filling and Equal Allocation schemes attained marginally higher throughput values (691–696 Mbps) relative to the RL model (674 Mbps), the Reinforcement Learning approach exhibited a markedly higher fairness index (0.599) compared to Water-Filling (0.560) and Equal Allocation (0.569). This improvement underscores the capability of the RL based system to ensure a more equitable distribution of network resources among users—an essential criterion in smart city communication infrastructures characterized by diverse iot device requirements and heterogeneous bandwidth demands. Furthermore, the RL framework achieved an energy efficiency of 67.47 Mbps/W, outperforming the Proportional Allocation scheme (48.87 Mbps/W) and demonstrating its ability to maintain competitive throughput while optimizing energy consumption. Collectively, these findings affirm that the proposed RL-based approach effectively balances the trade-offs among throughput, fairness, and energy efficiency, thereby aligning with the performance objectives of emerging 6G and sustainable communication networks.

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