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Enhancing the optimization of resource distribution for eMMB and URLLC services within 5G wireless network architectures

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Abstract

The complex dilemma of resource allocation and management in the 5G network priority system, particularly for eMBB and URLLC services, is a pressing and critical issue that necessitates comprehensive research and strategic actions to enhance the performance and user experience of modern digital communications. This situation urgently requires the development of innovative spectrum sharing strategies, prioritization methods, and adaptive algorithms to cope with real-time fluctuations in network conditions. The fusion of machine learning and artificial intelligence can significantly enhance these methods by predicting traffic trends and proactively adjusting resources, ensuring that both eMBB and URLLC services meet their respective quality of service standards. This paper introduces a Q-learning-based particle swarm optimization algorithm for efficient resource allocation techniques. The implementation of edge computing can further alleviate some of these challenges by performing data processing close to the user, thereby reducing latency and improving the response time of URLLC applications while meeting the high throughput requirements of eMBB.

Keywords: eMMB, Optimization, URLLC services, Wireless network, 5G

1. Introduction

The Internet of Things (IoT) has experienced rapid growth, driven by the proliferation of smart handheld devices and the advancement of 5G technologies. Healthcare, transportation, and the military are among the industries that utilize IoT [1]. Industrial IoT-enabled technologies improve productivity, save implementation costs, and simplify management. With the rapid advancement of technology, smart gadgets such as smartphones and IoT devices have become increasingly sophisticated, offering advanced functions [2]. Online gaming, AR, VR, video streaming, and infotainment apps consume a significant amount of traffic and computing power. Thus, cloud computing, which provides computational and storage capacity, is a viable model to reduce mobile device loads. Among the wireless communication technologies, the fifth generation of mobile networks, formulated by the 3rd Generation Partnership Project (3GPP), represents a significant advancement in telecommunication technology [3], commonly referred to as 5G, which is increasingly being recognized as a significant advancement in facilitating communication between mobile communication devices and their corresponding base stations. The 5G technology enables much higher bandwidth, lower latency, and more connections than the conventional wireless protocols. The rapid advancement of artificial intelligence and machine learning is indeed noteworthy [4]. Additionally, the entrance of the 5G mobile communication generation has made processing power, network transmission efficiency, and speed critical. This is the reason why another major factor that has led to the popular acceptance of cloud computing is its ability to provide significant processing power and massive data storage capacity without user control The current setting within which there is a sudden fast pace of technological inventions and the digitization of everything has many entities offering a wide range of paid services for cloud servers, which among them but not limited are the big players in the industry that includes Microsoft Azure, Google Cloud Platform, and Amazon Web Services, where each of them has its special features and competencies equipped to cater to wide varieties of needs from business houses as well as individual users [5]. To mitigate the challenges faced, users have the option to select suitable services.

Nevertheless, a notable disadvantage of cloud servers is the potential for a substantial escalation in expenses attributable to the transmission latency experienced between consumers and cloud servers [6]. Real-time video analytics systems impose severe limitations on network congestion and bandwidth. Thus, the goal of our effort is to provide a high-quality computing system that exhibits minimal latency. The Internet of Things is facilitated by the swift advancements and innovations in wireless communication technologies, particularly with the advent of 5G, which has resulted in a substantial augmentation in the number of smart devices interconnected through wireless networks [7, 8]. Processing multi-source data streams produced by IoT devices is a common use case for connected devices. 5G will significantly enhance and improve the spectrum productivity, energy savings, and cost-effectiveness of wireless networks, and expand the growth space of the cell phone industry. The fifth generation of wireless technology, commonly referred to as 5G, is poised to fulfill the specific requirements of various applications that demand exceptionally high service throughput, an exceedingly high density of simultaneous connections, remarkable mobile velocity, and ultra-reliable performance coupled with minimal latency [9]. The development of carriers in the future depends on 5G networks. To fully utilize 5G technology, new developments in marketing and communication technologies are necessary to encourage the adoption and widespread use of 5G.

However, even in situations with high user density, 5G technology enables users to access the network and receive personalized business experiences [10, 11]. There are three predominant and significant classifications of applications and services that the New Radio (NR), which is more commonly referred to in academic and technical discussions as the fifth generation of wireless access technology, or 5G, has been meticulously engineered to support and facilitate:

i) the enhancement and augmentation of enhanced Mobile Broadband (eMBB) services, which is accomplished by skillfully leveraging the exceptionally superior transmission rates and markedly improved network coverage capabilities afforded by 5G technology, ultimately striving to provide users with a considerably enhanced level of Internet accessibility that was previously unattainable;
ii) the provision of Ultra-Reliable Low Latency Communications services, which are designed for a remarkably diverse array of applications that encompass critical areas such as interactive telemedicine assessments, sophisticated transportation logistics, and advanced automation control systems, all of which require a high degree of reliability and minimal latency;
iii) the massive Machine Type Communications (mMTC) framework is specifically aimed at facilitating sporadic, yet necessary, small-scale data transmissions from a vast multitude of Internet of Things (IoT) devices during their various operational phases, ensuring seamless communication within an increasingly interconnected technological ecosystem [12, 13].

The accelerated advancement of mobile computing technologies has led to a growing prevalence of computation-intensive tasks generated by mobile applications and services, including those for augmented reality and virtual reality [14]. The 5G NR enables a triad of service offerings: mMTC, URLLC, and eMBB. The eMBB service can accommodate high-data-rate applications, including 4K video streaming and virtual reality (VR) experiences [14]. In particular, the advanced Long-Term Evolution (LTE) internet service, which facilitates accelerated data rates and advanced coding over large communication blocks for prolonged durations, can be conceptualized as an extension of the eMBB service [15]. Consequently, the eMBB service's objective is to achieve a balanced level of reliability while ensuring high data throughput and an acceptable packet error rate (PER). Broadband enables rapid data transfer speeds, continuous online connectivity, and the ability to transmit and receive information swiftly. Broadband is presently characterized as any service exceeding 2 Mbit/s. Unfortunately, it is not consistently viable to provide such speeds to all individuals in contemporary contexts [16]. The two primary scenarios presented by 5G wireless networks are driven by the demands for enhanced eMBB and URLLC telecommunication [17].

A critical aspect of 5G and beyond 5G networks is the resource slicing of various traffic types, which enables the coexistence of multiple services with distinct requirements, such as URLLC and eMBB, within a single network framework. The Quality of Service (QoS) requirements for these two traffic categories diverge; while URLLC is subject to stringent minimum latency and reliability standards, eMBB users necessitate substantial throughput capabilities [18]. As a result, Cloud Radio Access Networks have emerged as a prominent solution capable of economically accommodating hundreds of gigabits of data speeds without compromising performance. Another innovative 5G technology is the C-RAN, which was developed to optimize network resource utilization, improve system architecture, enhance coverage efficiency, reduce operational and deployment costs, and increase energy efficiency [19, 20]. The evolution of future mobile networks is expected to be predominantly underpinned by the innovative architecture of cloud radio access networks, commonly abbreviated as C-RAN, which represents a significant advancement in telecommunications technology This paradigm encompasses the consolidation of baseband processing for numerous radio remote heads (RRHs) within a singular baseband unit (BBU) repository, alongside the disassociation of the relationship between baseband units (BBUs) and RRHs. This framework not only promotes enhanced management of network resources but also facilitates dynamic resource allocation in accordance with real-time demand, consequently augmenting the overall flexibility and responsiveness of the network [21].

1.1. Motivation and objectives

These objectives would be achieved by applying deep learning methodologies to the resource allocation of eMMB and URLLC services in the C-RAN architecture of wireless 5G networks. Designing advanced algorithms that dynamically distribute resources to solve problems of latency, reliability, and throughput, thereby enhancing network performance, will constitute the principal target of this paper. The research would yield an informative paper that sheds light on the practical resource management efforts necessary to enhance the capabilities of 5G networks in meeting diverse service requirements. These are not entirely sufficient because they have been too high in complexity, considering the scale, reliability of resource allocation, and system performance in earlier works. The current study will further develop previous research by integrating predictive models that can forecast network demands and adapt resources to achieve optimal service provision in dynamic environments.

Furthermore, the incorporation of real-time data analytics will enable the proactive management of network resources by allowing for instant adjustments to changes in traffic and user behavior. Furthermore, a detailed comparative study and evaluation of various machine learning algorithms, along with their pros and cons, will enhance the decision-making process in terms of effectiveness, leading to a more flexible and responsive approach to network management. This will, in turn, elevate the overall user experience to new heights in terms of satisfaction and engagement. The literature review in related work presents the following key challenges.

- Energy consumption: The prevailing operational framework encounters significant obstacles that are deeply intertwined with the limitations imposed by the available energy resources for edge servers, necessitating the development and implementation of a comprehensive approach to substantially reduce energy consumption while safeguarding the system's ability to achieve and maintain optimal performance standards.

- Resource allocation improvement: It is of utmost importance to methodically improve and advance the existing techniques currently employed across a variety of sectors, while simultaneously maintaining a focused commitment to the thorough and exacting enhancement of slice allocation procedures, as well as comprehensively addressing and resolving the intricate fundamental challenges that are inherently linked to the optimization of network resources within a singularly unified and cohesive infrastructural framework that encompasses numerous operational parameters. In the realm of practical implementations and complex situations that inherently involve the sophisticated intricacies associated with global business operations, it is exceedingly crucial to adeptly and efficiently confront and alleviate the cross-domain obstacles that affect a diverse range of factors, including but not limited to resource management, accurate scheduling, effective load balancing, and the nuanced alignment of interests among a multitude of varied end users and several service providers who are concurrently functioning within the same operational ecosystem.

The principal aim of this comprehensive scholarly investigation is to markedly improve the allocation and governance of resources within the frameworks of enhanced mobile multicast broadcast and ultra-reliable low latency communications services, which represent critical components of the C-RAN architecture that delineates the operational functionalities of modern wireless fifth-generation networks, by implementing a systematic methodology that incorporates advanced reinforcement learning techniques, which have been formulated and perfected within the broad domain of artificial intelligence, thus guaranteeing a more efficient and effective deployment of technological resources.

- Formulate and develop extensive methodologies designed to mitigate the urgent energy dilemmas currently permeating the system infrastructure by diligently enhancing the operational efficacy of edge servers, while simultaneously endeavoring to reduce the total energy expenditure associated with these activities, thereby fostering sustainability and optimizing resource utilization.
- Elevate and refine the existing methodologies through a rigorous enhancement of network slice allocation, while systematically tackling the intricate challenges associated with the optimization of network resources, which encompass the deployment of efficacious resource management strategies, the formulation of resilient scheduling frameworks, the implementation of load balancing methodologies, and the reconciliation of interests among end users and a diverse array of infrastructure providers, thus promoting a more integrated and efficient network ecosystem.

1.2. Research contribution

The primary objective is to optimize the allocation of resources for enhanced mobile multimedia broadbands and ultra-reliable low-latency communications services within the cloud radio access network paradigm of wireless fifth-generation networks, through the implementation of reinforcement learning methodologies. The main contribution of this research is given below;

- It focuses on the critical role of resource allocation in 5G networks, emphasizing the significance of efficient practices for eMMB and URLLC services within the C-RAN.
- Processing velocity is optimized by Particle Swarm Optimization to minimize energy consumption, thereby enhancing the comprehensive system performance in the challenging context of 5G networks.
- In this paper, several contributions are made to improve resource allocation between eMBB and URLLC services in 5G networks. Most importantly, the thread is woven around fusing the Particle Swarm Optimization algorithm with Q-learning techniques for improved effectiveness at work and flexible, efficient resource allocation. Significant contributions are explained in the following sections.

- Integrating PSO with Q-learning to enhance solution exploration: The standard PSO algorithm is combined with Q-learning to improve the effectiveness of prospecting and exploitation in the pursuit of optimal solutions. Q-learning helps direct particles to more favorable areas in solution space by utilizing information stored in the Q-Table; thus, it enhances decision-making in particles and reduces the number of iterations required to find the optimal solution. Contribution: Combining these two algorithms yields a novel approach to exploring multidimensional spaces with enhanced effectiveness, thereby reducing the likelihood of converging to local suboptimal solutions.

Inertial dynamics to help in the search space: The dynamic adjustment of the inertia weight parameter has been included as one of the modifications to the particle swarm optimization algorithm, where the parameter is initially set at a high value to encourage exploration during the early stages of optimization and is then reduced gradually as the iterations proceed. This tends to maintain a good balance between exploration and exploitation, thereby improving the ability of the particles to explore a more expansive space initially and converge toward the optimum solution. Contribution: Better ways to explore solutions reduce the need for random initial values and ensure a more expansive space of solutions is examined at the start of optimization.

Speed update based on hybrid individual-social factors with Q-learning tuning: Equation for speed update underwent a complete overhaul redesign that involved a hybrid of personal learning, social learning as well as updates based on the values encoded in the Q-Table for the same to express adaptive more effectively for each particle to be able to exploit gathered experience while making a choice based on the same to effectively realize the optimal and simultaneously open up the possibility for exploring its surrounding space.

- Diverse metrics augmented fitness function for resource allocation: The fitness function was developed to be loosely defined, typically involving throughput, and sometimes latency and energy consumption as well, considering the proper weight of each parameter to balance between efficiency in throughput optimization and low expenditure in terms of both latency and energy. Contribution: The elaborated fitness function will enable resources to be allocated in line with the Quality-of-Service requirements pertinent to both eMBB and URLLC services, thereby ensuring a fair and effective allocation of resources.
- Utilization of Q-Table for the Advancement of dynamic policies: The implementation of the Q-Table enables the progressive refinement of optimization policies for particles, influenced by the rewards obtained from the environment (i.e., the outcomes of the fitness function). This characteristic significantly increases the algorithm's adaptability to fluctuations in conditions and promotes superior decision-making processes over Time. Contribution: The ongoing refinement of the Q-Table enhances the algorithm's dynamic efficacy and ensures the continual improvement of resource distribution in fluctuating environments. Abstract: This paper presents a novel methodology for improving resource allocation in 5G networks, which combines the PSO algorithm with Q-learning techniques. This combination enhances the overall network performance by increasing the efficiency of resource allocation, taking into account the QoS requirements of both eMBB and URLLC services across multiple environments.
- Through these contributions, the research presents a new methodology for improving resource allocation in 5G networks, leveraging the combination of the PSO algorithm with Q-learning techniques. This combination enhances the overall network performance by increasing the efficiency of resource allocation, taking into account the QoS requirements of both eMBB and URLLC services across multiple environments.

1.3. Paper organization

The remainder of the work is organized as follows: Section 2 provides an overview of the literature assessment and analysis of the existing gaps. The precise issue description and related answers from the previous studies are explained in Section 3. The suggested work is presented in Section 4, where all the works are thoroughly described using mathematics, pseudocode, and relevant illustrations. The mathematical model of the proposed work is introduced in Section 5. The simulation setup, comparison analysis, security analysis, and study summary are the main topics of Section 6, which presents the experimental data. The suggested work's conclusion is provided in Section VII.

2. Literature survey

This section describes the literature evaluation of existing state-of-the-art methods for secure resource allocation in eMMB and URLLC services within 5G C-RAN. Additionally, this section addresses and identifies the research gaps in existing approaches.

In this paper [22], the two-timescale RAN slicing is designed to balance the performance of URLLC and eMBB services, viewed from the perspective of a small-time-scale multi-agent Markov decision process (MDP). It offers a two-timescale RAN slicing to balance the performance between URLLC and eMBB services. The paper presents a resource allocation problem that necessitates a solution to a nonlinear binary program and demonstrates its NP-hardness. The significant time-scale problem is cast as a single-agent Markov decision process and hence solved by the exponential-weight algorithm for exploration and exploitation (EXP3). The small-time-scale multi-agent MDP problem can be effectively solved by a multi-agent deep Q-learning (DQL) algorithm. Extensive simulations under various network parameter configurations and settings indeed verify the effectiveness of the approach. In this paper [23], a solution to dynamically allocate resources in a 5G heterogeneous network scenario is proposed, which aims to identify a trade-off between the overall QoE perceived by the users served by the network when consuming video content and the overall network energy consumption. The paper proposes a solution for dynamically allocating resources in a 5G heterogeneous network scenario, focusing on balancing the quality of experience (QoE) perceived by users and the network's overall energy consumption. It defines appropriate QoE and energy consumption models for three types of devices: TV, laptop, and smartphone. Extensive simulations were conducted, assigning different levels of importance to QoE and energy consumption to evaluate the trade-offs between these two factors. The results indicate that network energy consumption can be significantly reduced while maintaining satisfactory QoE, especially for smartphone users. In this paper [24], resource allocation for coexisting eMBB and URLLC services in multi-UAV aided communication networks for cellular offloading maximizes fairness and reliability while achieving high data rates. The users are then clustered via a low-complexity scheduling algorithm in the subsequent time slot for resource allocation in eMBB downlink. It is in this regard that a stability-oriented matching algorithm is introduced to identify appropriate eMBB-URLLC pairs in the superposition scenario. NOMA-enabled superposition enhances system throughput, and thus the numerical results concerning system throughput, minimum expected achieved rate (MEAR), and fairness concerning eMBB users are pretty effective in proving the efficacy of the proposed work.

In this academic discourse [25], this paper presents the optimization problem for jointly provisioning eMBB and URLLC services under MEC solutions, considering a dual key performance metric comprising energy consumption and latency. It further elaborates on an iterative methodology to approach the approximate optimal solution. The paper employs a structured optimization framework to minimize energy consumption and latency when co-deploying eMBB and URLLC services in MEC environments. It also breaks down the main optimization problem into several convex optimization subproblems in a systematic way, making the resolution process more feasible. The deployment of an iterative methodology for achieving an approximately optimal solution significantly contributes to the more efficient utilization of resources within the MEC framework. The proposed method demonstrates lower energy consumption compared to its alternatives, as supported by the results obtained from simulation experiments.

In the present study [26], the approach is to present multi-agent reinforcement learning for radio resource slicing in 5G networks. Here, a methodology is proposed wherein each autonomous slice is an intelligent agent competing for available radio resources through an applied-correlated Q-learning technique for inter-slice RB allocation. The following study describes an approach to a multi-agent reinforcement learning framework for radio resource partitioning in the 5G network architecture. In that, a single slice will act as an intelligent agent participating in the competition to acquire scarce radio resources. The correlated Q-learning-based interslice RB allocation methodology was identified as COQRA. The proposed framework is tested using various diversified alternative methods, including Nash Q-learning, PPF, and LRTQ approaches. This paper [27] addresses the sum-rate maximization problem subject to latency and slice isolation constraints under specific reliability requirements by utilizing AMC and by relaxing the intractability of AMC and binary assignment variables. The methodology paves the way for a slicing-based resource allocation approach that can efficiently multiplex enhanced mobile broadband (eMBB) and ultra-reliable low-latency communication (URLLC) users on the same radio resources. The methodology formulates the radio resource allocation problem as a combinatorial integer nonlinear programming optimization problem. AMC is applied in the study to optimize resources by considering channel quality for the effective selection of the most suitable MCS. The work presents a procedure for numerical simulations that addresses the mathematical intractability of AMC and binary assignment variables. The paper [28] formulates a joint optimization problem of bandwidth and power allocations, respecting long-term constraints related to queue backlogs, and introduces a one-to-one matching procedure to solve the integer programming in resource block (RB) allocation as well as slicing puncture problems. The above manuscript employs the Lyapunov drift-plus-penalty (DPP) approach to relate long-term constraints to short-term optimization challenges, ensuring that long-term constraints are progressively satisfied at each iterative step. It breaks down the short-term optimization challenge into two subproblems, which are solved with a block coordinate descent (BCD) algorithm to ease the computation burden. Moreover, it introduces a bijective matching technique to tackle integer programming related to resource block allocation and slicing puncture dilemmas. These methodologies collectively address the scheduling complexities of eMBB and URLLC services.

In the current investigation [29], another work utilizes dynamic programming to find an optimal resource assignment at the transmission time interval level for uRLLC traffic, which maximizes its constructive impact on the average throughput of eMBB while maintaining a fair level of fairness among UE. The work presents the resource allocation challenge for both uRLLC and eMBB as an optimization problem of maximizing the average throughput of eMBB UEs under stringent latency requirements of uRLLC applications. At this point, we will introduce a dynamic programming framework that helps optimize resource allocation for uRLLC traffic at the TTI level. This framework can be sympathetically merged with heuristic scheduling algorithms, and therefore, allows the uRLLC traffic to preempt the pre-allocated resources designated for eMBB UEs upon its arrival. The methodologies are illustrated through numerical simulations to demonstrate enhancements in data rate, spectral efficiency, and fairness. In the present work [30], we address the complex issue of joint resource allocation between eMBB and URLLC schedulers to maximize the minimum expected achieved rate (MEAR) for eMBB users while meeting the QoS targets of URLLC users. This work presents a comprehensive joint resource allocation solution designed for eMBB and URLLC schedulers, aiming to maximize the minimum expected achieved rate (MEAR) for eMBB users while respecting the QoS constraints of URLLC users. The mapping of resources related to eMBB traffic occurs at the boundary of time slots, while URLLC traffic mapping occurs at a minislot temporal resolution using NOMA superposition. The proper matching of eMBB and URLLC users is defined using the one-to-one matching theory, which incorporates fair matching among eMBB users. Reference [31] introduced an improved crossover genetic algorithm-based framework for resource allocation in 5G networks. The framework unifies Advanced Hybrid Search Techniques and Weighted Summation Methodologies to enhance overall efficiency collectively. It therefore develops techniques to improve the operational efficiencies of UDNs from small-cell users by fine-tuning the sharing of both transmission power and resources. The approach is subjected to high simulation-based testing, which indicates a marked improvement in efficiency over any alternative solutions. Additionally, this study examines the convergence properties and computational requirements of the approach.

In the study [32], the learning paradigm combines DRL and deep learning methods to investigate resource allocation in 5G Radio Access Networks (RANs) within the context of the authors' work. In this work, the A3C algorithm will be explicitly implemented through the DRL methodology paradigm. The same has been implemented with the SBiLSTM architecture for the supervised DL approach. Furthermore, the energy-efficient power allocation (EE-PA) problem is formulated as a non-convex optimization problem, which can be solved effectively using an iterative algorithm. For this purpose, this methodology facilitates the simultaneous allocation of power and resource blocks while keeping slice isolation. In the academic manuscript at hand, the authors propose the establishment of the Intelligent Energy Efficiency (IEE) algorithm, which aims to enhance throughput, Quality of Service (QoS), and energy efficiency in the setup of 5G dense heterogeneous cellular networks (HetNets). A deep neural network (DNN) is utilized to determine the cell capacity ratio for small base stations (SBSs), which serves as a decisive element for transitioning the SBSs into a quiescent state. Furthermore, transferable payoff coalitional game theory is employed to prioritize real-time applications over their non-real-time equivalents, thereby improving performance for critical traffic categories. The effectiveness of the proposed methodologies is corroborated through a series of computer simulation results.

In the cited publication [34], the authors proposed a deep reinforcement learning (DRL) optimization strategy designed to enhance the average efficacy of resource allocation in 5G mobile networks. This strategy involves allocating resources to specific network slices designated for audio, messaging, video, and browsing services. This paper proposed a deep reinforcement learning framework for resource allocation in 5G systems. It is developed by introducing the concept of network slicing to support connectivity for IoT devices, whereby resource allocation is parameterized through individual slices for specific services, such as audio, messaging, video, and browsing services. This not only solved questions associated with pruning the user resource request queue but also relaxed traffic management for resource sharing. The paper addresses issues related to network slice distributions to users, resource block balancing, and quality of service, aiming to maintain fair resource allocation.

In this article [35], the authors conducted the first systematic study, via an extensive measurement campaign across four major US cities and two major mobile operators, of resource allocation policies in current 5G mmWave mobile network deployments. The paper presents the first systematic study of resource allocation policies in 5G mmWave networks, conducted through an extensive measurement campaign across four major US cities and two major mobile operators. It focuses on analyzing how resource allocation among multiple flows is governed by cellular operators, emphasizing that flows do not compete in a shared queue. The study reveals the use of simple threshold-based policies by operators, which often involve over-allocating resources to new flows with low traffic demands or reserving capacity for future usage. Anomalous behaviors observed during experiments across different cities and operators are also discussed. In this article [36], the authors propose a deep reinforcement learning (DRL) optimization method to maximize the average resource allocation performance in 5G mobile networks, where resource allocation is based on individual network slices, specifically audio, texting, video, and browsing. The paper proposes a deep reinforcement learning (DRL) optimization method to enhance resource allocation performance in 5G networks. It utilizes network slicing concepts to improve connectivity for IoT devices, with resource allocation tailored to specific slices such as audio, texting, video, and browsing. A round-robin scheduling algorithm is implemented to manage user resource request queues, thereby helping to control traffic for resource sharing. The study addresses key issues, including the allocation of network slices to users, balancing resource blocks, and ensuring quality of service to achieve a fair distribution of resources. Table 1 represents the summary of the literature survey.

Table 1. Summary of related works

References	**Objectives**	**Algorithms or methods used**	**Limitation**
[22]	Optimize the performance of ultra-reliable low-latency communication (URLLC) and enhanced	Markov decision process (MDP)	Resource allocation issue

References	Objectives	Algorithms or methods used	Limitation
	mobile broadband (eMBB) services within 5G networks.		
[23]	Dynamic resource allocation in 5G heterogeneous networks.	focusing on balancing the quality of experience (QoE)	Scalability
[24]	A novel framework that utilizes multiple unmanned aerial vehicles (UAVs) for cellular offloading.	K-means++	Scalability
[25]	Establish an optimization problem focused on minimizing both energy consumption and delay associated with these services.	convex optimization	Resource allocation issue
[26]	Multi-agent reinforcement learning (MARL) method for radio resource slicing	correlated Q-learning based interslice RB allocation (COQRA)	Resource allocation issue
[27]	The sum-rate maximization problem is subject to latency and slice isolation constraints, while assuring specific reliability requirements	adaptive modulation coding (AMC)	Resource optimization challenges
[28]	The Lyapunov drift-plus-penalty (DPP) method is used to establish a relationship between long-term constraints and short-term optimization problems.	Lyapunov drift-plus-penalty method	Heterogeneous integration challenges
[29]	A dynamic programming approach is employed to achieve optimal resource allocation for uRLLC traffic at the Transmission Time Interval (TTI) level.	Heuristic scheduling algorithms	Impact of evaluation challenges
[30]	Improved Metaheuristic Algorithm-Based Distribution of Load in a 5G technology C-RAN	non-orthogonal multiple access (NOMA) superposition technique	Resource optimization challenges
[31]	Address the critical task of resource allocation in wireless communication systems, particularly in the context of 5G networks	Modified Crossover Genetic Algorithm (MCGA)	interference alignment issues and security flaws
[32]	Address the challenges associated with resource allocation in 5G Radio Access Networks (RANs) due to network dynamics and varying application requirements.	deep reinforcement learning (DRL)	energy-efficient issue
[33]	Propose an Intelligent Energy Efficiency (IEE) algorithm aimed at enhancing throughput, Quality of Service (QoS), and energy efficiency in 5G dense heterogeneous cellular networks (HetNets)	deep neural network (DNN)	Quality of Service (QoS) issues
[34]	improve connectivity for the Internet of Things (IoT) through the implementation of network slicing concepts within 5G mobile networks	deep reinforcement learning (DRL)	energy-efficient issue
[35]	It utilizes Grey Wolf Optimization (GWO) to enhance the reliability of the resource allocation strategy for heterogeneous requirements.	Grey Wolf Optimization (GWO)	Resource allocation issue
[36]	Utilizing blockchain technology for resource trading and implementing autonomous RAN slicing in 5G with advanced reinforcement learning.	deep reinforcement learning (DRL)	Scalability

3. Method

3.1. Problem statement

This section outlines some of the specific issues addressed in previous works. The paramount and overarching challenges that are recurrently encountered within the domain of the extant academic literature are primarily linked to the notions of scalability, the dependability of resource allocation frameworks, and the exhaustive performance indicators of the holistic system architecture. In conjunction with these broad categories of concern, there exists an array of specific obstacles that have been scrupulously analyzed and addressed within the parameters of the contemporary academic discourse, which are subsequently delineated and expounded upon in the ensuing sections.

The authors in [37, 38] utilized the PSO algorithm to enhance the management of network resources within a 5G framework, with a particular focus on bandwidth distribution among tenant networks. The manuscript elaborates on the dynamic resource adjustment module integrated within the Software-Defined Networking (SDN) controller, which encompasses sub-modules dedicated to network surveillance, resource distribution, and updates to network mapping. Furthermore, the paper emphasizes several strategies for managing position information vectors that surpass the constraints of the search space during PSO iterations, including the infinity method, nearest method, random method, and scaling method. The results of the research work indicate that the Particle Swarm Optimization algorithm is highly effective in managing network resources in 5G by recalibrating bandwidth values for each tenant network. This results in a "post-adjustment stabilized rate of resource utilization" in the range of 0.3–0.7; thus, a more redesigned PSO equitably distributes bandwidth among congested and inefficient networks. By incorporating self-organizing features, retaining memory, and simplicity in implementation, the PSO algorithm outperforms alternative algorithms. It is thus established as a viable solution for enhancing network efficiency and adaptability. The study points out that low utilization rates of existence in the current dynamic resource adjustment methodologies need rectifying, and further elaboration on the following research issues is as follows:

The paper at hand addresses the issue of low utilization of current transmission networks, despite efforts to increase bandwidth and meet the growing demand for data transmission. This results in inefficient resource management, causing congestion and, simultaneously, waste in tenant networks. The authors highlight the shortcomings of current dynamic resource adjustment approaches and propose a novel dynamic resource adjustment framework to enhance utilization. Particle swarm optimization (PSO) is proposed as a viable approach for improving the efficiency and adaptability of inter-tenant network bandwidth allocation.

The researcher in [39] introduced an advanced power management strategy that anticipatively modifies the operational CPU frequency of Base Station (BS) units in accordance with anticipated core load. It utilizes data from multiple BSs combined at a central management entity (CME) to ensure better generalization and avoid overfitting the prediction model. Simple mathematical formulas for core load prediction are derived using reinforcement learning (RL) at the CME. The method is tested using real network traces at the RAN Distributed Unit, which includes various core groups such as Internet Protocol (IP), transport layer, radio link control (RLC), and Linux applications. The following is a list of the problems with this work:

The paper addresses the significant power consumption of base stations (BS) in radio access networks (RAN), which include distributed units (DUs), central units (CUs), and radio units (RUs) that consume substantial amounts of energy. It highlights the lack of proactive methods in existing power management strategies, which do not adapt to varying network traffic patterns and lack real-time training capabilities. The proposed solution aims to intelligently adjust the operating CPU frequency of BS units based on predicted core loads, thereby enhancing energy efficiency during periods of low traffic.

The author in [40-42] presents an adaptive RL-based resource allocation algorithm for multicarrier interchange systems, which considers numerous consumers and multipath channel characteristics under the assumption of millimeter-wave propagation. The communication system, known as Cyclic Prefix—Orthogonal Frequency Division Multiplexing (CP-OFDM), is proposed to be described using a flexible Markovian approach, defined by the channel's states and the queuing states of buffers. We introduce and evaluate novel utility coefficients for the Q-learning technique centered on the Markovian framework. Through computational simulations that account for actual traffic traces, the effectiveness of the proposed adaptive resource allocation strategy based on the Markovian model RL is confirmed. The following is a list of the problems with this work:

The size of the transition probability matrix represents the primary drawback of their suggested Markov model-based Q-learning method. It is a three-dimensional matrix that expands when more states and actions with elements are added. It isn't easy to calculate the values of every one of these transition probability matrices and then train an agent using an adaptive QL method within a time frame comparable to a TTI. In actuality, the complexity of the problem rises with the number of states and actions. When it comes to agent training, this is a bottleneck.

The author in [43] employed a modified resource allocation (RA) scheme that utilizes a learning-based resource segmentation (RS) technique to manage resources in a 5G wireless network. It incorporates a modified random forest algorithm (RFA) to address the RA problem, which is based on the signal-to-interference-and-noise ratio (SINR) and the end-users' positional coordinates. The methodology involves computing the spatial coordinates of end-users on a frame-by-frame basis to facilitate the establishment of connections between end-user devices and remote radio heads (RRHs). The simulation analysis evaluates the effectiveness of the proposed technique in terms of throughput and energy efficiency. The principal issues are elaborated upon in greater detail in the subsequent sections.

Effective management and segmentation of resources are imperative, given the intricate nature of distributed networks. The precision of positional coordinates is crucial for the accuracy of input parameters, including signal-to-interference and noise ratio (SINR), which is consequential for the network's operational efficiency. Establishing dependable connections between end-user devices and remote radio heads (RRHs) is necessary to ensure optimal communication and resource allocation. The necessity for enhanced throughput and energy efficiency within the proposed resource allocation framework is underscored through simulation analysis.

The scholar referenced in [44] employed deep reinforcement learning (DRL) as the primary methodology to address the complexities associated with maximizing enhanced Mobile Broadband (eMBB) throughput and ultra-reliable low latency communications (URLLC) latency within the framework of 5G networks. The agents undergo training in a meticulously structured environment that integrates a reward framework designed to facilitate the simultaneous enhancement of eMBB throughput and URLLC latency. The Colosseum O-RAN COMMAG Dataset is employed for training and assessing the efficacy of the DRL agents. The principal issues are elaborated upon in greater depth in the subsequent sections. In this academic treatise, specific attention is scrupulously devoted to the investigation and evaluation of the proximal policy optimization (PPO) algorithm, which is fundamentally perceived as the crucial mechanism or tool utilized for the methodical training and augmentation of deep reinforcement learning (DRL) agents, consequently enabling their capability to acquire knowledge and adjust within intricate environments.

The discourse underscores the paramount importance of implementing robust resource management strategies to effectively mitigate the aforementioned optimization challenges, which are vital for enhancing the operational efficiency of 5G networks The scholarly investigation primarily centers on the application and deployment of advanced deep reinforcement learning (DRL) methodologies, particularly highlighting the significant role of the proximal policy optimization (PPO) algorithm, which is meticulously designed to effectively address and resolve these pressing and critical challenges that have emerged in the contemporary landscape of artificial intelligence and machine learning The findings of the research elucidate the intricate nature of attaining a harmonious equilibrium between elevated throughput and diminished latency within the realm of 5G communications.

3.2. Research solutions

Presents an ability to enhance edge server deployments to reduce energy consumption while maintaining good performance levels and being able to effectively navigate and exploit solution landscapes to deal with varying workloads amongst the edge servers and energy constraints. This paper introduces several novel approaches of combining the PSO algorithm with Q-learning techniques for optimized resource allocation towards enhanced mobile broadband eMBB, and ultra-reliable low latency communication URLLC services in 5G networks. Addressing the complex challenges in the modern wireless network to achieve the most desirable energy efficiency, coupled with quality of service. The illustration of the new approaches is done in the subsequent sections as follows:

- Integrating PSO with Q-learning to achieve dynamic resource allocation: The integration of PSO with Q-learning offers an intelligent and dynamic approach to resource allocation. For the exploration of high-quality solutions based on rewards accrued, Q-learning utilizes Q-tables to facilitate decision-making during the process. As such, the algorithm will dynamically adjust resource allocation for eMBB and URLLC in response to dynamic factors such as workloads and varying service requirements. Solution: With this integration, fast changes from users can be detected, and as a result, the effectiveness of resource allocation is enhanced through the mitigation of delay and interference among services.
- Dynamic inertia to explore the best solutions: Within the framework of the Particle Swarm Optimization, dynamic inertia, acting as a scaling factor, gradually reduces the particle velocities. Initially set at a high level, this is where possible solutions to the solution space are explored in great detail, as there is a minimal risk of premature convergence to local optima. Eventually, over time, the inertia decreases to a lower level, causing the particles to shift towards the already detected optimal regions and providing the algorithm with an exploitation capability.
- Speed update based on a combination of personal, social, and reinforcement learning factors: The equation governing speed updates in PSO is revised by introducing the three most significant factors — individual learning, collective learning, and values obtained through Q-learning. Thus, in this synergistic approach, each particle updates its velocity considering the good positions found so far by it and other factors, based on the rewards from the environment as described by Q-learning. Solution: This unified approach significantly enhances the adaptiveness of the particles, increasing the likelihood of solution improvement at each step and precisely what is needed to make the system responsive to changing environmental conditions.
- Develop a customized fitness function for resource allocation in fifth-generation mobile networks. The fitness function, encompassing several dimensions of metrics such as throughput, latency, and energy consumption, optimizes resource allocation for high throughput, considering not only quality but also other factors. It combines quality and throughput into a single equation to maximize each parameter in harmony, but the values depend on the service type (eMBB or URLLC). This special function helps to achieve the optimal balance between maximizing data transfer and providing a service with low initiation and energy usage, ensuring the quality of service required for both types of services.
- Use Q-learning to update particle decisions: In our optimization process, we integrate Q-learning to update particle decisions continuously. At each iteration, the Q-table is updated based on the rewards obtained from the fitness function. This updated information then enables the algorithm to make decisions in subsequent iterations, allowing it to adapt to changes in its environment. As a result, the Q-Table is continually refined, improving over Time to better assist the system in optimizing resource allocation. This would mean that the Q-table is continuously updated, allowing the algorithm to better adapt to changes in its environment and thereby optimizing resource allocation over a long-time horizon.

Through these methodologies, a more effective model of resource provisioning in fifth-generation (5G) networks is developed, which can support fluctuating workloads while guaranteeing the required quality of service. The framework optimizes energy consumption while maintaining high performance, thereby presenting practical solutions to the challenges in resource allocation for both eMBB and URLLC services.

3.3. Proposed work

The primary goal is to enhance the efficiency of resource distribution in eMBB and URLLC services within the C-RAN architecture of 5G wireless networks by implementing deep learning methodologies. The subsequent essential measures are undertaken as a component of this research, with Figure 1 illustrating the comprehensive architecture of the proposed approach:

3.3.1. Resource allocation

The proposed framework integrates PSO with Q-learning to create a complex resource allocation system for eMBB and URLLC services, ensuring quality of service (QoS) criteria are met for each category. This meticulously crafted framework not only enables a swift and effective response to the varying demands of network conditions and disparate workloads but also scrupulously accounts for the differing priorities inherent in each of the services involved. This is accomplished through the use of PSO to explore the available solution spaces. At the same time, Q-learning guides the decision-making process, informed by the historical experiences cataloged in the Q-table of each particle.

Resource allocation optimization for eMBB and URLLC: The proposed framework aims to meet the requirements for both low latency and high reliability that URLLC will demand, as well as the high throughput that eMBB will require. The proper balance will be achieved by considering the strategic distribution of resources to meet the specific quality of service (QoS) needs, based on prioritization criteria for each service. In this framework, PSO can generate potential solutions for resource allocation, while Q-learning continually improves the selection process by learning the relationship between allocation strategies and their corresponding rewards or fitness values. In this way, the system would not only come up with optimal solutions and improve them effectively, but also would have changed its requirements over Time.

3.3.2. Optimization

The optimization process in the proposed framework involves improving resource allocation over Time using an interactive methodology that combines the exploration of new solutions and the exploitation of discovered optimal solutions. This is done through a set of basic optimizations.

- Dynamic inertia to improve solution exploration where the inertia weight is dynamically adjusted over Time. The inertia weight starts at a high value to encourage particles to explore the solution space more in the early stages of optimization, then gradually decreases to direct particles towards exploiting the best discovered solutions in the later stages.
- Speed update using cognitive and social learning factors and reinforcement learning was improved by incorporating cognitive and social components with additional adjustment based on Q-learning. The speed of particles is adjusted based on their personal experience, collective experience (the best location discovered globally), and learning from past experiences stored in the Q-table.

3.3.3. The overall architecture of the proposed method

1. Start

2. Initialization:

- Commence with the initialization of N particles (indicative of potential resource distributions) with stochastic positions and velocities.
- Initialize the Q-Table with null values for each particle.
- Establish learning parameters: α (learning rate), γ (discount factor), ε (exploration rate), and the maximum number of iterations.

3. For each particle i:

- Assign the personal best position p_best to the current positional coordinates.
- Designate the global best position g_best as the most optimal position among all participating particles.

4. Iterate until the maximum number of iterations is attained:

- For each particle i:

a. Assess the fitness of particle i predicated on throughput (T), latency (L), and energy consumption (E).

fitness = T - (0.5 * L + 0.3 * E)

b. Determine action a for particle i utilizing the ε-greedy policy:

- With a probability of ε, select an arbitrary action.
- Alternatively, select the action that yields the highest Q-value (exploiting existing knowledge).

c. Revise the velocity of particle i:

v_i(t+1) = w * v_i(t) + c1 * r1 * (p_best - x_i(t)) + c2 * r2 * (g_best - x_i(t)) + α * Q(s, a)

d. Update the position of particle i:

x_i(t+1) = x_i(t) + v_i(t+1)

e. Reassess the new fitness of particle i after the positional update.

f. Modify the personal best (p_best) for particle i if the newly computed fitness surpasses the former p_best.

g. Adjust the global best (g_best) if the new fitness of any particle exceeds the previously established global best.

h. Compute the reward r based on the revised fitness:

reward = fitness(x_i(t+1))

i. Update the Q-Table:

Q(s, a) ← (1 - α) * Q(s, a) + α * [reward + γ * max_a' Q(s', a')]

5. Evaluate whether the termination criteria are satisfied (max_iterations or convergence):

- If affirmative, cease operations.
- If negative, proceed with the subsequent iteration.

6. Present the global best position (g_best) as the optimal resource distribution.

7. End

4. Mechanism of reinforcement learning for the dynamic revision of policies

The suggested framework utilizes Q-learning to facilitate the modification of dynamic policies concerning resource allocation, contingent upon the rewards acquired from the surrounding environment. The Q-Table of each particle is used to determine the optimal strategy based on past experiences. The Q-Table is updated after each iteration based on the rewards (fitness value) achieved, allowing particles to improve their performance over Time.

Continuous Q-Table update: After each step of optimization, the Q-Table is updated based on the rewards achieved, which helps improve future particle decisions. This system reinforces solutions that have led to high rewards and continuously improves system performance even as network conditions and workloads change.

4.1. Proposed system architecture

Figure 1 illustrates the system architecture of the proposed methodology, which incorporates key components, including the PSO algorithm, a Q-learning module, and a customized fitness function tailored to the system's specific requirements. In this architecture, particles will interact with the environment and refer to past experiences, which are stored in the Q-Table, to inform their decisions on resource allocation. This design integrates exploration mechanisms with reinforcement learning to dynamically and optimally allocate resources throughout the entire system.

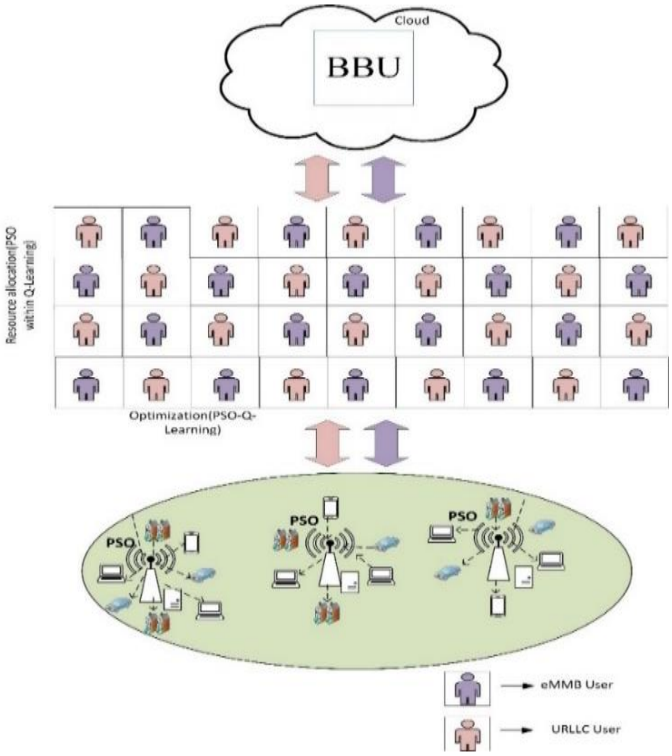

Figure 1. The overall architecture of the proposed method

4.1.1. Mathematical model of proposed work

- Integration of PSO with Q-Learning for enhanced solution exploration: In this study, we significantly enhance the traditional PSO algorithm by integrating Q-learning, a reinforcement learning technique, to balance exploration and exploitation. This hybrid approach should mitigate the risk of premature convergence to local optima by incorporating historical experience through a Q-Table. Specifically, Q-learning helps maintain the state-action dynamics of each particle, enabling them to learn an optimal strategy for resource allocation based on the rewards (or fitness values) they receive. Thereafter, the Q-learning agent would update the Q-values as follows:

a. Q-Table Update Equation:

$$Q(s,a) \leftarrow (1-\alpha)\, Q(s\,,a) + \alpha\,(r + \gamma \max Q(s',a'))$$

Where $Q(s,a)$ is the Q −value for state s and action a, α is learning rate controlling the weight of new information, r is the reward derived from the fitness function (to be described), γ is the discount factor for future rewards and $\max Q(s',a')$ is the maximum expected future Q −value for the next state s' for all possible actions a'.

b. Particle action selection (using ϵ −epsilonϵ-greedy method):

$a = arg \max Q(s,a)$ with probability $1-\epsilon$, otherwise choose a random action.

This strategy ensures that each particle balances between exploring new solutions and exploiting known reasonable solutions. Over Time, as the particles gather more experience, they tend to converge on better allocation decisions.

c. Dynamic Inertia Weight to Balance Exploration and Exploitation: To further improve PSO's exploration abilities, a dynamic inertia weight w is introduced, which gradually decreases as iterations progress. Initially, a high inertia encourages exploration of the search space, and as the process advances, a lower inertia encourages exploitation of the best solutions discovered.
d. Inertia weight equation:

$$w = w_{max} - \left(\frac{w_{max} - w_{min}}{iterations}\right) \times t$$

Where w_{max} is the maximum inertia weight at the beginning; w_{min} is the minimum inertia weight at the final iteration, and t is the current iteration number.

4.1.2. Velocity update with PSO and Q-learning adjustments

The velocity update equation is a core component of PSO. In the proposed hybrid model, the traditional velocity update mechanism is modified by incorporating adjustments from Q-learning. Three main components influence each particle's velocity:

- Inertia: The particle's previous velocity.
- Cognitive: The particle's personal best position.
- Social: The global best position among all particles.
- Q-Learning: An adjustment based on the Q-values to account for learned experiences from past actions.

Velocity update equation:

$$v_i^{t+1} = wv_i^{(t)} + c_1 r_1 \left(p_i^{best} - x_i^{(t)}\right) + c_2 r_2 \left(g^{best} - x_i^{(t)}\right) + \alpha . Q(s,a)$$

Where v_i^{t+1} is the updated velocity of particle i at iteration t, $v_i^{(t)}$ is the current velocity of particle i at iteration t, c_1, c_2 are cognitive and social acceleration coefficients, respectively, r, r_2 are random values uniformly distributed in [0,1], p_i^{best} is the best known position of article i, g^{best} is the best known position globally (among all particles) and $\alpha . Q$ is the adjustment based on the Q −value from the Q −learning algorithm.

Position update equation: Once the velocity is updated, the particle's new position is calculated. The new position is determined by adding the updated velocity to the current position.

$$x_i^{t+1} = x_i^{(t)} + v_i^{t+1}$$

Where x_i^{t+1} is the updated position of particle i, $x_i^{(t)}$ is the current position of particle i, and v_i^{t+1} is the updated velocity of particle i.

4.1.3. Fitness function for resource allocation optimization

The fitness function is designed to evaluate the quality of each particle's position. In the realm of resource distribution for enhanced mobile broadband and ultra-reliable low latency communications services, the fitness function incorporates essential performance indicators, including throughput, latency, and energy consumption. The primary aim is to optimize throughput while concurrently reducing latency and energy expenditure.

Fitness Function:

$$fitness = T - (0.5 \cdot L + 0.3 \cdot E)$$

Where T is throughput (total data transmitted), L is latency (delay in transmission), and E is energy consumption during resonance allocation.

5. Experimental results

To enhance resource allocation in eMMB and URLLC services within the C-RAN framework of wireless 5G networks through the application of deep learning techniques. The simulation setup, comparative analysis, and research summary are the three subsections of this experimental study. The outcome section demonstrates how the proposed work outperforms earlier work in terms of performance.

5.1. Experimental setup

The implementation of the simulation results of the proposed work by the NS-3.26 network simulator enhances the performance of this research. The proposed framework was compared to many performance indicators, and it was established that our work outperformed them. Table 2 outlines the system's configuration, while Table 3 describes the network parameters setup. Figure 2 represents the simulation environment.

Table 2. System parameters

Hardware configuration	Hard disk	40 GB
	RAM	4GB
	Processor	CPU: Intel(R) Core (TM) i7-3520M CPU @ 2.90 GHz x 4
Software configuration	Network simulator	NS-3.26
	Operating system	Ubuntu 16.04 LTS

Table 3. Simulation parameters

Parameters		Descriptions
Network Parameters	users	100
	5G gateway node	3
	Edge cloud server node	3
	Cloud node	1

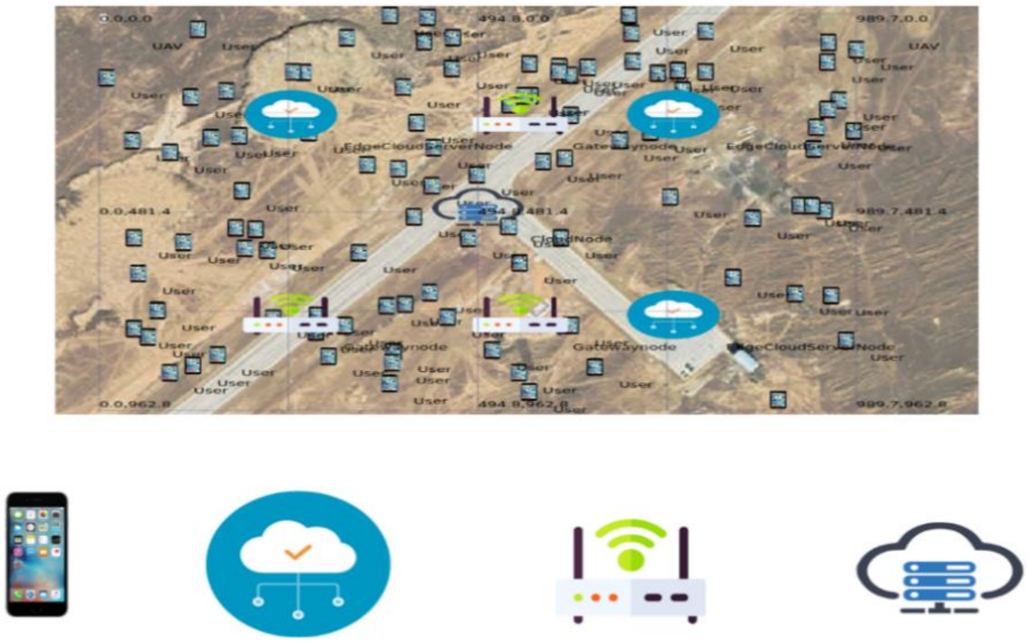

Figure 2. Simulation environment

5.2. Comparative analysis

The comparative analysis of the proposed framework in relation to existing literature is delineated in this section, wherein we consider prior studies such as edge server coverage (km) versus total energy consumption (kWh) [45], Time (seconds) in relation to resource utilization (%) [46], network nodes compared to latency (ms), and time (s) juxtaposed with packet arrival rate [47].

5.2.1. Edge server coverage (km) vs. total energy consumption (kWh)

The subsequent equation can be employed to illustrate the relationship between the total energy consumption (kWh) and the extent of Edge server coverage (km):

$$Total\ Energy\ Consumption = A \times Edge\ Server\ Coverage^{B}$$

Where A and B are constants that rely on specific network setups and settings.

In the context of wireless network systems, the presented equation illustrates the nonlinear relationship that exists between the spatial coverage of edge servers and their associated energy consumption.

The comparison of edge server coverage against total energy consumption (kWh) using the proposed methodology in conjunction with several contemporary methods is outlined in Figure 3 and Table 4. This illustrates the aggregate energy consumption (measured in kWh) corresponding to varying Edge server coverage (expressed in kilometers) for three distinct methodologies: EPMOSO (edge server placement method oriented towards service offloading), PSO, and the proposed approach. The proposed method consistently demonstrates superior efficacy compared to EPMOSO and PSO, achieving reduced energy consumption across all coverage parameters. For example, the advocated technique consumes 19,500 kWh at a coverage of 40 kilometers, in stark contrast to the 27,500 kWh and 27,000 kWh utilized by EPMOSO and PSO, respectively. This serves to exemplify the effectiveness of the proposed strategy in optimizing energy efficiency within the specified wireless network milieu.

Table 4. Numerical outcomes of energy consumption

(x-axis)-Edge server coverage	Total energy consumption (Kwh)-(y-axis)		
	EPMOSO	PSO	Proposed
10	22000	21000	12000
20	24000	23000	15000
30	25000	24500	17000
40	27500	27000	19500
50	28000	27500	20000
60	32000	30000	21100
70	33000	31000	22000
80	33500	33000	25000
90	35500	35000	27000
100	36500	36000	29000

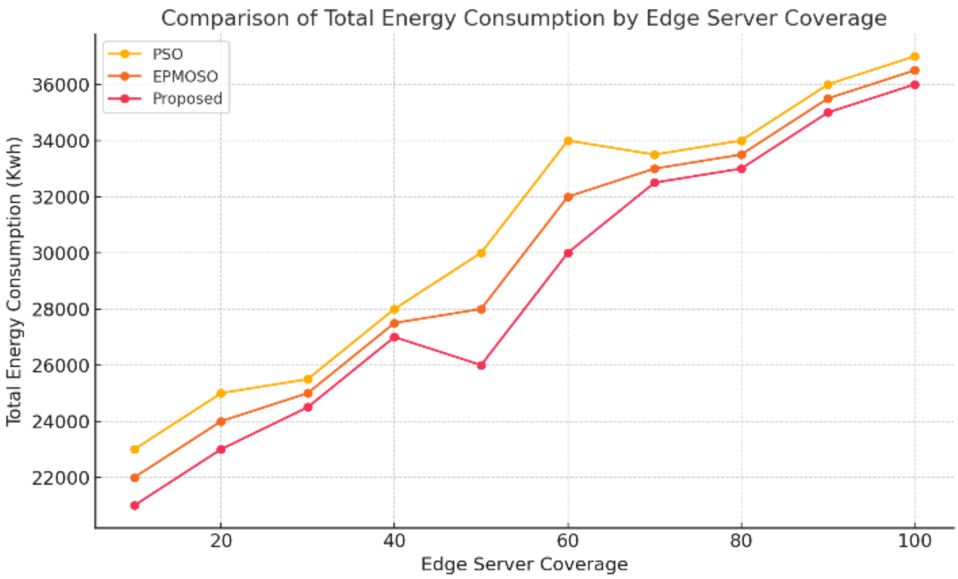

Figure 3. Edge server coverage vs. total energy consumption (kWh)

5.2.2. Time (seconds) vs. resource utilization (%)

The subsequent mathematical formulation can be employed to delineate the correlation between temporal duration (seconds) and resource consumption (%) within the framework of wireless fifth-generation (5G) networks:

$$Resource\ Utilization = C \times e^{-\frac{t}{D}}$$

Here t is the duration in seconds, C is the constant that indicates the starting resource use, and D is the parameter that regulates the pace at which resource utilization decreases with time. The diminishing utilization of resources within the network scenario is illustrated by the equation, which epitomizes an exponential decay model.

The analysis of edge server coverage in relation to total energy consumption (kWh) between the proposed methodology and various existing methodologies is illustrated in Figure 4 and Table 5. The resource utilization (%) over a temporal framework (in seconds) for three distinct optimization algorithms - namely, GA (Genetic Algorithm), PSO, and the proposed approach - is delineated in this comparison. In contrast to GA and PSO, the proposed methodology consistently exhibits superior performance while sustaining lower percentages of resource utilization. For example, at the 60-second mark, the proposed method utilizes 43% of the available resources, in contrast to 56% and 45% for GA and PSO, respectively. This finding indicates that, within the defined network context, the proposed technique effectively optimizes resource utilization over time.

Table 5. Numerical outcomes of resource utilization

(x-axis)-Time(s)	Resource utilization (%)- (y-axis)		
	GA	PSO	Proposed
10	15	10	8
20	19	17	14
30	36	25	22
40	39	36	33
50	45	39	37
60	56	45	43
70	62	56	50
80	70	60	52
90	80	62	55
100	90	75	58
110	90	80	61
120	110	100	62

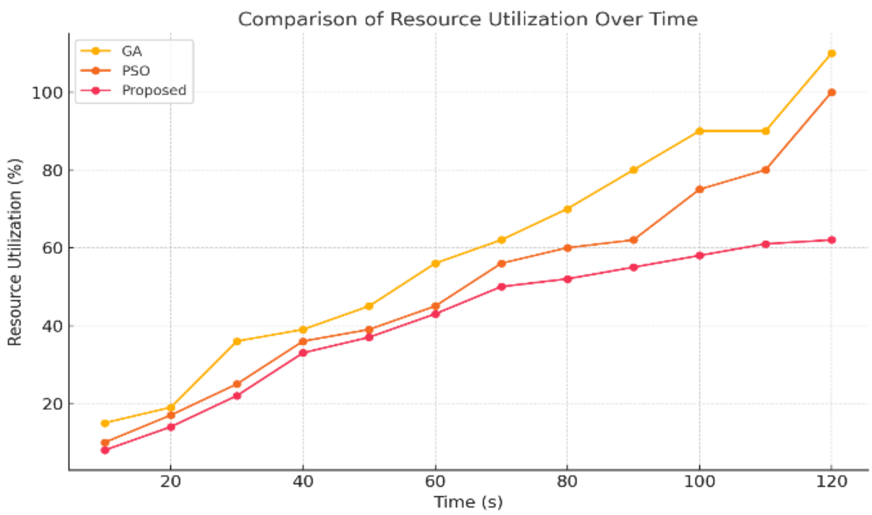

Figure 4. Time(s) vs. resource utilization (%)

5.2.3. Network nodes vs. latency (ms)

The following formula may be used to denote the relationship between the number of network nodes and latency (milliseconds) in a 5G network:

$$Latency = E \times \sqrt{F \times Network\ Nodes}$$

The square root term denotes the nonlinear character of the connection between the number of network nodes and latency, E stands for a constant representing baseline latency and F is for a parameter indicating the influence of network nodes on latency.

The analysis of network nodes versus latency (ms) between the proposed methodology and various contemporary techniques is illustrated in Figure 5 and Table 6. The latency percentages for three distinct scenarios - namely, NSSF (network sub-slicing framework), PSO, and the proposed methodologies - corresponding to varying quantities of network nodes, are presented. In comparison to NSSF and PSO, the proposed methodology consistently demonstrates lower latency percentages, indicating superior performance. In this context, the proposed methodology attains a latency of 33% at 50 network nodes, whereas NSSF and PSO exhibit higher latency values of 63% and 50%, respectively. This highlights the effectiveness of the proposed methodology in reducing latency within the specified network architecture across various node densities.

Table 6. Numerical outcomes of latency

(x-axis)-Network Nodes	Latency(ms) (%)- (y-axis)		
	NSSF	PSO	Proposed
10	20	10	8
20	39	20	13
30	43	38	21
40	52	45	27
50	63	50	33
60	66	60	38
70	82	68	45
80	94	80	51
90	100	92	56
100	120	100	63

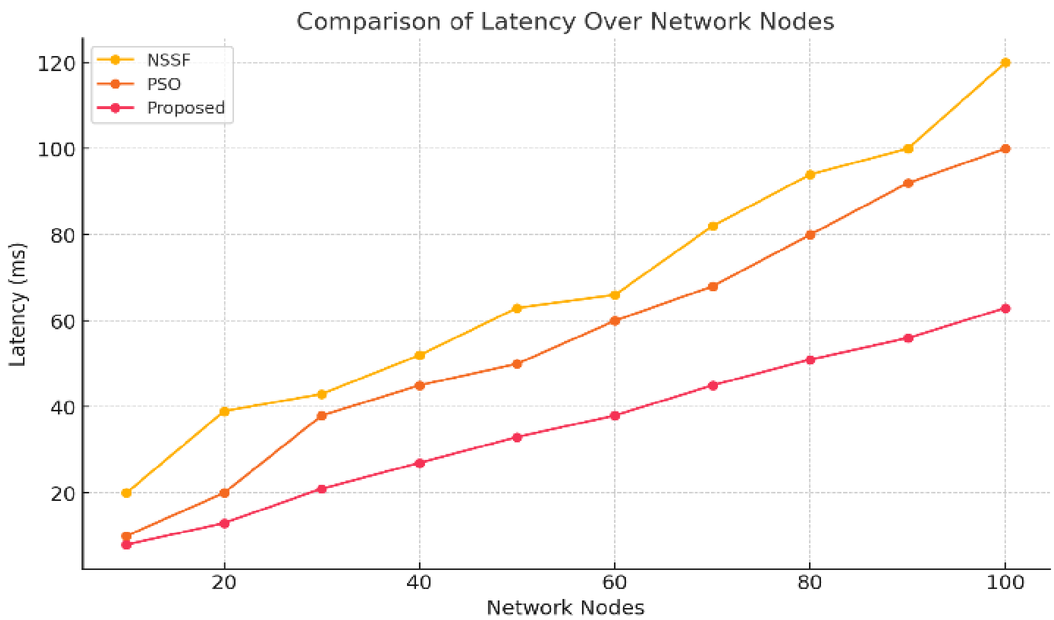

Figure 5. Network nodes vs. latency (ms)

5.2.4. Time (s) vs. packet arrival rate

The following equation represents the relationship between Time (seconds) and packet arrival rate in a network scenario:

$$Packet\ Arrival\ Rate = G + H\ \times T$$

Here t is the time in seconds, G is the initial packet arrival rate and H id the coefficient that determines the rate of change.

The equation illustrates how the packet arrival rate changes over Time in the specified network environment, utilizing a linear growth model.

The analysis of time (s) in relation to packet arrival rate (%) between the proposed methodology and several contemporary methodologies is illustrated in Figure 6 and Table 7. The packet arrival rates (%) for three distinct methodologies - namely, FUZZRA (a fuzzy logic-based algorithm for resource allocation), PSO, and the proposed methodology - are depicted on the graph as a function of time (measured in seconds). The proposed technique consistently yields lower packet arrival rates compared to both FUZZRA and PSO across all Time intervals examined. For example, at the 40-second mark, the packet arrival rate of the proposed technique is recorded at 19%, whereas FUZZRA and PSO exhibit higher rates of 45% and 35%, respectively. This illustrates the efficacy of the proposed method in effectively managing and progressively reducing packet arrival rates within the specified network context.

Table 7. Numerical outcomes of packet arrival rate

(x-axis)-Time(s)	Packet arrival rate(%)- (y-axis)		
	FUZZRA	PSO	Proposed
10	12	9	5
20	25	18	10
30	37	25	16
40	45	35	19
50	52	42	26
60	65	55	29
70	77	62	36
80	85	75	43
90	90	82	46
100	92	90	48

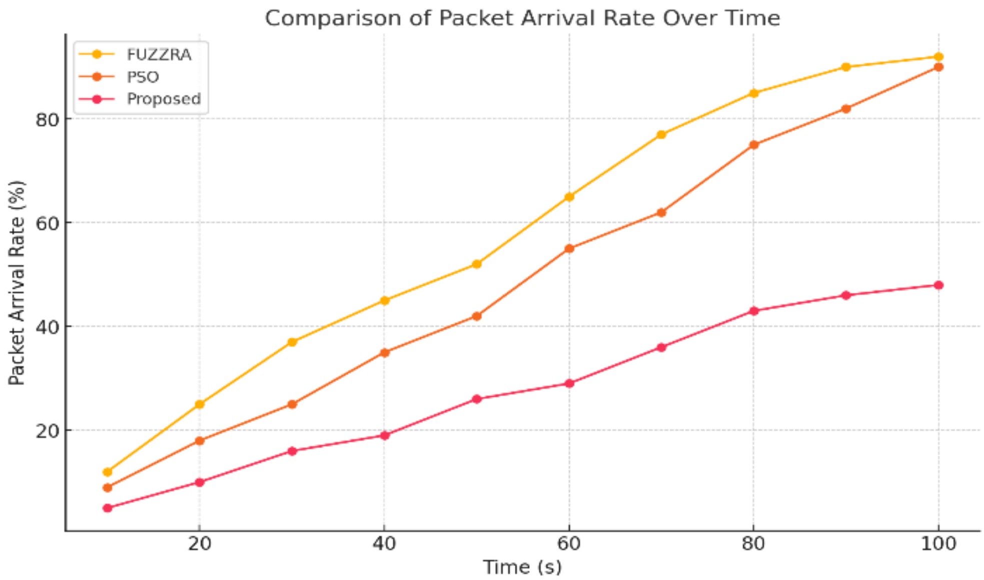

Figure 6. Time (s) vs. packet arrival rate (%)

5.3. Research summary

The initial completion of this project will establish a network within a C-RAN-based 5G environment, comprising 100 user nodes, 3 5G gateways, 3 edge cloud server nodes, and 1 cloud node. It highlights the pivotal role of resource allocation in 5G networks and the best practices for the eMBB and URLLC service classes within C-RAN for delivering these services. PSO (particle swarm optimization) is fundamentally applied step by step, with an insight into its primary objective, which is the drastic reduction in energy consumption levels. Meanwhile, there is an added advantage of increased processing speeds, which, when considered jointly, play a key role in enhancing the overall effectiveness of systems functioning in a complex environment with the high-tech framework of fifth-generation (5G) networks. In the purview of this scholarly research work where a significant input towards the existing knowledge is expected, a new methodology is put forth detailing the union of basic principles of PSO with that of Q-learning which is a reinforcement learning paradigm; this shall be elaborated upon in a detailed and systematic manner to describe how this new approach has been developed and put into practice to ensure the marked improvement in overall efficiency for resource allocation mechanisms across sectors. The hybrid model employs the best balance of these two key, fundamentally different - here, the unique swarm- intelligence characteristics of PSO that inherently support dynamic, collective problem-solving and also the adaptive learning capabilities of Q-learning that enable systems to learn from their experiences over Time in a generational manner - for strategically achieving the critical dual objectives of continually exploring new, perhaps more effective ways of allocating resources and simultaneously exploiting the best-known configurations identified through earlier analyses and implementations.

6. Conclusions

The work provides a comprehensive framework for resource management in 5G networks, explicitly addressing the allocation of resources for services related to eMBB and URLLC in C-RAN architectures. In this paper, we introduce such a framework that consists of Particle Swarm Optimization embedded with Q-learning to form a hybrid optimization methodology, enabling dynamic resource distribution in a network and leading to reduced energy consumption. With careful implementation in our hybrid advanced framework, designed with great attention to the requirements that emerge from modern communication infrastructures, resources are allocated and distributed to users with customization tailored to their specific service requirements. This can vary greatly, as it may pertain to high-throughput eMBB users who require extended data delivery capabilities, or to ultra-reliable low latency communication users who are exceptionally stringent about maintaining low latency with high reliability in their communication sessions. There are other variations in between. The resource distribution mechanism considers the real-time conditions of the network and the specific requirements for each service at all times, ensuring that QoS standards are consistently maintained throughout the network. We also collected the user network data and stored it in the edge cloud server. This data will provide insight into how the network behaves and current traffic trends, and will be used to inform resource allocation in subsequent iterations more effectively. By using PSO, energy management is handled efficiently, ensuring optimal performance while minimizing energy consumption. The PSO algorithm facilitates optimal resource allocation, adapting in real-time to variations in user demand and network conditions.

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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Author contribution

Ammar Abdulhadi Abdullah, Mehdi Ebady Manaa: study conception and design; Ammar Abdulhadi Abdullah: data collection; Ammar Abdulhadi Abdullah, Mehdi Ebady Manaa: analysis and interpretation of results; Ammar Abdulhadi Abdullah: draft preparation. All authors approved the final version of the manuscript.

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