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5G and Internet of Things: Next-Gen Network Architecture

Ahmed Jumaa Lafta[1], Aya Falah Mahmood[2]*, and Basma Mohammed Saeed[3]

[1]Department of Electronic and Communications Engineering, College of Engineering, Al-Nahrain University, Baghdad, Iraq
[2]Department of Prosthetics and Orthotics Engineering, College of Engineering, Al-Nahrain University, Baghdad, Iraq
[3]Department of Electronic and Communications Engineering, College of Engineering, University of Baghdad, Baghdad, Iraq

Abstract

This study examined the integrated benefits of 5G New Radio, network slicing, and reinforcement learning (RL) mechanisms in addressing the challenges associated with the increasing proliferation of intelligent objects in communication networks. This study proposed an innovative architecture that initially employed network slicing to efficiently segregate and manage various service types. Subsequently, this architecture was enhanced by applying RL to optimize the subchannel and power allocation strategies. This dual approach was proven through simulation studies conducted in a suburban setting, highlighting the effectiveness of the method for optimizing the use of available frequency bands. The results highlighted significant improvements in mitigating interference and adapting to the dynamic conditions of the network, thereby ensuring efficient dynamic resource allocation. Further, the application of an RL algorithm enabled the system to adjust resources adaptively based on real-time network conditions, thereby proving the flexibility and responsiveness of the scheme to changing network scenarios.

Index Terms: Network Slicing, Power Control, Quality of Service, Reinforcement Learning

I. INTRODUCTION

The proliferation of smart objects, leading to increasing interpersonal connectivity, raises serious concerns about the performance of established mobile networks under the new demands of recent developments. The rising need for Internet connectivity and applications goes beyond traditional modes of connectivity, such as 3G and 4G [1]. The heart of 5G New Radio (NR) lies in its promise as a complete solution that goes beyond traditional technologies [2]. This change is expected to be revolutionary in addressing the complex challenges presented by the ever-growing number of smart devices and the different types of applications that drive them [3]. Despite these deficiencies among existing infrastructures, as operators struggle to cope, 5G NR has emerged as a revolutionary concept and promises to reform connectivity conventions. This has resulted in an improved and reliable networking system. This study proposed a novel paradigm that integrates 5G NR and reinforcement learning (RL) to overcome these problems [4].

The introduction of 5G networks has been accompanied by several technologies, including network slicing, massive multiple-input multiple-output (MIMO), and beamforming. Network slicing is defined as the possibility of defining multiple logical networks over a single physical network to adapt to the different requirements of an application [5]. However, the management and optimization of these network slices are difficult, particularly when the requirements of users and the state of the network change. To mitigate these challenges, the following research questions are formulated: In this study, RL techniques were incorporated with 5G NR technology. RL is a subcategory of machine learning

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***Corresponding Author** Aya Falah Mahmood (E-mail: aya.falah.elc@nahrainuniv.edu.iq)
Department of Prosthetics and Orthotics Engineering, College of Engineering, Al-Nahrain University, Baghdad, Iraq

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(ML) that facilitates the design of systems capable of learning and autonomous optimization. Thus, by integrating RL algorithms into 5G network management [6], we proposed a design for an intelligent network capable of learning from the environment and making decisions to improve performance. The resource management can be strengthened, the number of channels per unit area can be increased, and the network parameters can be adapted to new quality of service (QoS) demands.

The primary purpose was to consider the capabilities of network slicing to improve the performance of 5G networks by identifying major problems such as bit rate, delays, and bandwidth. By incorporating RL algorithms into the network, the network becomes responsive and facilitates effective subchannel assignment and power control. The adaptive nature improves spectral efficiencies and adds flexibility to provisioning for different QoS requirements [7].

II. BACKGROUND AND RELATED WORK

Intelligence has delved into the entirety of our lives It has invaded our lives through a vast array of smart objects that exchange information [8]. These devices are indispensable in everyday routines that continuously increase their range of services to simplify our lives. From simple intelligent transformations of regular everyday objects, such as domestic appliances to smart metropolises [10]. According to a recent report by the Statista Research Department, more than 75 billion connected devices are expected to exist by 2025, that is more than three times higher than that in 2019 [11]. Simultaneously, the escalating demand for connectivity and smart services poses several challenges [12] that must be addressed, such as upgrading the capacities of IoT networks [13], strengthening network security, improving QoS [14], and improving network performance during the optimization of the energy resources of every connected device [15].

To address the- increasing challenges brought about by the expanding network of connected devices and services, 5G-IoT technology has emerged as a viable solution. With creative designs, abilities, and substantial data transmission rates, it is a key player [16]. Positioned as the best solution when compared to its predecessors in mobile network technologies, and several studies have focused on identifying the optimal model for deploying 5G-IoT networks. Rahimi et al. [17] proposed a novel 5G-IoT network model that integrated cutting-edge technologies, including machine communication, device communication, and any wireless or software communication, along with the known functions of networks.

The integration of these applications enhances the efficiency of the planned theory compared with conventional architectures. QoS paradigms and three-level architectures [18,19] are important aspects. Other studies have focused on the leveraging of 5G technology, particularly in the context of authenticating IoT architecture. Torroglosa-Garcia et al. [20] introduced a relinquishing wander framework for leveraging the dependable 5G network for key management and authentication of IoT devices. This approach ensured the interoperability between 5G and LoRaWAN, showcasing their properties and services in terms of security. In a different scenario where 5G is deployed to ensure a specific QoS for many communicating IoT devices [21], Asad et al. proposed a framework based on a client's entry into their devices in a scenario featuring several radio access technologies. This method facilitates the definition of node-specific QoS requirements for every device, ensuring enhanced network sociability [22]. The algorithm surpasses conventional access node selection techniques, such as the best signal-to-noise ratio (B-SNR) and maximum bandwidth (M-BW), thereby presenting a promising perspective for the future of 5G in empowering IoT networks with robust infrastructure and innovative smart services [23].

In parallel, Gupta et al. [24] enriched the discourse by examining the 5G-IoT architecture, offering fundamental insights, and suggesting a stratified 5G-IoT substructure based on important applications such as software-defined networking. The results of this synthesis reinforce the efficacy of the proposed framework and the argument that 5G is the optimal method to empower IoT systems. Although there is significance in the search endeavors that contribute to the expanding knowledge base of IoT networks and strive to overcome the encountered challenges, the 5G-IoT infrastructure grapples with persistent interference effects stemming from the prolific transmissions of numerous devices [25].

Network slicing (NS) assumes a pivotal role in advancing the 5G-IoT framework, designed to cater to diverse requirements [26]. The model delineates three scenarios with high reliability: 5G mobile broadband (MBB), 5G massive IoT (MIoT), and 5G ultralow latency high reliability [27]. This effort combines the two initial use cases to address the resulting environmental requirements. Lin et al. [28] confirmed the efficacy of NS in satisfying the demands of 5G-IoT applications, specifically investigating three cases in their performance evaluation.

Using SimTalk as an imitator for IoT employment collection, they replicated the transport NS traffic and evaluated the efficiency of the proposal concerning any loss of packets and poor performance. The proposed slicing diffusion network performance yielded noteworthy results. Escolar et al. [29] introduced an NS model for 5G-IoT networks based on an SDN approach, dynamically overseeing a diverse array of mixed IoT network slices as needed. Several practical vertically oriented IoT situations were considered to empirically verify the proposed application.

The results confirmed that the proposed framework delivers compelling advantages in terms of flexibility, stability, isolation, and fulfillment of rigorous QoS requirements, even in intricate scenarios. Addressing the allocation of resources is paramount in 5G-IoT networks, particularly within the framework of the network-slicing architecture [30]. This architectural framework demands independent allocation of diverse resources among different slices, each providing various services to meet the QoS requirements of the devices.

Fossati et al. [30] focused on the complexities of equitable needs distribution to other slices, particularly in scenarios wherein the network grappled with insufficient resources to fulfill all slice demands. They conceptualized this challenge as several distributions, which created a problem, thereby introducing a versatile optimization framework employing the ordered weighted average (OWA) method. This approach facilitated the implementation of new multi-resource allocation schemes in addition to existing ones.

Wang et al. [31] reported another innovative perspective, exploring NS dimensioning alongside a resource-pricing strategy. The dimensioning framework introduces the slice customer problem (SCP) to improve the problem we obtain and the slice provider problem (SPP) to boost net social well-being, that is, resource efficiency. The study revealed that increasing net social well-being and slice provider (SP) gains were coherent goals in case of resource scarcity; otherwise, a tradeoff existed. Consequently, they proposed a decreased complexity and distributed a rule to achieve near-optimal net social well-being with SP/SC increase assurance, which was validated through quantitative simulations.

In the domain of 5G user-defined heterogeneous networks (UD-HetNets), Amine et al. [32] addressed the user equipment (UE)-association problem by proposing a new NS composition utilizing the matching game [32]. They introduced the UE-slice association algorithm (U-S. AA) to compute stable matching between the UEs and different network slices that also matched. Harnessing the effectiveness of the Markov decision process (MDP) as a potent calculation device for improving issues [33], particularly those amenable to resolution through dynamic programming [34], is indispensable for crafting a creative 5G-IoT model tailored to address resource allocation challenges.

Tang et al. [34] contributed significantly to this discourse by proposing a slice-based practical process-order model employing non-orthogonal multiple access (NOMA) technology. They aimed to attain the maximum data rates for users in authorized studies on power allocation (limited MDPs). They suggested an approach for distribution based on flexibility, which used the newest procedures of code writing to address these problems. The simulation results exhibited efficiency, which increased the user's data transmission rates.

Xi et al. [35] considered resource allocation for partitioned 5G networks and addressed the present-day issues of user needs within network slices. A virtual network provider can react appropriately to different consumption demands at a certain moment and time using a virtual network provider. Deep reinforcement learning is their "resource slicing" approach, which facilitates both high short and high long run gains, resulting in an increase in the overall performance of the network. Another aspect is the use of network services. Network service is an essential optimization tool in the middle of developing new interconnectedness and increasing demand for assets, primarily in the field of smart attached things. Thus, it is distinctly unique in the literature on how to apportion scarce radio link resources among numerous slices dedicated to different services such as voice and data. Many independent network segments at a time constitute large areas for powering several signal types, whereas devices choose relevant network segments depending on the current strengths and needs of these facilities.

III. 5G NR AND NS ARCHITECTURE

A. NS Architecture Overview

NS splits a network into virtual pieces. It employs a software to control parts of both the RAN and core network [9]. Consequently, NS can create many "slices," each with its unique features. This is important because it helps manage different IoT application requirements [10]. NS is flexible and can change the manner in which resources are used to satisfy the specific requirements of various applications. Thus, it can adapt well and efficiently use what it has for many different applications that require connections in their own ways. The architecture also integrates the principles of softwarization and virtualization, contributing to a decrease in expenditure on any processes and operations. [11]

B. 5G-IoT NS Architecture

The architecture described in Fig. 1 encompasses the physical infrastructure, illustrating the foundational elements of the system, such as the main device and antennas. The virtual picocell is depicted visually to showcase its virtualized nature and pivotal role in facilitating communication within a specific coverage area. Various NSs are visually represented, each delineating distinct characteristics and purposes, such as the enhanced MBB (eMBB) slice emphasizing high data rates and enhanced mobile broadband capabilities of the mMTC [12] slice, which highlights massive machine-type communications for supporting a multitude of IoT devices, and the ultra-reliable low-latency communications (URLLC) slice, which shows ultra-reliable reduced latent period communications tailored to applications with rigorous latent period requirements. Interactions are illustrated through arrows or lines connecting the physical infrastructure, virtual

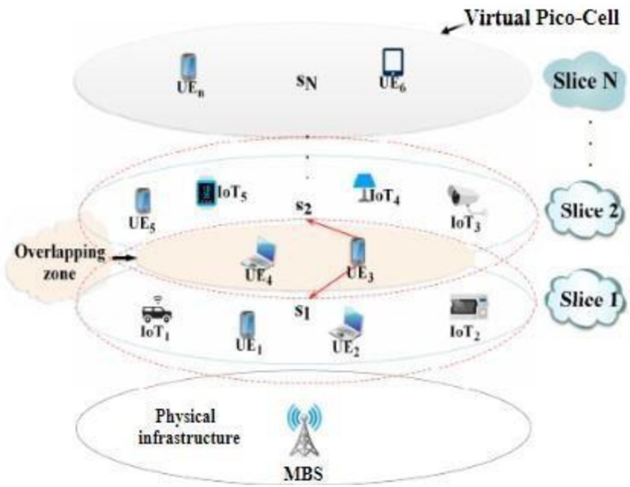

Fig. 1. 5G network architecture with network slicing Illustrates physical infrastructure, virtual pico-cell, and three network slices of enhanced mobile broadband (eMBB), massive machine-type communications (mMTC), and ultra-reliable low-latency communications (URLLC) with their interconnections and isolation.

picocell, and different slices, exemplifying, for instance, the connection between the eMBB [13] slice and the virtual picocell, thereby elucidating its handling of high-speed data transmission. The isolation aspect is visually emphasized using cues such as dashed lines or distinct colors, symbolizing the independence and reduced interference achieved through the innovative architecture of NS [14]. The overall diagram explains the foundational role of the physical infrastructure, the distinct virtualized nature of the pico-Cell, the unique characteristics of each slice, the communication pathways, and the visual representation of isolation to enhance clarity and understanding [15].

C. Network slicing characteristics and benefits

NS provides a range of characteristics and benefits that render it particularly suitable for the diverse and dynamic nature of 5G-enabled IoT environments. It provides many benefits such as scalability. NS can scale resources quickly to adapt to the growing number of connected devices. Other benefits include flexibility, which is the ability to create custom slices tuned for specific applications or services means there is nothing that can't be done, and isolation, which is the logical isolation of networks eliminates interference, thereby improving the overall reliability and performance.

Optimizing equipment: NS as a platform also becomes part of the 5G NR framework and resource utilization [12]. This is innovative architecture. The continuous search for increased efficiency allows network resources to be dynamically redeployed in response to the varied and exacting demands placed on them by IoT applications [11].

Efficiency gains are achieved because NS creates logically separate networks or segments that are carved out to perform specific tasks or applications [13]. Such isolation implies that every slice precisely obtains the required bandwidth and latency, ultimately in accordance with its QoS criteria [12]. For example, when eMBB slices that focus on high data rates and enhanced broadband capabilities are run concurrently with an mMTC slice designed to serve many IoT objects. Using the intrinsic flexibility of network slicing, resources are adjusted in real time according to each slice's needs at any time to avoid overallocation or underutilization [14].

Moreover, the isolation provided by NS reduces interference and improves resource utilization. NS can optimize resource allocation, and [15] emphasizes the importance of this technology for addressing various requirements characterizing different IoT applications on resources, such as spectra.

The virtualization of network services is crucial for enhancing resource efficiency. By employing software-defined principles, network functions can be dynamically instantiated or scaled in response to the changing resource demands of different slices [16].

IV. NETWORK PROPOSED MODEL

To determine a solution to the challenges posed by massive 5G (NR)-IoT infrastructures, a few modeling approaches can be explored. ML, with its adaptive learning capabilities, has emerged as a promising avenue, particularly through the utilization of reinforcement learning algorithms, as shown in Fig. 2.

A. RL algorithms

RL refers to a branch of ML that employs multistep decision making and involves training agents to make sequential decisions while maximizing cumulative rewards. Bulley: With the Internet becoming ubiquitous in our daily lives, it should not be any different from virtual reality, where we would have more active roles than just being spectators. Under dynamic and continuously changing conditions, 5G

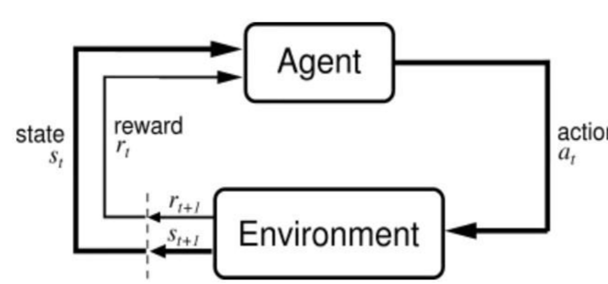

Fig. 2. Reinforcement learning interaction cycle between agent and environment. The model learns from the environment and then takes action on new data.

NR-IoT networks are not static. In accordance with this environment, the digital twin approach supports rebuilding devices as needed to adapt to any changes in the demands of use or environmental conditions.

B. Problem Formulation

Thus, it is possible to translate the association problem into a RL decision stage; however, here, the network devices act as agents that learn and interact in an environment defined by their environment. The agents make decisions in the form of devices interacting with one another via a network slice choice mechanism designed to maximize an accumulated award function that reflects how ideally the system performance ought to be improved while restrictions on the QoS are maintained. For each time step, they proceed through most steps for every training iteration N, and agent A can make K choices.

C. State Representation

A complete state representation is of great importance in RL. The window of observation owing to interference in the 5G NR-IoT may be considered as the state. This can include different quantities, such as network loading, device features, and the historical associations between them. If the system is represented in this manner, it naturally becomes more complex, and its complexity becomes a part of what the RL algorithm learns.

D. Action Space

The action space is the agent's choice set. This is true for the association problem, which refers to choosing which network slice is suitable for a piece of equipment. The action space must be tailored to differences in the characteristics and needs of IoT devices.

E. Reward Design

To be more precise, the RL algorithm uses the reward function as a navigational tool to arrive at the promised conclusions. The reward function must reflect the quality of the entire system with indicators such as the data rate, latency, and energy efficiency. These factors must be balanced; otherwise, the learning process will lead only to associations that improve the network.

F. Exploration and Exploitation Trade-off

Exploration (setting up new associations) and the ability to exploit existing associations are delicately balanced in RL. It is important to establish an appropriate balance; otherwise, the network may converge to a suboptimal solution. In addition, changes in network conditions require continuous adjustments and reinventions.

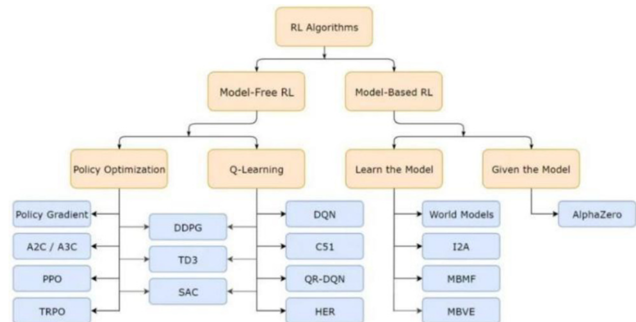

Fig. 3. Taxonomy of reinforcement learning algorithms and approaches following a hierarchical structure, which presents various categories and types of reinforcement learning algorithms.

As shown in Fig. 3, the use of RL models for a large association induces dynamic and adaptive dimensions to the problem in the 5G NR-IoT infrastructure with four different network topologies. Thus, by enabling devices in the system to gradually prototype and learn over time, their associations can be optimized to improve efficiency, resource utilization, and network performance. In the following sections, we discuss the implementation details, considerations, and criteria for assessment as RL is applied to solve user-association problems.

V. EVALUATION SETUP

A. Data collection and preprocessing

The training and testing of ML models in this study incorporated data from a few sources designed to display a complete 5G-IoT environment. The main data formats were user history and items of network performance.

1) User Interactions

All types of IoT devices were replicated in the experiment to collect data to record user interactions within a 5G-IoT network, faithfully reflecting real usage patterns. This also refers to data on user-device links, communication speed (data transmission rate), and device-specific encounters.

2) Network Performance

This potential solution was assessed using network performance metrics. Data from network devices and base stations included latency, throughput rates, and interference ratios. This enabled a comprehensive understanding of the dynamic aspects of a network. Our programmers were required to carefully prepare the data before training the ML models.

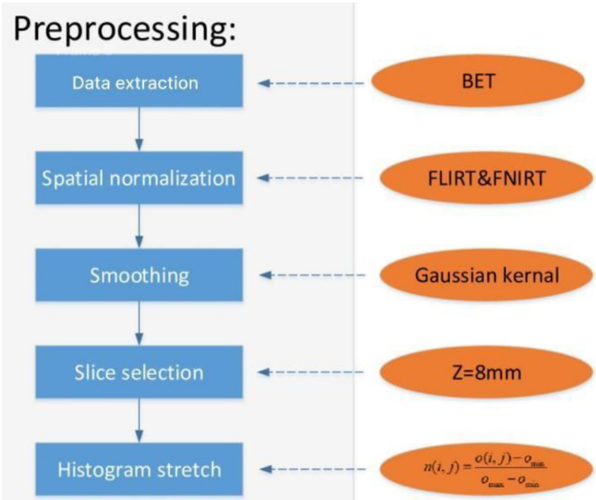

Fig. 4. Steps in preprocessing data, including data extraction (BET), spatial normalization (FLIRT&FNIRT), smoothing (Gaussian kernel), slice selection, and histogram stretching. Each step is paired with its corresponding technique or parameter.

We had to clean and normalize the data and extract the key points.

- Cleaning: The data we must continue are insignificant. Sometimes, the tuff slips, which is a mistake or an unusual bit that affects how the model learns. This was how we eliminated the bad data points by cleaning them up.
- Normalization: A normalization process was adopted to ensure that all features in the dataset were on a similar scale. This prevented any one feature from overwhelming the model training owing to its large size.
- Feature Extraction: Feature extraction was employed to identify and select the most pertinent data from the set. The goal was to simplify the model and maintain the essential traits for effective training.

Fig. 4 shows how the data moved through the steps before they were ready. At each part, the raw data improved, thus the ML model could be trained.

B. Model selection and training procedure

The training of ML models for the 5G-IoT involved a detailed method. This sharpened the scope of the studies. Let us consider the following steps.

1) Model Selection

Selecting the right ML model is key. For the 5G-IoT scenario, RL was the primary focus.

2) Dataset Splitting

The prepared data were split into training and testing parts. It is often a mix of 80-20 or 70-30, balancing practice with a good test of a model's skills.

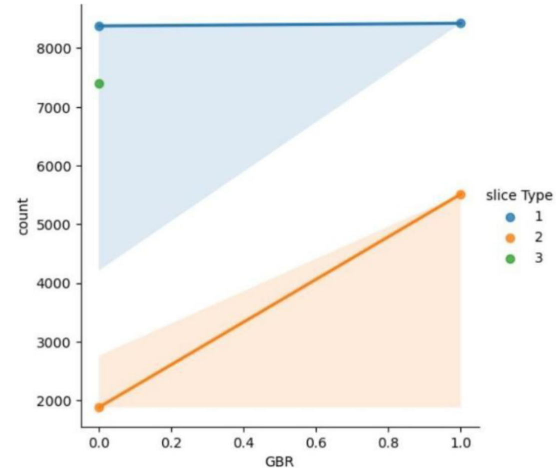

Fig. 5. Chart illustrating the training curve. It shows how the model improves over time considering different scores and using different parameters.

3) Hyperparameters

This step involved adjusting critical settings, such as the learning rate, and then teaching the model through a cycle of trial and error. We watched it learn using graphs and plots to ensure that it was correct.

C. Evaluation metrics

Several different assessment criteria were used to elevate the performance of the ML models to determine their current success. The following metrics were used.

- Precision: Proportion of positive observations correctly predicted by the model to the total number of positive observations predicted. This demonstrates the accuracy of the model when it makes positive predictions.
- Recall: Proportion of the total number of correctly predicted positive values to the total number of actual positive values. This demonstrates the degree to which the model can correctly classify all the positive samples.
- F1-score: This is the geometric mean of the precision and recall scores, and presents an overall score that considers both values. This is particularly useful when the class distribution is unbalanced.
- Support: The counts of each class in the real data.
- Accuracy: Number of observations correctly predicted to the total number of observations. This reflects the accuracy of the model in general, as it shows the combined error of all parameters.
- Macro avg: Average of the metrics for all classes regardless of their size. It does not distinguish between classes, even when certain are supportive.
- Weighted avg: Average of the metric for each class, where the average is considered over the number of true instances of each class. This explains class imbalance.

VI. RESULTS AND DISCUSSION

A. Test Runs and Evaluation

This section summarizes the results obtained using the new model. We draw certain important conclusions and find interesting patterns that are made clearer using diagrams. These visuals helped us obtain a bigger picture and the primary benefits of our findings.

The simulated results in Fig. 6 and 7 demonstrate the feasibility of a 5G network using NS and an RL algorithm, along with the setup subchannels installed to mimic the presence of a residential area with randomly positioned small cells within a macrocell. Although the macrocell covered 500 m, each small cell was responsible for an area of only 10 m. Certain important system parameters were a carrier frequency of 2 GHz, bandwidth of 10 MHz with a subchannelization of 50, minimum distance between two small cells of 20 m, and maximum transmitter power for small cell and macrocell user of 23 dBm. Therefore, an RL algorithm was used to maximize the chances and resources available. In the macrocell, 50 users requesting IoT services were randomly located and multiple requests for URLLC or eMBB operations were placed in each small cell. The channel model considered path loss both indoors and outdoors, as well as frequency-selective fading. This design facilitated a realistic assessment of network performance during the training of the RL algorithm to manage the available network resources and slice configurations.

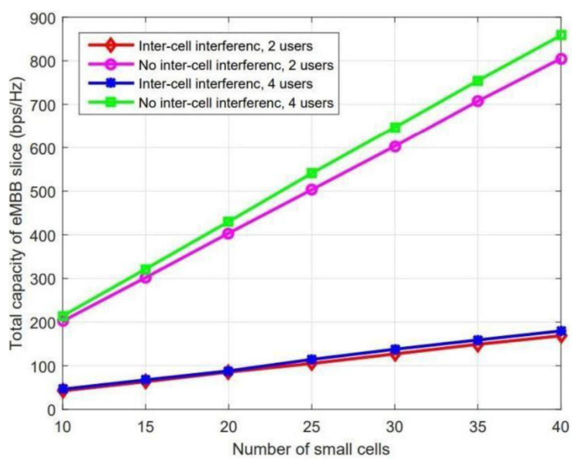

Fig. 6. Impact of Inter-cell interference and user count on eMBB slice capacity vs. number of small cells

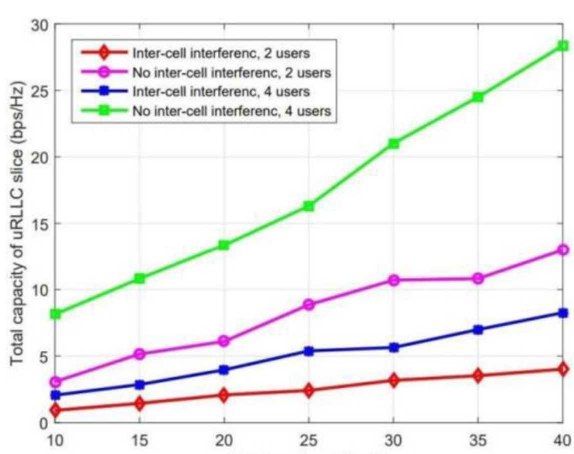

Fig. 7. Impact of inter-cell interference and user count on URLLC slice capacity vs. number of small cells

Table 1 presents our evaluation, highlighting the key metrics introduced in the previous sections, such as the accuracy, recall, and precision curves. These results aided in better understanding the model's performance in a 5G-IoT setting. Using the RL in our simulation was the key to boosting the performance of our 5G network. This worked even better when combined with our architecture to divide the network and our plan to spread subchannels and power.

We have also plotted our table results focusing on the three test runs and the Macro Avg parameter to see the ratio of our false positives to our true positives, which accounted for 1.00. Other parameters such as precision and F1-score were tested and achieved an accuracy of 1.00, as shown in Fig. 8.

Table 1. Test Runs and Results Analysis

Test Runs	Precision	Recall	F1-score	Support
Test 1	1.00	1.00	1.00	3360
Test 2	1.00	1.00	1.00	1479
Test 3	1.00	1.00	1.00	1778
	Accuracy		1.00	6317
Macro avg	1.00	1.00	1.00	6317
Weighted avg	1.00	1.00	1.00	6317

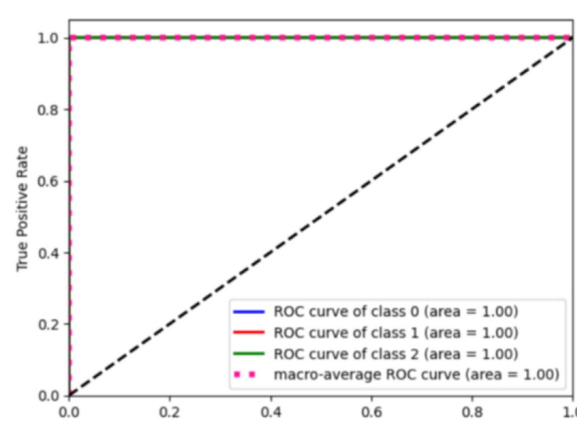

Fig. 8. Testing several parameters and checking the false to true positive ratio, results of our parameters account to 1.00.

B. Discussion

The findings presented in Table 1 provide useful information regarding the effectiveness and possibilities of the developed 5G network model based on the network slicing and reinforcement learning algorithms. First, when the proposed approach of combining network slicing with reinforcement learning was implemented, the resource allocation and overall network performance improved significantly. This was expected because of the ability of the RL algorithm to control network resources and slice configurations dynamically, rendering it ideal for the heterogeneous network environment depicted in the simulation, which includes both macrocells and small cells. The performance metrics of the eMBB and URLLC slices indicated that the system could support different services within the same physical infrastructure. This is important for handling the diverse traffic expected to be carried by 5G networks, including media streaming and low-latency IoT.

The feasibility of the solution was observed from the fact that the system was capable of handling 50 IoT users in the macrocell, along with multiple URLLC and eMBB requests in each small cell. This demonstrated that the proposed approach could handle dense urban environments, as shown in this example. Surprisingly, the inclusion of both indoor and outdoor path losses and frequency selectivity in the fading of the channel provided a more realistic scenario for our simulations. This approach to model the propagation of a signal was considerably more elaborate than the previous approach, thus rendering the results more credible. The evaluation of resource management based on reinforcement learning was quite promising in terms of solving the problem of dynamic assignment of resources in 5G networks. It also focused on the algorithm's capacity to learn about network conditions and user requirements.

However, it is necessary to state that although the presented simulations provided promising outcomes, the real-world implementation of the described approach may encounter issues that were not considered in the model. These may include interference from other networks, system hardware, or environmental conditions. In summary, the proposed model exhibited a high level of effectiveness in improving the characteristics of 5G networks and increasing the efficiency and flexibility of their work using network slicing and reinforcement learning. These findings indicate that this strategy is a feasible remedy for fulfilling the diverse and challenging specifications of next-generation wireless communication. Future work could involve fine-tuning the RL algorithm, testing the algorithm under different network conditions, and studying the ability of the algorithm to scale up to very large and complex networks.

VII. CONCLUSION AND FUTURE WORK

This study explored the use of the combination of combine energy learning techniques with NS to increase the performance of 5G networks in suburban environments using the proposed subchannel and power distribution methods with energy learning flexibility, advantages, and strengths. The algorithm demonstrated its effectiveness in optimizing subchannel allocation and power regulation by dynamically responding to changing conditions, which led to an overall increase in network performance and adaptability. There are several promising avenues for future research in this area. Further investigations should delve into the refinement of reinforcement models, exploring superior algorithms and education methodologies to enhance their adaptability and mastering efficiency. In addition, the scalability of the proposed technique can be examined in extra-significant network situations and deployment eventualities, considering the complexities introduced by using a larger range of small cells and varying user densities. The exploration of the mixing of emerging technologies with facet computing and artificial intelligence could also be a fruitful future endeavor, opening new opportunities for optimizing 5G network performance and satisfying the evolving demands of diverse applications. Overall, the findings of this study are expected to inspire persistent research and improvement within the dynamic and ever-evolving panorama of 5G community optimization.

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Ahmed Jumaa Lafta
received his Ph.D. degree in Data Telecommunications and Networks Engineering from the University of Salford-Manchester, United Kingdom in 2017. He received his M.Sc. and B.Sc. degrees in Electronic and Communications Engineering from the University of Baghdad, IRAQ in 2005 and 2002, respectively. He has been working an academic staff in the Department of Electronic and Communications Engineering at the Al-Nahrain University, Baghdad, IRAQ since 2006. His research interests include telecommunications networks, communications systems, wireless and mobile communications, and computer networks.

Aya Falah Mahmood
received her M.Sc. and B.Sc. degrees in Electronic and Communications Engineering from the University of Baghdad, IRAQ in 2018 and 2014, respectively. She has been working as an academic staff in the Department of Prosthetics and Orthotics Engineering at the Al-Nahrain University, Baghdad, IRAQ since 2023. She worked as an academic staff in the Department of Electronic and Communications Engineering of the Uruk University - Baghdad, Iraq from 2018 to 2023. Her research interests include telecommunications networks and electronic and communications Systems.

Basma Mohammed Saeed
received her Ph.D. and M.Sc. degrees in Electronic and Communications Engineering from the Al-Nahrain University, IRAQ in 2007 and 2001, respectively. She received her B.Sc. degree in Electronics and Communications Engineering from the University of Baghdad, IRAQ in 1998. She has been working as an academic staff in the Department of Electronics and Communications Engineering at the University of Baghdad, IRAQ since 2003. Her research interests include communications Systems, digital signal processing, telecommunications networks, and wireless and mobile Communications.