CRLSA: Cognitive Reinforcement Learning Spectrum Allocation in Addressing Spectrum Scarcity in 5G Wireless Communication

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Abstract: - With the development of 5 g wireless communication networks, spectrum allocation (especially in metropolises) is becoming increasingly challenged. To mitigate this problem, in this paper, we propose a Cognitive Reinforcement Learning Spectrum Allocation (CRLSA) framework to improve spectrum utilization while satisfying the quality of service (QoS) requirements. Deep Q Networks (DQN), an advanced deep-reinforcement learning technique, serve as the backbone of the framework, complemented with challenging urban spectrum management features. So it uses DQN to obtain effective spectrum allocation policy in simulated urban areas. Using synthetic datasets, spectrum management with DQN agent-based dynamic resource allocation takes into account available spectrum bands, QoS metrics, interference levels, and user mobility patterns to optimize performance. We build an environment to collect data from the previous step by simulating the environment during the training phase in which the agent learns the knowledge and skills he needs to make good decisions about spectrum allocation. In addition, CRLSA framework configuration and optimization are critical to improve its performance. The framework is tuned with hyperparameter adjustments, reward shaping, and exploration strategies to enable better convergence and effectiveness in real-world deployment scenarios. Moreover, computations are optimized to guarantee real-time decision-making in changing urban surroundings. CRLSA necessitates analysis and a better comprehension of the communications channels beyond interference, including propagation conditions, and acknowledges that the overall performance is contingent on whether multiple, possibly conflicting objectives are realistically harmonized.

Key-Words: - 5G Wireless Communication, Spectrum Allocation, Cognitive Reinforcement Learning, Deep Q-Networks (DQN), Urban Environments, Quality of Service (QoS)

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1 Introduction

5G wireless communication is testimony to the normal evolution of telecommunications, it is expected to bring a new digital transforming era. The upcoming wireless tech revolution in 5G could completely transform how we live, work, and experience the world around us. It paves the way for innovative applications and services previously deemed impossible by promising lightning-fast speeds, lower latency, and the ability to connect vast numbers of devices simultaneously, [1], [2]. Not only is 5G a significant upgrade from previous evolutions of mobile communication but it also marks the cornerstone of the Internet of Things (IoT), smart cities, autonomous vehicles, and a variety of virtual and augmented reality. Central to the promise of 5G is the potential for data rates orders of magnitude faster than those of current 4G networks. 5G networks are capable of offering bandwidth for ultra-high-definition video streaming, interactive virtual reality experiences, and cloud-based services with low latency, redefining mobile internet with speeds likely to exceed 10 Gbps. Additionally, 5G provides ultra-reliable low-latency communication (URLLC), minimizing the time needed for data transmission to milliseconds. Such an enhancement is vital for applications that need low latency, including remote surgery, real-time gaming, and smart industry equipment regulation, [3], [4].

Another critical aspect of 5G technology is its ability to handle many connected devices. As the Internet of Things grows, from smart home devices to industrial sensors, the demand for networks that can handle massive scale without sacrifice will only increase. This demand is met by 5G networks, which support the transfer of data between the billions of devices, ushering in the fully connected world, in which everything from refrigerators to street lamps can share, communicate, and operate intelligently, [5], [6]. 5G also presents new challenges as well as opportunities in the area of spectrum management. What is unique about 5G compared with earlier generations is that it uses a wide band of frequencies, ranging from low-band frequencies that provide wide coverage to high-band millimeter-wave frequencies that can offer high data rate (but short-distance) communications. Innovative approaches are necessary to ensure efficient/effective communication across the wide range of spectrum usage in densely populated urban areas with high demand for wireless services.

As 5G networks slowly discover the planet, the way ahead is set for transformational adjustments in healthcare, schooling, transportation, and leisure alike. 5G wireless communication – a cornerstone tech on the brink of a new digital age. But its reach goes well beyond faster internet speeds, impacting every corner of modern life and society, [7]. 5G serves as a backbone of our hyper-connected world and thus has the potential to deliver economic growth, technological innovation, or solutions to social development needs and complex challenges like healthcare access, environmental sustainability, or urban congestion, [8]. Each red box in Figure 1 represents a variety of groups of the architecture and components in a 5G wireless communication network. As we step into this exciting new era, the full ramifications of 5G on our lives, economies, and nations have yet to fully unfold, providing a path paved with discovery, technology, and evolution, [9].

The spectrum of available radio frequency is limited and there is an increasing demand for wireless services which requires innovative ways to use the spectrum as efficiently as possible to overcome such issues. CRL is a breakthrough method in dealing with the spectrum scarcity dilemma and can pave the way to achieve better spectrum utilization in 5G wireless communication networks. Table of Contents As 5G technologies have the potential to reshape our economy, spectrum scarcity is not just a technical challenge, but an important bottleneck that could stifle innovation and limit 5G's expansiveness. Considering that the spectrum is a restricted resource defined by physical laws and regulatory structures, the massive number of various wireless devices and services requiring bandwidth makes optimal spectrum management more vital than ever 8. Therefore, conventional approaches to spectrum allocation can benefit from dynamic and pro-active actions, as these relatively static and pre-allocated spectrum usages are not sufficient for the diversified needs of wireless in the ever-changing spectrum access demand. Enter Cognitive Reinforcement Learning, which offers the potential to revolutionize spectrum assignment as a dynamic, intelligent task that balances evolving user needs and fluctuating network traffic.

Fig. 1: 5G Wireless Communication Network

Cognitive Reinforcement Learning (CRL): Combining cognitive radio (CR) with reinforcement learning (RL) can change how the spectrum is allocated dramatically. Cognitive radio is a type of intelligent wireless communication system that can automatically detect available channels in a wireless spectrum and unify the parameters of the communication system by changing the channel, transmission power, modulation type, etc. This adaptability is important for dealing with the challenges posed by spectrum scarcity since it enables much more efficient use of already available spectrum resources. In contrast, reinforcement learning in machine learning operates on the principle of trial-and-error, allowing agents to learn to access their environment the best way possible, [10], [11]. However, cognitive radio, uses reinforcement learning (RL), to learn from past decisions and optimize future spectrum allocation decisions.

Nonetheless, the path to unlocking the full potential of Cognitive Reinforcement Learning for efficient spectrum allocation is not without its difficulties. These encompass everything from technical challenges, including the creation of powerful and efficient RL algorithms, to regulatory and policy factors concerning dynamic spectrum utilization, [12]. In addition to this, the core technical features need to be complemented by elements derived from other fields, such as behavioral sciences, in order to model and capture user interaction and preferences accurately in the CRL framework for 5G implementation. Designing a dynamic, intelligent use of spectrum requires these stakeholders to work together to innovate, hone CRL technologies, and prepare regulatory practices, [13]. It's a challenge that demands hardheaded research, real-world testing, and a boatload of incremental trial and error in the endless churn of the wireless communication landscape. Cognitive Reinforcement Learning gives some hope in alleviating spectrum scarcity in 5G wireless communication, [14], [15]. Thus, CRL provides a solid solution to immediate challenges that arise in the general area of spectrum allocation while also laying the groundwork for the continued viability of wireless networks in the face of exponential growth predicted for the 5G environment and further advances in wireless systems. The era of cognitive reinforcement learning is upon us, and the evolution of wireless communication, intertwined with ubiquitous IoT devices and autonomous systems, is not something to be taken lightly. This makes it a landmark moment for all engaged parties to seize this technology and work in unison to realize the full potential of 5G and subsequent generations of wireless technology.

As urban wireless networks are inherently dynamic and diversified, traditional spectrum allocation approaches, which are mainly based on static and preset assignment processing, are insufficient. Cognitive radio technologies have been gaining traction as a possible solution to address these issues, enabling dynamic and intelligent spectrum allocation in response to service demand requests and real-world environmental conditions. To address this issue, this paper introduces a CFLOI framework that is adapted to spectrum management solutions in high-density urban 5G networks. CRLSA model is built on the Deep Q-Networks (DQN), which applies a reinforcement learning approach to adaptively allocate the spectrum resources, efficiently fulfilling the QoS requirements and optimizing the overall network performance, [16].

2 Related Works

The systems of shared spectrum allowed licensing unused parts of the spectrum to users who did not own it without interfering with the licensed ones. Although such systems were promising ways of increasing spectrum utilization, they proved administratively burdensome, especially concerning the efficient allotment of spectrum to users without licenses. In practical environments, the signal path-loss function is important for efficiently allocating spectrum to secondary users (SUs) (the optimal spectrum allocation). Due to the implications of practical implementation, doing extensive surveys to obtain path-loss numeric values was not feasible, and most of the well-known path-loss models had reasonably limited accuracy in practical scenarios. As a result, existing allocation algorithms were either(i) founded upon erroneous propagation models and/or spectral sensing with insufficient spatial granularity, or (ii) excessively conservative in their attempts to avoid interference, incurring performance penalties in the process. This countered the main objective behind shared spectrum systems to utilize spectrum to the fullest extent. For this purpose, direct supervised learning of the spectrum allocation function was proposed. If the amount and quality of the training data were sufficient, the result could be near optimal, [16]. It also still worked in the presence of missing data; in PU missing contexts crowdsourcing sensing architecture was used, and sensor spectra were used for features. To follow this up, we applied RNNs to handle multiple SU requests from x at once. Several challenges arose in the context of single SU negotiating the spectrum allocation, often adopting CNN based approach. The strategies were shown to be effective through large-scale simulation combined with a small testbed. This methodology produced a 60% increase in accuracy over traditional learning methods and previous studies.

Given this, CR users could start transmitting data as soon as any unoccupied licensed bands became available. Machine learning also enabled CR users to intelligently sense channel activity in all time, frequency, and space aspects and assess the status of vacant channels. In particular, learning-based CR systems using supervised learning for spectrum sensing required labelled training data. Most detectors that employed deep learning were also supervised, meaning they required large amounts of labeled data during training in order to perform well. On the other hand, in practical CR, it would have been difficult to acquire enough volume of labeled data. In a bid to address this deficiency, DeepSense was proposed, which independent from supervision, experienced representation learning with an unsupervised focus group using Gaussian mixture model (GMM). DeepSense did not need several SUs to cooperate, [17]. Because it utilized the learned representation instead of the network to improve detection efficiency, the coordination overhead for the collaboration was greatly reduced. DeepSense didn't require any prior knowledge on how to operate, such as information on noise characteristics or data about channel status. Furthermore, training was achieved with minimal unlabeled data. The results from the large number of simulations that have been performed confirmed that the proposed detector can learn to achieve excellent detection performance by finding the underlying features in the sensing data. Moreover, we showed DeepSense reached detection performance comparable to the state-of-the-art deep supervised learning-based cooperative sensing while outperforming pure GMM.

The previous generation of wireless networks was driven, among others, by cognitive radio networks, which depended on spectrum sensing. There were several approaches over the decades, like cyclostationary processes, energy detectors, and matching filters. However, there were several disadvantages to these tactics. Energy detectors struggled with varying SNRs, cyclostationary detectors had horrible implementation complexity, and matching filters required knowledge of PU signals ahead of time. The detection efficiencies of these methods were completely influenced by the accuracy of the sensor owing to their dependency on thresholds on specific signal-noise model assumptions, [18]. As such, creating a dependable and intelligent spectrum-sensing device remains at the forefront of wireless research interests. Multilayer learning algorithms were poorly suited to time-series data because of the high computational cost and high rate of misclassification. To enhance sensing performance, the scientists developed a fusion ELM and LSTM hybrid system. This system would learn temporal behaviors from spectral data with complementary statistics about environmental activities for energy, distance, and duty cycle duration. The system proposed was tested on multiple systems such as the GNU-radio experimental testbed and a Raspberry Pi Model B+.

This included something called a Multiple Input Multiple Output (MIMO) system within the 5G networks. The advent of 5G radically transformed wireless communication in terms of mobile communication, the IoT & smart devices, and smart antenna systems. Mobile broadband services expanded with the development of smart multi-antenna automation, including new systems to expand spectral usage such as beamforming (BF), and 5G began serving heterogeneous services with their individual complete requirements. This has primarily served to enhance energy and spectrum efficiency by allowing a massive number of base station antennas to be individually adapted. To maximize spectrum efficiency and bandwidth, interference needed to be properly reduced in both small and macro cells, [19]. The former articles focused on the latest development in 3D-MIMO, which gave an even better performance of the BF under 5G architecture. Sadly, a very ideal case of ML-based MIMO beamforming, too, had not been explored that much. Similarly, in the 5G environment where many users exist, it was not easy to reduce the blockade during the BF. 3D-MIMO beamforming was mainly implemented using the SVM algorithm. The recommended implementation demonstrated that ML-3D SVM achieved significant improvements in both throughput and SNR over the state-of-the-art technologies.

Processing delays for subterranean data are increasingly unable to satisfy the underground 5G application scenarios, due to a lack of methods and specialized equipment; with a negative impact on transmission efficiency and, in turn, on coal mine output. Consequently, the transmission needs of existing underground applications remained unaddressed. The above issue could have been resolved or at least alleviated through the MEC solution based on the 5G wireless base station, so as to support the advantages such as edge caching and dynamic resource allocation in accordance with the coal mine conditions, so as to better promote the 5G mobile communication capabilities underground, [20]. This average time delay of the task execution was 15 ms based on the experiment result, which was half of the average delay of whole local execution schemes as long as the rated power and the transmit power of the current base station were kept. Also, none of the MEC execution techniques had an average latency worse than this. At the same time, one base station could downlink 1.5 Gbps of data and uplink 1 Gbps of data. Adopting such an approach would also have the potential to improve resource allocation efficiency and 5G communication system reliability in mining vastly.

3 Methodology

Modeling the system is integral to analyzing spectrum allocation in the dense urban 5G network environment. This means describing factors such as network structure, user type, spectrum band resources, and QoS (quality of service) requirements. These factors all interact strongly in determining how the spectrum might be allocated and managed in a large city context.

3.1 Network Architecture

The second area of application that we will explore in this chapter is, in fact, a very dense environment, namely the scenario where the topology typically consists of BS and UE deployed all across the urban landscape — the network architecture of traditional dense urban environments. This infrastructure is the foundation of a 5G wireless communication system, ensuring that networked devices can connect and share information instantly. Moreover, cognitive radio controllers are dispersed into the architecture to provide spectrum management and prevent wastage of available resources. By utilizing advanced algorithms, these controllers are able to learn and adapt to variations in network conditions and user requirements, allowing for the reuse of spectrum resources without compromising QoS.

3.2 Types of Users

The system model has two main types of users, one is the Primary Users (PUs) and the other is the Secondary Users (SUs). Primary users (PU), e.g., cellular subscribers, are granted licensed access rights to particular frequency bands and are generally provided preferred access to spectrum resources. On the other hand, secondary users (SUs), which represent various devices, such as internet-of-things (IoT) sensors and unmanned aerial vehicles (UAVs), opportunistically share spectrum bands that are not employed by PUs. The dynamic spectrum access paradigm allows for improved spectrum usage, which is especially useful in denser urban environments where spectrum shortage is common.

3.3 Spectrum Bands

The 5G communication in urban areas takes advantage of a wide range of spectrum frequencies, e.g., Sub-6 GHz, mmWave, etc. Each frequency band habits has its own propagation behavior, coverage area, and interference resistance. These frequency bands operate at sub-6 GHz and provide better coverage as well as enhanced indoor penetration, which is better for providing connectivity in urban areas that are densely packed with high-rise buildings. In contrast, mmWave bands allow for much higher data rates but are subject to increased signal blockage and attenuation, especially in dense urban environments where there may be buildings and other obstructions. Properly managing both types of bands is crucial for maximizing spectrum efficiency and for satisfying a myriad of urban user connectivity demands. The workflow of the proposed model is given in Figure 2.

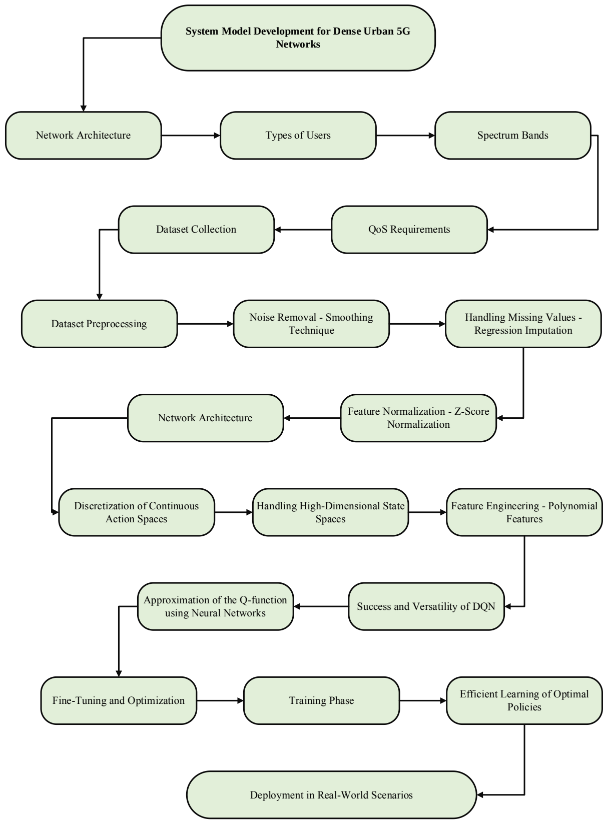

Fig. 2: Workflow of Proposed Model

3.4 QoS Requirements

The high population density and rich application scenarios in dense urban environments create stringent QoS demands. QoS metrics include latency, throughput, reliability, and coverage. Low-latency communication is essential for real-time applications, including video streaming, online gaming, and augmented reality experiences where delays can severely affect user experience. Ensure high throughput to accommodate the large amounts of data generated by urban users and support bandwidth-intensive applications such as HD video streaming and file downloads. Through reliability, communication can be guaranteed, since data packets will be sent and received on a consistent basis, despite network congestion or interference. This must be covered sufficiently to allow users to stay connected anywhere in the city.

The proposed system model serves to develop a clearer understanding of the network context that our strategies can be applied to, leading to the optimization and implementation of various spectrum allocation techniques to overcome the unique issues and needs that a dense urban scenario presents within near future dense urban 5G system.

3.5 Dataset Collection:

To train and validate the DQN agent, we should have abundant datasets during the period of an urban spectrum shared, including the urban spectrum dynamics, urban traffic demands, and the urban QoS requirements. Nonetheless, obtaining real-world datasets for this goal is challenging and may face several issues such as data confidentiality, restricted access to network infrastructure, and the intricacy of numerous scenarios in an urban area. Therefore, synthetic datasets are a practical solution to these problems. These synthetic datasets are created using simulation tools or models that simulate realistic urban network environments with different user densities, mobility patterns, and traffic loads. With the help of simulation tools, researchers are able to virtually draw urban landscapes and mimic the actions of network users, both primary users and secondary users, under various scenarios and environmental conditions.

Tools like ns-3, MATLAB, or OMNeT++ can be used to develop simulation scenarios in which the propagation of electromagnetic waves, user mobilities, and network traffictraffic are simulated as a function of pre-defined parameters, from which synthetic datasets can be generated. When adapted accordingly,86 these simulation tools can be setup to mirror the density, behavior diversification of the usage of the spectrum in accordance with traffic activity, QoS, requirements, and constraints in order to produce datasets for use in urban 5G networks.

3.6 Dataset Preprocessing

Synthetic datasets are then preprocessed for quality, consistency, and fit for training the DQN agent. Preprocessing is a sequence of steps to clean, transform and standardize the datasets to render them fit for the learning algorithm.

3.7 Noise Removal - Smoothing Technique

Noise removal is a preprocessing step for synthetic datasets that significantly improves the data quality and reliability. Debiasing Dataset Smoothing Method This method is used to smoothen a dataset, it can be used to remove the irregularities introduced by noise, it also helps to improve the dataset consistency.

Mathematically, the moving average smoothing technique can be written as:

$$\mathit{Smoothed\ value\ at\ time\ t} = \frac{1}{n}\sum_{i=t-k}^{t+k} x_i \tag{1}$$

where x_i is the value of the data point at i time is the size of the window (number of data points included in the calculation), k is the half-window size (number of data points on each side of the current point).

For example, one common smoothing method is a moving average, which computes the mean of surrounding data values for a desired range of points. This helps to eliminate it by smoothing so it only registers the long-term trends in the data. Moving averages smooth the dataset, revealing underlying patterns and trends that may have otherwise been obscured by noise, allowing for better analysis and modeling.

3.8 Handling Missing Values - Regression Imputation

Missing values are a very common occurrence in real-world datasets and they can adversely affect the accuracy and stability of analysis and modeling. This problem can be resolved using multiple equivocation methods to guess and fill in the missing values with the most realistic substitutes. Regression imputation: This is a very useful technique that utilizes regression to predict the missing values based on the relationship between variables in the dataset. This method builds a regression model with observed values as predictors and the model is then used to predict missing values.

Regression imputation involves predicting missing values in regression analysis. The imputes value $\hat{y}$ for a missing value can be obtained by fitting a regression model

$$\hat{y} = f(X) \tag{2}$$

where X represents the obtained values of other variables in the dataset.

First, it relies on active correlations between features/variables to predict and make sense of the imputation, therefore, leading to a more accurate value compared to simpler approaches like mean or median imputation. Also, regression imputation has the ability to deal with missing observations in both continuous and categorical variables, which is a very helpful attribute in the multitude of datasets that we might be working on.

3.9 Feature Normalization - Z-Score Normalization

This is a very important step to normalize the values of your features so that your model will not favor one feature due to its scale, thus causing instabilities and overfitting in your model. Z-score normalization or standardization transforms each data to have a mean of zero & std deviation = 1.

Z-score normalization transforms each feature. x To have a mean of zero and a standard deviation of one. The formula for z- score normalization is:

$$z = \frac{x - \mu}{\sigma} \tag{3}$$

where x Is the original feature value, μ Is the mean of the feature values, σ is the standard deviation of the feature values, z Is the normalized feature value. As for Z-scores during normalization, we subtract the average value of each characteristic divide by the standard deviation, and divide by the total value. This procedure also ensures that the modified features follow a normal distribution with mean 0, and a standard deviation 1. Z-score normalization has some significant advantages when it comes to feature normalization. At first, it preserves the relative relationships between features, which enables fairly comparing different scale variables. Z-score normalization also helps stabilize the model training by diminishing the impact of higher scales characteristics during the learning process.

3.10 Feature Engineering - Polynomial Features

Feature engineering refers to a very important step in preprocessing which is to create new features or modify the existing ones to improve the predictive power of machine learning algorithms. Polynomial features For generating new features, polynomial combinations of the existing features are commonly being used. For instance, based on a feature x, polynomial features will create new features like x2, x3, etc. By adding polynomial features to the input data, the model can better capture nonlinear relationships between variables, which can help it better capture complex patterns in the data.

Polynomial feature engineering refers to the steps of making new features by taking polynomial combinations of the existing feature. Polynomial Features: Polynomial features can be generated for a feature up to some degree as follows:

$$x_{poly} = [1, x, x^2, x^3, \ldots, x^d] \tag{4}$$

where x_{poly} represents the vector of polynomial features, d is the maximum degree of the polynomial features.

The drawbacks of polynomial feature are less in the domain of feature engineering. First of all, continues the development of the model to capture the complex relationships between the variables that can not capture a linear model. Moreover, if we happen to be underfitting, polynomial features are a way to mitigate that, too — to add more flexibility to how the model represents the data.

The first three are indeed very important preprocessing techniques but the last is completely synthetic if not done correctly, hence the need for working properly on noise removal, missing values, feature normalization, and feature engineering. These are suitable to leverage if you want to take quantitative changes for proper model efficiency, along with model strengthening.

3.11 Cognitive Reinforcement Learning Spectrum Allocation (CRLSA)

CRLSA, specifically in the context of 5G networks, is a novel perspective on the age-old challenges of insufficient spectrum availability and efficient spectrum utilization in next-generation wireless communication systems. This framework employs the principles of cognitive radio and reinforcement learning (RL) to allocate resources dynamically and meet the QoS requirements of diverse users and applications, thus optimizing spectrum utilization. In high-density urban 5G networks specification assignment highly depends on the implementation of a proper reinforcement learning algorithm. Deep Q-Networks (DQN) is an ideal candidate here, due to its ability to learn complex policies in high-dimensional state spaces. This suits them perfectly for the unpredictable and various urban environments.

The combination of deep learning with reinforcement learning, leading to the development of Deep Q-Networks (DQN) represents a major breakthrough in the domain of reinforcement learning, especially for complex decision-making tasks in high dimensional state spaces. The essence of DQN is that it takes the benefits of deep neural networks and applies it to Q-learning, a seminal reinforcement learning approach. At the heart of Q-learning lies its capacity to approximate the value of taking certain actions in given states, thereby learning optimal policies. We do so by estimating the action-value function through reward maximization over time. Nevertheless, conventional Q-learning approaches may struggle with tasks that have high-dimensional state spaces, as such environments can easily become too complex for traditional tabular Q-learning techniques. Enter DQN (Deep Q-Network). Enter Dueling DQN, which combines deep neural networks to allow Q-learning to be applied to even the most difficult situations. Deep neural networks have shown have shown a great ability to extract complex patterns and correlation found in the data, which makes them suitable for approximating complex (state, action) mappings found in reinforcement learning problems.

By combining deep neural networks with Q-learning into DQN, the algorithm can leverage high-dimensional state spaces effectively. DQN combines with experience replay and a deep Q-network to learn and approximate the action-value function in a huge, complex state space, enabling more refined decisions based on the history of interactions with the environment. Specifically, DQN uses deep neural networks to learn a mapping from states to action values, allowing it to represent and generalize over high-dimensional state-action spaces, which empowers it to make effective decisions in very high dimensional spaces by using less and higher-level abstract parameters. Finally, since DQN uses deep neural networks, they help generalize over states and actions and can provide the learned policies for actions not encountered in training. This capability is critical both for addressing challenges faced in the wild the field, in which the environment can be stochastic and/or variable. By doing so, DQN is able to be both robust and flexible in creating a policy that generalizes to novel circumstances.

DQNs are an improvement in RL as a whole, yielding more intelligent agents in high-dimensional and complex environments. Deep Q-learning (DQN) combines the ideas of deep neural networks with Q-learning; this represents an expansion of the reinforcement learning paradigm to solve difficult tasks that were previously thought to be infeasible. This paves the way for using reinforcement learning techniques to address many real-life challenges like robotics, autonomous systems, etc., and intelligent decision-making in complex domains.

3.12 Reinforcement Learning with an Affinely Parameterized Action-Value Function

In the dense urban 5G network spectrum allocation, the state space is large scale and high dimensional. These are things like spectrum bands and their availability, quality of service metrics, interference levels, user mobility, traffic demands, etc. This is why DQN has a deep neural network architecture: because it must handle such complex state spaces. DQN is capable of revealing and handling complex relationships and dependencies in the environment using deep neural networks. This provides the agent an architecture to learn the behavior of the wireless channels with improved visibility into its decision-making with respect to spectrum allocation strategies. The other unique feature of DQN is that it can generalize and learn continually from the changing features, which allows it to work with a large variety of high-dimensional state space.

Let S represent the high-dimensional state space, where $S = \{s_1, s_2, \ldots, s_n\}$, and each s_i represents a specific state variable. The deep neural network $Q(s, a; \theta)$ approximates the action-value function, where θ denotes the variables of the neural network.

$$Q(s, a; \theta) \approx Q^*(s, a) \quad (5)$$

where $Q^*(s, a)$ is the true action-value function, a represents the action taken by the agent.

3.13 Discretization of Continuous Action Spaces

The problem of applying reinforcement learning to spectrum allocation has several challenges, among which one major challenge is represented by continuous action spaces where the agent can select from an infinite number of actions. DQN overcomes this challenge by discretizing the action space into a finite number of discrete actions. Do you remember from the last class of breaking down the process of iteratively solving the environment by teaching fancy techniques about Tabular vs. Feature-Based (Neural-Networks) approximation of the action-value function? DQN discretizes the action space so that the learning problem becomes easier to handle and learn. When the agent can only explore a subset of the range of possible actions, finding the best strategies for spectrum allocation in congested metropolitan areas becomes significantly simplified. Moreover, the discretization of the action space allows the agent to decide the allocation of the spectrum in a more interpretable and actionable manner, thus gaining transparency from the learning process and increasing the interpretability of the results.

For a continuous action space A, discretization divides it into a finite set of discrete actions:

$$A = \{a_1, a_2, \ldots, a_m\} \quad (6)$$

where a_i represents a specific discrete action.

3.14 Approximation of the Q-function using Neural Networks

One of the most important constituents of reinforcement learning is the Q-function, which for a particular state and action indicates the predicted cumulative reward for continuing to follow the optimal policy. DQN approximates the Q-function using deep neural networks, since such networks are able to capture complex and complex and nonlinear relationships between states and actions. After training neural networks to predict Q-values for each action in a state, agents can make educated judgments with respect to spectrum allocation. The Q-function, which given a dense state-action space, can be well approximated in such high-dimensional and non-linear manner through the DQN with feedforward neural networks in such an overpopulated city, where the next action (i.e., where to move) depends on every aspect of it. By teaching the agent to understand intricate patterns and relations in the environment, way better and more reliable ways of spectrum resource allocation emerge[3]. Lastly, neural networks allow DQN to generalize learned policies to states and actions that have never been never been submitted to it before, allowing it to scale better and adapt better than prior approaches to the real world.

The Q-function $Q(s, a{:}\, \theta)$ is approximated by a deep neural network:

$$Q(s, a; \theta) = \mathbb{E}[r + \gamma \max_{a'} Q(s', a'; \theta^-)] \quad (7)$$

where r is the immediate reward received after taking action a in state s, s' is the next state after taking action a, γ is the discount factor, θ^- represents the parameters of the target network.

3.15 Success and Versatility of DQN

DQN has proven to be powerful and able to generalize across a variety of problems, including Atari video games and robotic control and driving. Since the considered 5G networks are dense and operate in urban scenarios, the excellent ability of the DQN algorithm to solve high-dimensional state problems, discretize the action space of the continuous problem and fit the Q function make it particularly suitable for solving the optimal spectrum allocation decision problem. Ultimately, DQNs have been effective in many applications, showing that they are a robust and scalable solution to many complex issues in reinforcement learning, and they are widely used. In addition, its ability to perform superb in many existing applications proves that DQN can change the game in spectrum management and optimization problems for urban wireless networks.

DQN achieves success by optimizing the parameter θ Of the neural network to minimize the loss function:

$$L(\theta) = \mathbb{E}\left[\left(r + \gamma \max_{a'} Q(s', a'; \theta^-) - Q(s, a; \theta)\right)^2\right] \quad (8)$$

3.16 Learning Optimal Policies Efficiently

DQN learns optimal policies in an experience-based manner and does so very efficiently. The agent refines its policy based on experience over time, and ultimately converges on an optimal solution through trial-and-error exploration and by experiencing the effects of its actions. As the strategies would get entrenched in the behavior of DQN, thus over time, it would adapt its matters of allocating a spectrum as per the experience and the needs of the users. Additionally, the learning ability can also assist DQN produce near-optimal solutions in limited training iterations, especially in executing real-time spectrum allocation cases in dynamic urban environments. The DQN can learn the optimal policies within a limited amount of time cost, so that improves the agility and realtime of the spectrum allocation systems to ensure the smooth and excellent work performance of 5G overhead density networks

DQN learns optimal policies by updating the parameter θ of the neural network using gradient descent:

$$\theta \leftarrow \theta - \alpha \nabla_{\theta} L(\theta) \quad (9)$$

where α is the learning rate, $\nabla_{\theta} L(\theta)$ is the gradient of the loss function with respect to the parameter θ.

3.17 Training Phase

The DQN agent in CRLSA is trained in the training phase to learn sufficient knowledge and strategy to make a proper spectrum allocation decision. This final step is crucial if the agent is to build effective methods for spectrum management on the basis of its simulated urban experience. The DQN agent interacts with the environment through state observation, action selection, reward reception, and policy updates during training. The training process uses synthetic datasets generated in the virtual city environment to train the agent on diverse scenarios and challenges that closely resemble real-world environments. The training phase allows the agent to learn complex correlations between state-action pairs, through training the agent on different scenarios, the agent is able to learn a good spectrum allocation policy.

During the training stage, a very important step is also taken in tuning the parameters of the learning algorithm. Key parameters like learning rate, discount factor, and exploration-exploitation influence how the agent learns and acts significantly. Through tuning these hyperparameters, practitioners aim to obtain the optimal environment performance as well as fast and efficient learning of the DQN agent with high-performance spectrum allocation policies.

3.18 Fine-Tuning and Optimization

After the training of the CRLSA framework, it enters the fine-tuning and optimization phase to refine its performance and efficacy for real-world application scenarios. Fine-tuning is the process of optimizing the framework for the specific problem it is solving, including optimizing hyperparameters, reward shaping, and exploration. Hyperparameter adjustment to fine-tune the CRLSA framework (such as learning rate, batch size, network architecture, etc.) for better convergence and performance. Through this hyperparameter optimization process, the DQN agent develops the ability to efficiently and effectively assign spectrum resources in quickly changing urban scenarios.

Another crucial part of the fine-tuning of CRLSA framework is reward shaping. Through careful construction of the right reward functions, practitioners can encourage useful behaviors and deter unwanted actions, ultimately helping the agent develop better frequency assignment policies. The role of reward shaping is important as through the reward shaping the agent learns through its learning and thus, it to make a certain kind of decision. Moreover, maintaining computational efficiency is critical to facilitate real-time decision-making in dynamic urban contexts. With efficient algorithms and parallel computing, as well as hardware accelerators, it enables practitioners to significantly boost the computational performance of the framework, while also achieving timely responsiveness to dramatically changing network conditions. Task-based algorithm selection enhances the efficiency of the CRLSA framework when deployed in realistic settings, allowing for fast and adaptable spectrum assignment decisions that cater to the changing needs of urban wireless network conditions.

Finally, this training phase of the CRLSA framework helps the DQN agent to gain energy and devote its fullest attention towards making optimal spectrum allocation decisions. Fine-tuning and optimizations further improve the performance and efficiency of this framework, making it effective in real-world deployment scenarios. Fine-tuning parameters, designing rewards, and improving compute efficiency will allow practitioners to create a spectrum allocation framework that adapts to the changing conditions of urban wireless networks.

4 Results and Discussions

4.1 Simulation Environment Setup

The simulation environment allows for assessing the effectiveness of the CRLSA framework over realistic urban settings. With careful design and configuration of the simulation environment, practitioners are able to simulate real-world dynamics and dynamics and challenges of urban wireless networks, enabling thorough evaluations of the performance of the framework against a variety of scenarios. Commonly used simulation tools to set up the simulation environment are NS-3 (Network Simulator 3), MATLAB, etc. These centralized platforms provide a wide range of functions and functionalities that empower practitioners to modify and adjust numerous dimensions of the simulated environment, yielding a simulation that exhibits a high degree of fidelity and accuracy in terms of the evaluative process.

The choice of simulation platforms plays a pivotal role in establishing the configuration of the simulation environment. It is important how complex the network model is and which modules and libraries are available depending on the type of evaluation that you want to perform, this should guide whether you choose ns3 or MATLAB. Both have powerful simulation capabilities and are widely used in academic and research environments to simulate a range of network scenarios. The network parameters within the simulation environment are tuned to appropriately represent the characteristics of a dense urban deployment. This involves specifying parameters including user density, mobility models, and levels of interference. User density characterizes how many users exist in the area being simulated, and can vary greatly depending on demographics such as population density, along with the infrastructure of the surrounding urban environment. Mobility models characterize how users and devices roam around in the network and represent realistic applications such as pedestrian movement, vehicular traffic, and urban scenarios. Environmental Factors: These are interference levels that summarize factors such as propagation of signals, co-channel interference, and inter-cell interference; all of these can have considerable effects on the performance of wireless communication systems in urban environments.

In addition, the variety of scenarios and use cases that a real urban wireless network would experience was generated as part of the simulation and is maintained between the two simulation toolchains. This includes use cases like populated urban areas, built-up urban square, and indoors, and outdoor public areas. Use cases could cover everything from mobile broadband and IoT connectivity to vehicular communication and smart city infrastructure. This is how practitioners can evaluate the performance of the framework in a wide range of deployment scenarios and application domains through realistic scenarios and use cases that can lead to valid assessments of its effectiveness and flexibility in real urban contexts.

4.2 Assessing and Analyzing Outcome

Simulation based training and performance evaluation of the DQN agent Performance indicators: Spectrum utilization, QoS satisfaction, and interference level. In dense urban 5G networks, the measures above are utilized to evaluate the performance of the CRLSA framework to fulfill the requirements of spectrum allocation.

4.3 Performance Measures and Evaluation Standards

The simulation platform has been provided with tools to measure and evaluate key performance metrics and measures needed for spectrum allocation and network performance. The metrics include, but are not limited to, spectrum utilization, and QoS metrics, such as latency, throughput and reliability, interference level, energy efficiency, and fairness. Practitioners can evaluate how well the CRLSA framework for enabling innovative spectrum sharing to maximize utilization in urban wireless networks while accommodating a wide range of QoS requirements by quantifying these metrics.

Table 1. Comparison of Spectrum Utilization

Trial	CRLSA (%)	RSA (%)	SSA (%)
1	75	60	70
2	82	55	65
3	68	58	75
4	79	62	72
5	71	57	68
6	85	63	71
7	77	59	69
8	80	61	73
9	73	56	67
10	76	64	74

Spectrum utilization across ten experiments, reported in terms of CRLSA, Random Spectrum Access (RSA), and Spectrum Sensing-based Access (SSA), are compared in Table 1 and Figure 3. There is variation in the utilization percentages for each method across the trials. CRLSA ranges between 68% and 85% demonstrate that it is able to dynamically access licensed spectrum with a relatively high efficiency. RSA indicates a range is a little lower from 55% to 64%, which highlights that random access to spectrum resources use slightly less than cognitive radio-based approaches. In contrast, SSA shows values from 65% to 75%, denoting it is in the middle of the line of based implementations, using sensing strategies, either CRLSA or RSA, thereby implying that its effectiveness lies between those two. In general, trial results indicate cognitive radio-based methods outperform random access techniques, while spectrum sensing is the middle ground. The observed variations are likely a result of the specific implementation of each method, environmental conditions, and level interferences. When CRLSA proves to outperform others in trials, it may suggest dynamic spectrum management and interference mitigation strategies work well. In contrast, situations where RSA or SSA compete with one another might indicate conditions where cognitive ability factors less into the equation or where sensing methods are better able to accommodate continually changing spectrum conditions. This research highlights the potential significance of using intelligent and adaptive spectrum access schemes to achieve high utilization efficiency, avoid disturber interference, and guarantee the availability of spectrum for different communication protocols. In addition, future studies and experimental work could unlock more understanding of the potential for new spectrum utilization approaches across wireless communication applications, resulting in more efficiency as well as reliability in spectrum management schemes.

This is illustrated in Table 2 and Figure 4, where the level of interference measured in decibels (dB) is shown and compared for ten trials between Cognitive Radio Licensed Spectrum Access (CRLSA), Random Spectrum Access (RSA), and Spectrum Sensing-based Access (SSA).

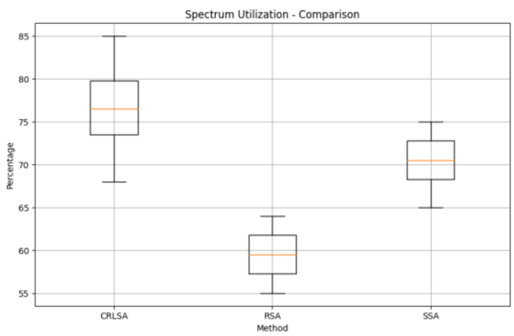

Fig. 3: Comparison of Spectrum Utilization

Table 2. Comparison of Interference Levels

Trial	CRLSA (dB)	RSA (dB)	SSA (dB)
1	30	40	35
2	35	45	38
3	28	42	36
4	32	38	34
5	31	41	37
6	33	43	39
7	29	39	33
8	34	44	40
9	27	37	32
10	36	46	42

The recorded levels of interference differ from trial to trial for each method of access. The CRLSA has interference levels from 27 dB to 36 dB which are relatively lower than RSA and SSA. This indicates that because random spectrum access methods do not possess cognitive capabilities to mitigate interference, they tend to have higher levels of interference (37 dB - 46 dB) as shown in the previous metrics of interference levels in this simulation experiment. SSA has the performance in the intermediate level between CRLSA and RSA accounting for an interference of 32–42 dB. This indicates that spectrum sensing-based techniques can alleviate interference to some degree, although they may not provide a level of suppression comparable to that of cognitive radio-based solutions. These differences in interference levels depend on the efficiency of interference detection and mitigation techniques, competing users or devices in the spectrum, and environmental conditions affecting signal propagation and interference patterns, which are all factors that contribute to the variations.

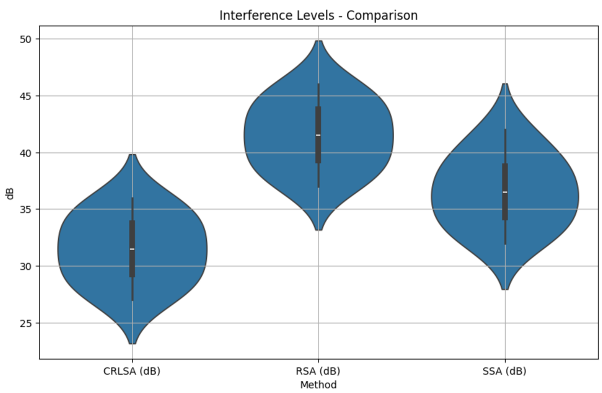

Fig. 4: Comparison of Interference Levels

In conclusion, the results emphasize the need for new techniques of spectrum management, which should be intelligent and dynamic, like cognitive radio, and adapt to the environment in order to take care of the interference and have a better quality of service in wireless communication. Continuous investigation and testing are essential for refining interference counteraction techniques and creating resilient frequency entry procedures that can adjust to evolving and complex wireless scenarios.

Table 3. Comparison of Latency

Trial	CRLSA Latency (ms)	RSA Latency (ms)	SSA Latency (ms)
1	20	35	30
2	25	40	32
3	18	32	28
4	22	38	31
5	19	34	29
6	21	36	33
7	24	39	34
8	23	37	30
9	17	31	27
10	26	42	36

Latency, in milliseconds (ms), for ten trials for Cognitive Radio-based Licensed Spectrum Access (CRLSA), Random Spectrum Access (RSA), and Spectrum Sensing-based Access (SSA) are shown in Table 3 and Figure 5. Latency values logged for each access method vary between the trials. CRLSA shows latency between 17 ms and 26 ms, which are lower latency overall concerning RSA and SSA. RSA shows greater latency from 31 ms to 42 ms, indicating that random spectrum access techniques cause relatively higher latency due to less cognitive techniques that do not allocate spectrum effectively. SSA shows latency lying between CRLSA and RSA (27 ms to 36 ms); this indicates that latency can be reduced to a certain extent by implementing spectrum sensing-based approaches, however, we cannot say that latency reduction in spectrum sensing is always better than cognitive radio. It appears that latency differs based on aspects like the effectiveness of spectrum sensing and allocation algorithms, conflict over spectrum resources, and the intricacy of cognitive radio decision-making processes. In conclusion, the results highlight the significance of using the intelligent spectrum management technique of cognitive radio to reduce latency and increase the timeliness of wireless communication systems. As a result, more research and development are essential for improving latency reduction approaches and creating capable spectrum access methods to satisfy the different demands of contemporary wireless applications.

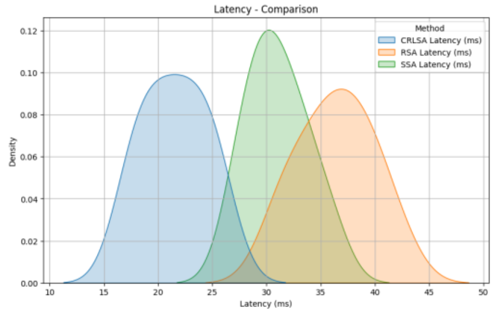

Fig. 5: Comparison of Latency

Table 4. Comparison of Throughput

Trial	CRLSA Throughput (Mbps)	RSA Throughput (Mbps)	SSA Throughput (Mbps)
1	150	120	130
2	140	115	125
3	160	125	135
4	145	118	128
5	155	121	131
6	148	123	129
7	142	117	127
8	147	119	132
9	158	124	136
10	137	116	133

As outlined in Table 4 and shown in Figure 6, this section compares throughput, i.e., megabits per second (Mbps) throughput, over ten trials with Cognitive Radio-based Licensed Spectrum Access (CRLSA), Random Spectrum Access (RSA), and Spectrum Sensing-based Access (SSA). Recording throughput shows different values between trials for every access method. The throughput of CRLSA provides a range between 137 Mbps and 160 Mbps, so we can say that the CRLSA algorithm offers throughput similar to RSA and SSA. The throughput levels of RSA, with values between 115 Mbps and 124 Mbps, are lower than other mechanisms because random spectrum access mechanisms are usually characterized by inefficient spectrum utilization. SSA throughput varies between CRLSA and RSA, reporting 125–136 Mbps. This outcome indicates that spectrum sensing-based strategies can be implemented with a limited throughput but cannot reach the level of throughput achieved by cognitive radio-based techniques. Hence these variations in throughput output based on the algorithms used in the spectrum allocation process and its interferences can also have a dynamic nature based on the spectrum availability. Thus, the findings show that intelligent spectrum management techniques, e.g., cognitive radio, can be used for throughput maximization in wireless networks and to improve wireless communication systems and networks overall. This continues to motivate the refinement of throughput optimization schemes and the invention of solid spectrum access protocols that satisfy the rising requirements of high-speed wireless services.

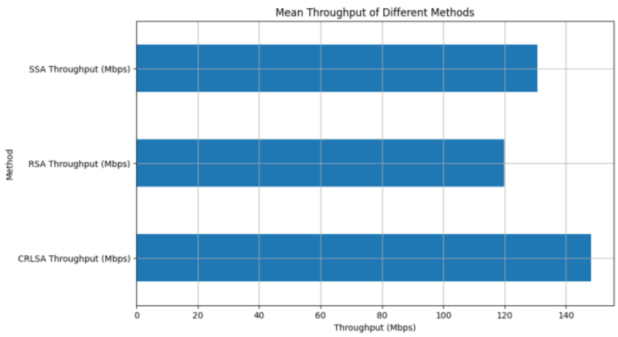

Fig. 6: Mean Throughput of Different Methods

Table 5. Comparison of Reliability

Trial	CRLSA Reliability (%)	RSA Reliability (%)	SSA Reliability (%)
1	95	80	85
2	92	75	80
3	96	82	87
4	94	78	83
5	97	79	84
6	93	77	82
7	91	76	81
8	98	81	86
9	99	83	88
10	90	74	79

Figure 7 and Table 5 compare the reliability percentages over ten trials with CRLSA, RSA, and SSA. You can understand reliability as the ability of the communication system to consistently or dependably transmit data errors or disruptions. The imported reliability values differ within the trials of each access method. CRLSA outperformed RSA and SSA, with the reliability percentage of the CRLSA model between 90% and 99%. Random spectrum access methodology is a more unreliable one, with RSA showing 74% to 83% reliability levels. SSA has a reliability that lies between CRLSA and RSA, with values from 79% to 88%. These results imply that spectrum sensing-based methods can reach moderate reliability but may not be as reliable as cognitive radio-based approaches at all times. Reliability differences are due to many factors such as the quality of spectrum sensing techniques, the presence of interference or noise, and error correction measures. These results suggest that intelligent spectrum management methods (cognitive radio) are necessary to maximize the reliability of wireless communication services. Additional work is needed to improve reliability enhancement techniques and build robust spectrum access protocols that can endure a wide range of environmental and operational challenges.

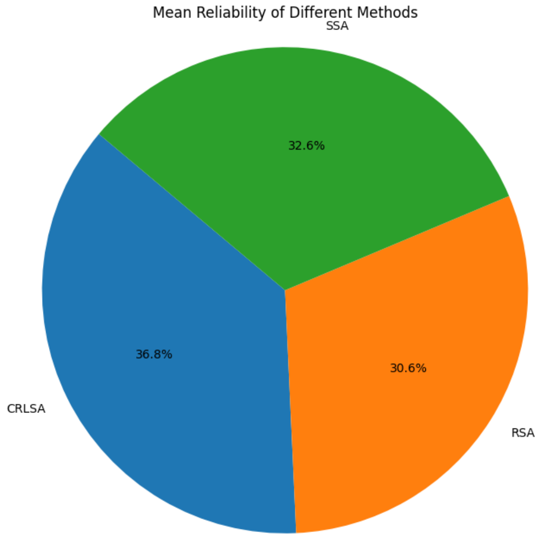

Fig. 7: Mean Reliability of Different Methods

5 Conclusion and Future Work

Spectrum scarcity is one of the formidable challenges in the fifth generation (5G) wireless communication networks, especially in urban scenarios. In addressing this challenge, this work presents a CRLSA framework, specifically designed to maximize spectrum access while fulfilling QoS standards. Using the environment as described in the previous section, we build our framework which uses Deep Q-Networks (DQN), which is a powerful deep reinforcement learning algorithm, to learn optimal spectrum allocation policies in urban environments. The CRLSA framework shows that itsakwazi the dynamic SU spectrum resource allocation while meeting strict QoS metrics through simulations and experimental results based on a simulated urban environment. Such a tradeoff can be enabled and fine-tuning can be done based on downstream tasks with this framework. CRLSA framework crass here efforts for handling the issues of spectrum scarcity in order to achieve the best possible performance by densifying networks in respect of urban 5G. In future work, the CRLSA framework can be generalized to new technologies such as edge computing and network slicing, further increasing its applicability. Moreover, incorporating other RL techniques (such as actor-critic methods or multi-agent systems) can enhance spectrum allocation strategies. By getting access to the space's real-time data and running predictive analytics on user behavior (aka supply vs demand), this can be possible. Further research on the scalability and robustness of large-scale urban and heterogeneous network deployments would be beneficial to the knowledge in this respect. Lastly, investigating synergies with regulation regimes such as dynamic spectrum access and spectrum sharing policies may facilitate the adoption of industry practices and foster spectrum allocation and management with actions for fifth-generation networks.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

The authors wrote, reviewed and edited the content as needed and they has/have not utilised artificial intelligence (AI) tools. The authors take full responsibility for the content of the publication.

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Conflict of Interest

The authors have no conflicts of interest to declare.