Comparative Analysis of RL-Based Resource Allocation Methods for Optimization in 5G MMWave Network

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Abstract. In this study, resource allocation techniques based on reinforcement learning (RL) for 5G millimeter wave (mmWave) networks are compared and analyzed. The high bandwidth and large available spectrum in mmWave networks offer a great opportunity for high data rate communication but also pose significant challenges in terms of resource allocation. RL, being a powerful tool for decision making in dynamic and uncertain environments, has been widely studied for resource allocation in mmWave networks. In this paper, we survey the state-of-the-art RL-based resource allocation methods for mmWave networks and we also discuss the challenges and open research directions in this field. This study presents an effective method for balancing stable, low-capacity mmWave links with reliable, high-capacity backhaul links designed using stochastic geometry and analytical channel modeling. We also propose a backhaul resource allocation strategy. To increase system utility with a mmWave network's limited backhaul capacity, a neural network-based backhaul resource allocation has been proposed.

Keywords: Reinforcement Learning (RL) · Resource Allocation · 5G mmWave · State-of-the-art · Q-learning · Optimization · Resource Allocation (RA)

1 Introduction

5G mmWave Network is a high-speed wireless technology that uses millimeter-range frequencies to deliver faster data, lower latency, and higher capacity than previous generations. Advanced beamforming and antenna technology is used to overcome mmWave challenges and provide high-bandwidth and low-latency services for various use cases [1].

With its initial launch in 2019, numerous companies that provide services around the world have been striving to improve their networks to include 5G, in order to be among the pioneers in offering this innovation in their respective regions or markets. High speeds and low latency, along with other advanced 5G features, have increased the amount of use cases as well as the need for data and performance [2]. The ability to provide connection for services with high expectations for availability, latency, and reliability,

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specific requirements were identified as the process of standardizing 5G began getting progress. These needs include improved broadband connectivity for mobile devices and other handheld devices, like social media video streaming and online gaming, which deem for a 1,000-fold increase in data volume, an additional increase in the number of connected devices, substantially greater typical user data rates, and a reduction in latency by a factor of five [3]. To address the requirement for improved data and performance, the 5G radio frequency range has been increased to encompass all frequencies previously utilized by 4G, as well as frequencies up to 6 GHz and the high band mmWave spectrum.

1.1 Generations of Networks

1G, also known as the first generation of wireless communication, was characterized by analog cellular technology and a frequency range of 150 MHz to 900 MHz. The bandwidth for analog telecommunication was limited to 30 kHz. With a data rate of only 2 kbps, the technology was considered to have poor voice quality. Additionally, the batteries on 1G cellphones were not very efficient. Despite these drawbacks, 1G was still considered a significant advancement in technology as it was the first generation of wireless and mobile communication [4]. From 1980 to 1990, 1G cellphones were large in size, but they were better than nothing, as they provided wireless and mobile capabilities that were not available before Communications (GSM) standard. The frequency range for 2G was 1.8 GHz (900 MHz) and the bandwidth was 900 MHz (25MHz). With a data rate of 64 kbps, 2G was a significant improvement over the first generation of wireless communication, 1G. From 1991 to 2000, 2G allowed for text messaging services and introduced the ability to send and receive emails and browse the web.

Additionally, 2G introduced the first camera phones. However, the signal quality of 2G was dependent on the strength of the signal, a weak digital signal resulted in poor connection. 2.5G and 2G cellular technology with General Packet Radio Service (GPRS) allowed for faster data transfer and better internet browsing experience [5].

3G, also known as the third generation of wireless communication, was characterized by digital broadband technology and increased speed. The frequency range for 3G was 1.6–2.0 GHz and the bandwidth were 100 MHz. 3G technology used CDMA, UMTS, and EDGE standards. The capacity or data rate for 3G ranged from 144 kbps to 2 Mbps, which was significantly faster than 2G. From 2000 to 2010, 3G allowed for the development of smartphones, which had the capability to make video calls, fast communication and even watch mobile TV [6]. However, 3G phones were rather expensive, compared to 2G. 3G was considered a major improvement over 2G because it provided faster data transfer and enabled a wider range of services such as internet browsing, video conferencing, and mobile TV.

4G, also known as the fourth generation of wireless communication, was characterized by high-speed data transfer and the use of all IP (Internet Protocol) technology. The frequency range for 4G was 2– GHz and the bandwidth were 100 MHz. The technology used for 4G was LTE (Long-Term Evolution) and WiFi. The capacity or data rate for 4G was impressive, ranging from 100 Mbps to 1Gbps, which is significantly faster than 3G. 4G networks allowed for faster internet browsing, streaming of high-definition videos, and smoother online gaming experiences [7] 4G technology also allowed for better connectivity and reduced latency, making it ideal for real-time applications such as video conferencing and telemedicine. With the emergence of 4G, wireless communication technology experienced an enormous advancement that resulted in high-speed data transfer while establishing the foundation for the creation of innovative services [8].

5G, is the latest and most advanced technology to date [8]. It has been rolled out from 2010 to today (2020) and is still being developed and improved. 5G technology is often referred to as MAGIC, an acronym for Mobile multimedia, Anytime, anywhere, Global mobile support, Integrated wireless solutions and Customized personal service. The goal of 5G is to provide high-speed, low-latency, and high-capacity wireless communication to meet the growing demand for mobile data services. One of the key features of 5G is its ability to deliver good Quality of Service (QoS) and high security. 5G networks are designed to support a wide range of applications, from traditional voice and text services to advanced multimedia and internet of things (IoT) services [9]. It supports a very high capacity and high speeds in a much more efficient way, allowing for more devices to connect to the network at once. This also allows for low-latency communication, making it suitable for critical applications such as self-driving cars, remote surgery and more. However, 5G also has a downside, one of which is the increased battery usage. As 5G technology is still in development, this may be resolved in the future with further advancements [9]. Nevertheless, 5G is expected to revolutionize wireless communication and enable new and innovative services that were not possible before. 5G is the fifth generation of mobile networks and it supports both voice and data with data rates up to 10 Gbps, it has advanced encryption for security, and it is fully packet-switched.

1.2 MmWave Technology in 5G

5G Frequency Range 2 (FR2) is now being scaled out. With the deployment of mmWave technology, consumers will experience faster data transfer speeds as a result of wider bandwidth availability. As depicted in Fig. 1, the mmWave spectrum is usually identified as the range between 30 GHz and 300 GHz.

The mmWave frequency range's wide bandwidth supports fast uplink and downlink rates. mmWave transmissions are also ideal for metropolitan areas with a significant number of devices due to their small form factor. To put it simply, the majority of 5G's advantages in terms of speed, bandwidth, and latency lie within FR2, not just for traditional wireless communication but also for emerging use cases.

The advantages of mmWave technology do, however, come with certain disadvantages, including route loss owing to poor mmWave signal propagation, increased signal noise as results of wideband communications' high noise level, and deficient frequency responses as a result of their fragile margin of error.

The development of 5G technology has led to significant advancements in the field of wireless communications, particularly in the millimeter wave (mmWave) frequency band. One of the biggest challenges in deploying 5G mmWave networks is optimizing resource allocation. This is due to the limited available bandwidth and high path loss in mmWave frequency bands. Reinforcement learning (RL) has emerged as a promising approach to optimize resource allocation in 5G mmWave networks. RL is a type

Table 1. Comparison of Wireless Network Generations

Technology	Gen. 1	Gen. 2G/2.5G	Gen. 3G	Gen. 4G	Gen. 5G
Bandwidth	2kbps	14–64 kbps	2 mbps	200 mbps	>1gbps
Technology	Analog	Digital cellular	Broadbandwidth/CDMA/IP	Unified IP and seamless combo of LAN/WAN/WLAN	4G+WWWW
Service	Mobile telephony	Digital voice, Short messaging	Integrated high quality audio, video and data	Dynamic information access, variable devices	Dynamic information access, variable devices with AI capabilities
Multiplexing	FDMA	TDMA/CDMA	CDMA	CDMA	CDMA
Switching	Circuit	Circuit/circuit for access network and air interface	Packet except for air interface	All packet	All packet

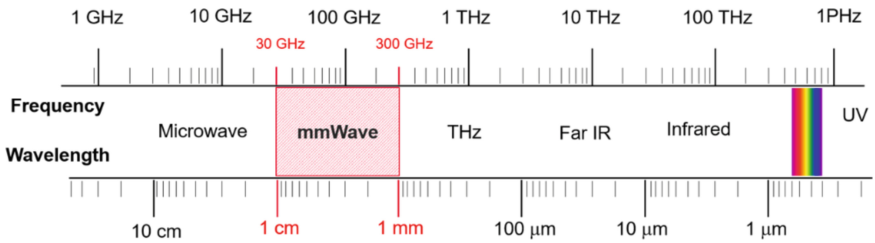

Fig. 1. The millimeter wave spectrum range.

of machine learning that allows an agent to learn from its interactions with the environment. It has been successful at resolving challenging optimization issues in wireless communications, like resource allocation [10].

1.3 Optimization of 5G Using MmWave Technology

In a millimeter wave (mmWave) 5G network, the main resources are the frequency bands that are used to transmit the data. These bands are typically in the millimeter wave frequency range (30 GHz to 300 GHz). The bandwidth available in these bands is much larger than in lower frequency bands, which allows for higher data rates and capacity in 5G networks. Other major resources in a mmWave 5G network include:

Antennas: mmWave frequencies have a shorter wavelength, which means that the antennas used to transmit and receive these signals need to be smaller. Antenna arrays with a large number of small antennas are often used to transmit and receive mmWave signals.

Base Stations: Base stations (also called cell towers) are the infrastructure used to transmit and receive mmWave signals. They are typically located on rooftops or other high points to increase the range of the signal.

Network Infrastructure: The network infrastructure includes the servers, switches, and routers that are used to manage and route the data traffic in a 5G network.

Backhaul: The backhaul is the connection between the base stations and the rest of the network infrastructure. It is used to transport the data between the base stations and the core network.

User Equipment (UE): User equipment (UE) refers to the devices that are used by users to access the 5G network. These can include smartphones, tablets, laptops, and other connected devices.

In this paper, we present a comparative analysis of RL-based resource allocation methods for optimization in 5G mmWave networks. We begin by providing an overview of the challenges and opportunities associated with the deployment of 5G mmWave networks. We then discuss the basics of RL and its application to resource allocation in wireless networks. Next, we review the state-of-the-art RL-based resource allocation methods for 5G mmWave networks, including actor-critic, Q-learning, and deep RL in section II. We propose integrating stochastic geometry with analytical channel modeling to incorporate the mmwave blockage effect in the real world in section III and IV. To enhance system usefulness with a mmwave network's limited backhaul capacity, a neural network-based backhaul resource allocation has been proposed in section V. Finally, we conclude by highlighting the challenges and future research directions in this field.

2 Reviews of Literature

2.1 Machine Learning Perspective

There are several popular algorithms for resource allocation in 5G millimeter wave networks, including:

Game Theory: Game theory algorithms, such as the Stackelberg game, can be used to optimize resource allocation by modeling the interactions between different network users and predicting the best resource allocation strategy. In the paper [11], provides a network-based mechanism for allocating cache storage resources. Using game theory, especially the bankruptcy game, for network slicing scenario in the core network of the 5G communications will enhance the end user's experience. Comparing the Shapley approach to the proportional allocation method, the user satisfaction index has increased by 5%. Shapley's allocation technique and proportional allocation method both outperformed the minimum-maximum approach in the fairness index by 27%.

Deep Reinforcement Learning: Deep reinforcement learning algorithms can be used to optimize resource allocation by training an agent to learn the best resource allocation strategy based on real-time network data and feedback. In the paper [12], for radio resource allocation and beam management in 5G mmWave networks, proposed a UK-means-based clustering and deep reinforcement learning-based resource allocation method (UK-DRL). Deep reinforcement learning (DRL) is used to dynamically distribute radio resources after UK-means was initially implemented as the clustering technique to reduce localization uncertainty.

Graphical Models: Graphical models, such as Markov Random Fields (MRFs) and Bayesian Networks (BNs), can be used to model the interactions between different network resources and predict the best resource allocation strategy. In this paper [13], For maximal resource reuse in 5G heterogeneous small cell networks, the author of this research proposes the combined resource allocation, interference reduction, user-level, and cell level fairness as an NP-hard issue. The author additionally proposes using a central point entity and a centralized algorithm to address the problem. It also suggests distributed and randomized algorithmic approaches for resource allocation while reducing interference, optimizing fairness, and maximizing resource reuse in feasible computing complexity to avoid the central point dependency.

Heuristic Algorithms: Heuristic algorithms, such as Genetic Algorithm, Ant colony optimization and Particle Swarm Optimization can be used to optimize resource allocation by exploring the solution space and identifying the best resource allocation strategy. In the paper [14], author proposes a simultaneously optimize latency, computational, and network load variations to establish an efficient resource allocation system for identifying ideal servers and routing pathways in the 5G MEC network. The aforementioned multi-objective problem is first formulated as a mixed-integer non-linear programming problem.

These algorithms can help to optimize the different resource allocation in 5G millimeter wave network and provide the best network performance and stability.

In this discussion, we will provide an overview of the various machine learning algorithms (MLA) that have been proposed by authors for use in 5G millimeter wave systems for optimizing various resources, before delving into a specific algorithm in more detail.

Spectrum: MLA can be used to optimize the use of mmWave spectrum by predicting the available spectrum resources, identifying the optimal frequency bands for different services and applications, and dynamically allocating resources based on the network usage. One example of an algorithm is the “**Spectrum Sensing Algorithm**” which uses supervised learning techniques to predict the available spectrum resources.

K-Nearest Neighbors (K-NN): It can be used to classify different types of signals in a given frequency band, making it useful for detecting primary and secondary users in a spectrum.

Gaussian Mixture Model (GMM): GMM can be used to classify different types of signals in a given frequency band, making it useful for detecting primary and secondary users in a spectrum. All these algorithms can help to detect the presence of different types of signals in a given frequency band and can be used to identify primary and secondary users in a spectrum, thus helping to optimize the resources of 5G.

Antennas: By determining the optimum antenna locations, forecasting the ideal antenna configurations, and enhancing the beamforming patterns, MLA may be utilized to improve the design and deployment of mmWave antennas. One example of an algorithm is the "Beamforming Algorithm" which uses reinforcement learning techniques to identify the optimal beamforming patterns.

Deep Learning (DL): DL can be used to optimize the beamforming weights by using neural networks to learn the channel state information and adapt the beamforming weights accordingly.

Reinforcement Learning (RL): RL can be used to optimize the beamforming weights by training an agent to learn the optimal beamforming strategy through trial and error.

Genetic Algorithm (GA): GA can be used to optimize the beamforming weights by evolving a population of potential beamforming solutions through a process of selection, crossover and mutation.

Particle Swarm Optimization (PSO): PSO may be used to improve the beamforming weights by modeling the behavior of a swarm of particles, each with a potential solution, and updating the solutions depending on their comparative performance.

Multiple-Input Multiple-Output (MIMO): MLA can be used to optimize the use of MIMO technology by predicting the optimal MIMO configurations, identifying the best channel state information, and optimizing the resource allocation [15]. One example of an algorithm is the "MIMO Algorithm" which uses unsupervised learning techniques to predict the optimal MIMO configurations.

Beamforming: MLA can be used to optimize the use of beamforming technology by predicting the optimal beamforming patterns, identifying the best location for antennas, and optimizing the beamforming parameters [16]. One example of an algorithm is the "Beamforming Algorithm" which uses reinforcement learning techniques to identify the optimal beamforming patterns.

Linear and Quadratic Programming (LQP): LQP can be used to optimize the beamforming weights by solving a set of linear or quadratic equations that describe the relationship between the channel state information and the beamforming weights.

Network Topology: MLA could be utilized to simulate the structure of the network topology by predicting the optimal network configurations, identifying the best location for network elements, and optimizing the routing and resource allocation [17]. One example of an algorithm is the "Network Topology Algorithm" which uses supervised learning techniques to predict the optimal network configurations There are several ML algorithms that could be considered. There are several ML algorithms that could be considered for network topology algorithms in 5G networks, including:

Graph Convolutional Networks (GCN): GCN can be used to learn the topological structure of the network and predict the optimal network topology.

K-Means Clustering: K-Means Clustering can be used to group similar nodes together in the network and identify the optimal network topology.

Ant Colony Optimization (ACO): ACO can be used to optimize the network topology by simulating the behavior of ants, who find the shortest path between two points, and updating the network topology accordingly. All these algorithms can help to optimize the network topology and provide the best network connectivity, thus helping to optimize the resources of 5G.

Scheduling and Resource Allocation: MLA can be used to optimize the scheduling and resource allocation by predicting the optimal scheduling policies, identifying the best resource allocation strategies, and optimizing the allocation of resources based on the network usage [18]. One example of an algorithm is the “Scheduling Algorithm” which uses reinforcement learning techniques to identify the optimal scheduling policies.

Deep Q-Network (DQN): DQN can be used to learn the optimal scheduling policy by training an agent to take actions that maximize a certain reward function.

Multi-armed Bandit (MAB): MAB can be used to learn the optimal scheduling policy by balancing exploration (trying different options) and exploitation (using the best known option).

Power Management: MLA can be used to optimize the power management by predicting the optimal power management strategies, identifying the best power control policies, and optimizing the power consumption of network elements [19]. One example of an algorithm is the “Power Management Algorithm” which uses supervised learning techniques to predict the optimal power management strategies. These are several ML algorithms that could be considered for power management algorithms in 5G millimeter wave networks, including:

Deep Neural Networks (DNN): DNNs can be used to predict the optimal power levels for different network components based on historical data and environmental conditions.

Decision Trees: Decision trees can be used to make decisions about how to allocate power to different network components based on various factors such as traffic load and channel conditions.

Random Forest: It is a method of collaborative learning for regression, classification, and various other tasks. It functions by building a large number of decision trees during the training phase, and then producing the class that represents the mean of the predictions made by each tree (for regression) or the mode of the classes (for classification).

Interference Management: MLA can be used to optimize the interference management by predicting the optimal interference management strategies, identifying the best interference mitigation techniques, and optimizing the interference management policies [20]. One example of an algorithm is the “Interference Management Algorithm” which uses unsupervised learning techniques to predict the optimal interference management strategies. There are several ML algorithms that could be considered for interference management algorithms in 5G millimeter wave networks, including:

Q-Learning: Q-learning is a type of reinforcement learning algorithm that can be used to learn the optimal policy for managing interference.

Deep Q-Networks (DQN): DQN is an extension of Q-learning algorithm that uses a neural network to approximate the Q-function.

Multi-armed Bandit (MAB) Algorithm: MAB algorithm can be used to decide which action to take in order to minimize the interference.

Mobility Management: MLA can be used to optimize the mobility management by predicting the optimal handover strategies, identifying the best location for network elements, and optimizing the mobility management policies [21]. One example of an algorithm is the "Mobility Management Algorithm" which uses supervised learning techniques to predict the optimal handover strategies. These are few ML algorithms that could be considered for mobility management algorithms in 5G millimeter wave networks, including:

Support Vector Machines (SVMs): SVMs are used to categorize mobile devices depending on their movement patterns and to make decisions about how to manage their connection to the network.

Hidden Markov Models (HMM): HMM algorithm can be used to predict the movement of mobile devices based on historical data and make decisions about how to manage their connection to the network. These algorithms can help to optimize the mobility management algorithm and provide the best network connectivity and coverage, thus helping to optimize the resources of 5G millimeter wave.

Security: MLA can be used to optimize the security measures by predicting the potential security threats, identifying the best security policies, and optimizing the security management [22]. One example of an algorithm is the "Anomaly Detection Algorithm" which uses unsupervised learning techniques to predict the potential security threats. There are several ML algorithms that could be considered for anomaly detection algorithms in 5G millimeter wave networks, including: One-class ***Support Vector Machines (SVMs):*** One-class SVMs can be used to identify anomalies in network data by training on normal network behavior and then identifying patterns that deviate from that behavior.

Isolation Forest: Isolation Forest algorithm can be used to identify anomalies in network data by isolating individual data points that deviate from the norm.

Auto Encoders: Autoencoders can be used to identify anomalies in network data by reconstructing network data and identifying patterns that deviate from the expected reconstruction.

2.2 Reinforcement Learning Perspective

5G mmWave networks are characterized by their high bandwidth and low latency capabilities as discussed in Sect. 1 of this paper, making them suitable for use in a many of applications, including VR, autonomous vehicles, and the Internet of Things. However, the deployment of 5G mmWave networks is challenging in view of high path loss experienced in the mmWave frequency band. This is due to the fact that mmWave signals are easily blocked by obstacles, such as buildings and trees.

Reinforcement learning is a machine learning approach that allows an agent to learn from its interactions with the environment. It is particularly well-suited for solving complex optimization problems, such as resource allocation in wireless networks. RL algorithms are designed to learn from the feedback received from the environment, such as the reward or penalty associated with a particular action [23]. This allows the agent to adapt its behavior over time and improve its performance.

Reinforcement learning (RL) has been increasingly used in the field of wireless communication, specifically in the area of resource allocation in 5G millimeter wave (mmWave) networks. RL is a powerful tool that enables the optimization of various performance metrics, such as throughput, energy efficiency, and fairness, in dynamic and uncertain environments.

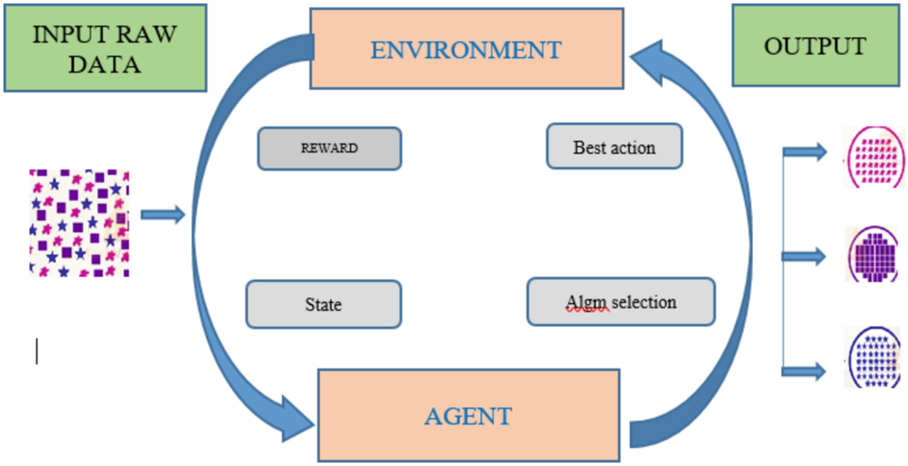

Fig. 2. Depicts Reinforcement Learning.

The first study to show the application of RL for resource allocation in 5G mmWave networks was presented by R. Combes et al. in the paper "Reinforcement Learning for Resource Allocation in 5G mmWave Cellular Networks" published in IEEE Journal on Selected Areas in Communications in 2017. For an integrated optimization of the power and subcarrier allocation in a multiple user's multi-cell mmWave system, the authors of this paper has developed an RL-based approach. The algorithm was able to modify itself to the fluctuating network circumstances and attain throughput and energy efficiency levels that were close to ideal.

In the article titled "Reinforcement Learning-Based Resource Allocation in 5G mmWave Cellular Networks" published in IEEE Transactions on Wireless Communications in 2018, X. Chen et al. presented an investigation that deployed RL for resource allocation in 5G mmWave networks. For the integrated optimization of the power, subcarrier, and beamforming allocation in a multiple user's multi-cell mmWave system, the authors of this article invented an RL-based approach. The algorithm was able to achieve near-optimal performance in terms of throughput, energy efficiency, and fairness.

In the paper [24], author has proposed a Q-learning based dynamic resource allocation algorithm for 5G mmWave cellular networks. The technique achieved approximately the optimal results in terms of throughput and energy efficiency by adapting to the variable channel conditions.

Another investigation using RL for 5G mmWave network resource allocation was presented by X. Gao et al. in the article "Deep Reinforcement Learning-based Resource Allocation in 5G mmWave Cellular Networks" published in IEEE Transactions on Communications in 2019. A deep RL-based approach has been laid forward by the authors of this paper for the coupled optimization of power, subcarrier, and beamforming allocation in a multi-user, multi-cell mmWave system. In terms of throughput, energy efficiency, and fairness, the algorithm was able to offer performance that was close to optimal.

In the recent paper "Joint Power and Beam Management for 5G mmWave Cellular Networks Using Reinforcement Learning" published in IEEE Communications Letters in 2020, L. Zhang et al. proposed a RL-based algorithm for the joint optimization of the power and beam management in 5G mmWave cellular networks. The algorithm was able to modify itself to the fluctuating network circumstances and attain throughput and energy efficiency levels that were close to ideal.

In conclusion, RL has been widely used in the field of resource allocation in 5G mmWave networks. The above-mentioned papers demonstrate the effectiveness of RL-based algorithms in achieving near-optimal performance in terms of throughput, energy efficiency, and fairness. The use of RL in resource allocation in 5G mmWave networks is an active research area and many other papers are published in the recent years.

2.3 Variations of RL

Actor-critic, Q-learning, and deep RL are all effective RL-based resource allocation methods for optimization in 5G mmWave networks. However, each method has its own strengths and weaknesses. Actor-critic methods are well-suited for environments with continuous action spaces, as the actor network can output a continuous action. Additionally, the use of a separate critic network allows for faster convergence and better performance.

Q-learning, on the other hand, is well-suited for environments with discrete action spaces, as it uses a table of Q-values to determine the best action. However, it can struggle in high-dimensional state spaces and may require a significant amount of training data. Deep RL, which uses deep neural networks, can handle high-dimensional state spaces and can be more robust to the variations of the network. However, it can require a large amount of data for training and can be computationally expensive.

In terms of performance, deep RL methods have been shown to achieve the best results in terms of resource allocation in 5G mmWave networks. This is due to their ability to handle high-dimensional state spaces and adapt to variations in the network. However, Q-learning and actor-critic methods can also achieve good performance, particularly in simpler environments with discrete action spaces.

3 Proposed Methods

In the proposed system model, there is a mmWave base station (BS) with M antennas that serves a maximum of K user equipments (UEs), where each UE has N antennas. The communication between the base station and user equipment k at time t (represented by Ck(t) bps) as in [25] is achieved through wireless mmWave links as shown in Fig. 3.

$$\mathrm{Ck(t)} = \mathrm{Blog2} \mid (\mathrm{I\ NxN} + \gamma \mathrm{k(t)Hk(t)Hk(t)H}) \mid; \tag{1}$$

Every UE-BS connection is given a bandwidth B in Hz by the system model. The channel matrix Hk(t) with a dimension of N X M from the BS of the kth UE at time t is used, together with a unitary matrix I N X N, a signal to noise ratio (SNR) γk(t) at k number of UEs at time t. Although the base station has a wired backhaul link to the primary network, its data rate is insufficient to maintain the highest rate of all mmWave BS-UE lines at once. The capacity of the backhaul connection, which is distributed among the UEs, is influenced by a number of orthogonal RBs. If each resource block has a capacity of c and there are R total resource blocks then, the overall backhaul capacity is Rc bps. Depending on the BS-UE link's channel state, the backhaul assigns various numbers of RBs to each UE k.

Rk(t) denotes the amount of resource blocks (RBs) provided in the backhaul network to User device k at t time. An actual speed encountered by each k, indicated as Ceffk (t), is calculated as a minimal value between an attainable capacity in the mmWave connection, Ck(t), and the backhaul capacity that was allotted to it, Rk(t)c:

$$\text{Ceffk (t)} = \min(\text{Rk(t)c}\ ,\ \text{Ck(t)}) \tag{2}$$

3.1 Proposed Channel Model

In joint of analytical [26] and stochastic geometry-based [27] channel model is offered for explaining the behavior of mmWave channel blockages in the real world [28] and to present the essential channel parameters. Figure 3 provides a visual representation of the suggested channel model. Line segments are used to represent UEs and BS, with the length of each segment being determined by angular dispersion and beamwidth. Line segment modeling is sometimes used to simulate barriers. The BSs, UEs, and barriers are initially distributed and oriented at random. The channel model comprises 'P' pathways, which can be likened to roads or sidewalks, where dynamic UEs and obstructions are in motion. A parallelogram, is employed as a visual tool for modeling blockages, created by connecting line segments between UEs and BSs situated on opposing sides. The interaction between these obstructions and the parallelogram is instrumental in determining the quality of the link for each UE-BS connection that can have:

Line of Sight: Inside the parallelogram, when there is Line of Sight (LOS) between a UE and a BS, it means that the signal can travel directly without any major blockages or interference along the P paths.;e.g., In Fig. 3 the UE 1-BS link is presented.

Non-LOS: This situation indicates that there is still Line of Sight (LOS) connectivity for at least one path between the UE and BS, despite the presence of blockages within the overall area represented by the parallelogram. e.g., In Fig. 3 the UE 2-BS link is presented.

Blocked: Given that obstructions may be present inside the parallelogram with no direct line-of-sight connection between the User Equipment and the Base Station; e.g., In Fig. 3 the UE 3-BS link is presented.

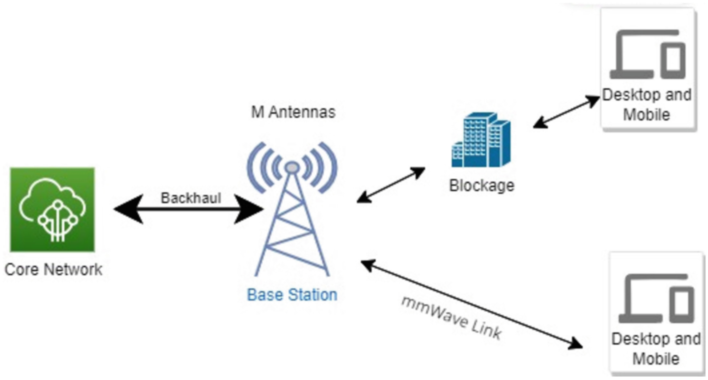

Fig. 3. Model of the mmWave communication system for an amount of UEs and BS.

The statistical model with channel matrix at UE k is represented by the model developed in reference [26] as:

$$H_k(t) = \frac{1}{\sqrt{N_{ray}}} \sum\nolimits_{i=1}^{N_{cl}} \sum\nolimits_{l=1}^{N_{ray}} g_{i,l}^{k}(t) a_r\left(\varnothing_{i,l}^{r}\right) a_t^{H}\left(\varnothing_{i,l}^{t}\right) \tag{3}$$

where N_{cl} is the number of scattering clusters in the environment, N_{ray} represents the number of propagation paths within each cluster. $g_{i,l}^{k}(t)$ represents the sophisticated fading gain given by i^{th} sub path of i^{th} cluster. $\left(\varnothing_{i,l}^{r}\right)$ and $(\varnothing_{i,l}^{t})$ represents the propagation path of angle of received and sent signal of the $(i, l)^{th}$ propagation path. $a_r\left(\varnothing_{i,l}^{r}\right)$ and $a_t^{H}(\varnothing_{i,l}^{t})$ are the normalized array response vectors both sender and receiver side, respectively. This representation allows for characterizing the channel behavior in terms of path angles, fading gains, and array responses for both the receive and transmit sides. It captures the multipath nature of the wireless channel and enables the analysis and design of communication systems considering the statistical properties of the channel [29].

$$g_{i,l}^{k}(t) = CN\left(0, \delta_i 10^{-.1PL(d_k)} e^{2\pi\sqrt{-1} t f_{d,max}} \cos(w_i, 1)\right) \tag{4}$$

In the mentioned equation, i is the fraction of power in i^{th} cluster, which indicates the relative contribution of each cluster to the overall channel power. The loss of path between User Equipment k and the BS is denoted by the notation $PL(d_k)$, where d_k is the distance between UE k and the BS. The loss of path accounts for the attenuation of the signal power as it propagates through the wireless channel, and it typically increases with distance. $f_{d,max}$ represents the maximum Doppler shift, which is a measure of the frequency variation due to the relative motion between the transmitter and receiver and $\omega_{i,l}$ is the angle of arrival for the (i, l) path with regard to the motion direction. This angle is associated with the direction from which a signal arrives at a particular location. As per the the results of the stochastic geometry-based channel model, $PL(d_k)$ is described as switching between multiple values. The switching between LOS, NLOS, and blocked is typically determined by the presence of line-of-sight (LOS) or non-line-of-sight (NLOS) conditions and possible blockages in the wireless channel model (Fig. 4):

$$PL(d_k)[dB] = \propto + \beta 10 log_{10}(d_k) + \varepsilon, \varepsilon \sim N(0, \sigma^2) \quad (5)$$

α and β are used to represent the coefficients obtained from a least squares fitting procedure applied to recorded data. The lognormal shadowing variance σ2 is another parameter used to account for the variability of the wireless channel due to the presence of obstacles, buildings, and other environmental factors. The values of these parameters for LOS and NLOS conditions may be different due to the presence of tall buildings, narrow streets, and other structures that can affect the wireless propagation as shown in for 73 GHz.

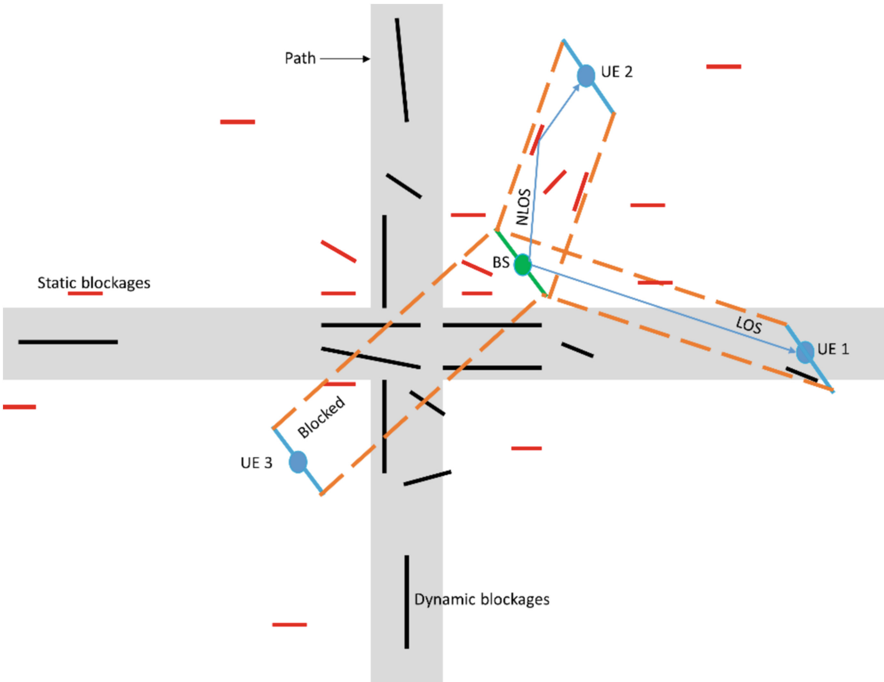

Fig. 4. Model setting for the stochastic geometry based channel model.

3.2 Formulation of Problem

The resource allocation algorithm determines the number of RBs allocated to each UE in the backhaul. This method aims to optimize system utility, which can often be defined in terms of a number of different factors, such as maximising sum rate, reducing the overall transmission delay, or maximising overall fairness among the UEs.

By allocating the RBs optimally among the UEs, the algorithm aims to balance the resource allocation to achieve better system performance and meet the quality of service requirements of the UEs. The associated problem is formulated as:

max f() 〖R_k (t)〗 ∑_(k-1)^K▒(f(C_k^eff (t))) (6a)

∑_(k-1)^K▒ 〖R_k (t)≤R,where R_k (t)∈ Z〗 (6a)

The goal of the resource allocation issue is to achieve the optimum sum of a concave function, f(.), of the system's user equipment (UE)s' effective capacities. The effective capacity represents the maximum achievable data rate for each UE, considering the channel conditions and other system parameters (6(a)). The f(.) relies on the specific objective of the system, which could be fairness, system efficiency, or any other metric of interest. For example, different forms of the function f(.) can be used to achieve proportional fairness or maximize system throughput. To do this, the resource allocation algorithm determines the quantity of resource blocks (RBs) given to each UE, indicated as $R_k(t)$, based on the circumstances of that UE's particular channel. The RBs are distributed so as to optimize the effective capacity for each UE's concave function, f(.). The sum of the backhaul RBs assigned to each UEs (6(b)) cannot be greater than the total number of backhaul RBs that are available. This restriction makes sure that the allocation is feasible considering the system's limited resources. $R_k(t)$ values must only be picked from integers (6(b)).

4 Neural Network Based Resource Allocation

We provide a resource allocation algorithm which is based on NN that operates in BS to address these problems and take into account the mmWave channels' dynamic properties. NN functioning can be described into two phases:

4.1 The Training Phase

The event flow is shown in Fig. 5 during both the training and testing phases. In the stochastic geometry-based channel model, denoted as $S_k(t)$, it outputs values of 1 (indicating Line of Sight or LOS), 2 (Non-Line of Sight or NLOS), or 3 (blockage). To optimize the cumulative utility (Eq. 6a) for a specific set of link states ($S_k(t)$), feasible capacities ($C_k(t)$), and path losses ($PL(d_k)$) for the mmWave connections between all User Equipments (UEs) and Base Stations (BS), we employ an exhaustive search approach to identify the index of the backhaul resource block division method. Let $i(t) \in \left\{1 \ldots \binom{R-1}{K-1}\right\}$ represent the observed index value during the training stage. It's important to emphasize that the actual data transmission from the BS to the UE is utilized to maximize cumulative utility. This is achieved by testing each of the $\binom{R-1}{K-1}$ methods and selecting the one that optimizes utility across all UEs. This method helps identify the most effective resource block allocation methodology for specific dynamic mmWave channel conditions. In the training phase, the expected output of the neural network (NN) is defined as a measure of the resource allocation strategy that optimizes the overall utility during actual data transmission. To reduce the error between the projected index value and the desired index value, the NN updates its bias b_k and weight w_k.

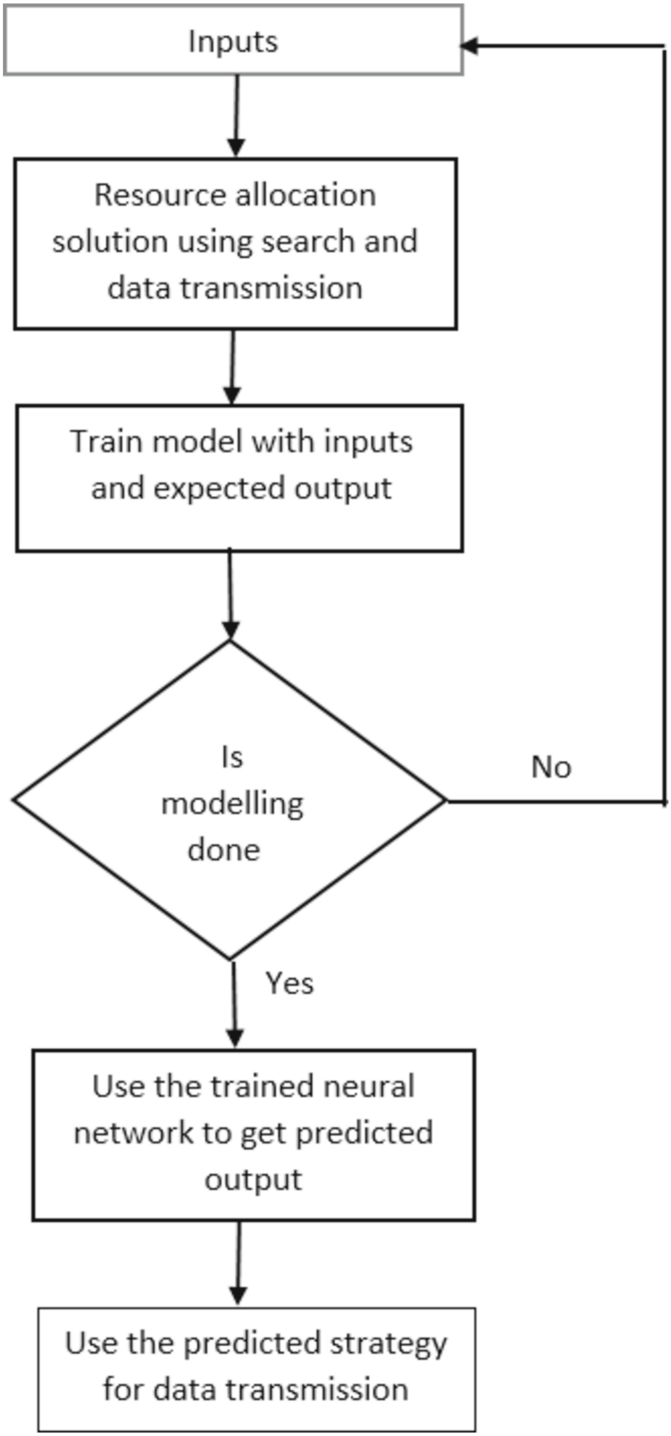

Fig. 5. The proposed NN-based resource allocation's event flow.

4.2 Testing Stage

The RB division strategy prediction relies on a neural network that has been trained for this purpose. In this process, the current link state, feasible capacity, and path loss for all connections between User Equipments (UEs) and the Base Station (BS) are used as inputs to the neural network (NN). The NN then produces a predicted index corresponding to the RB division strategy, which serves as the output. Subsequently, data transfer operations are executed using the predicted resource allocation approach. Even in scenarios where there is no exact match to the input data from the training stage, the utilization of a substantial training dataset leads to a highly accurate resource allocation strategy during the testing stage. This demonstrates the robustness of the neural network's predictive capabilities.

5 Result and Analysis

A single BS and various numbers of randomly distributed UEs are used to simulate a wireless network. It is considered that every UE is within the BS's coverage region. The signal to noise ratio, connection condition, and distance between the BS and the UE directly impact each BS-UE link's data rate. The required parameters are shown in Table 2 along with the channel parameters of the model.

For objective of creating training data for the NN, a sophisticated channel model is employed. We examine outcomes of the suggested method with those of the strategy in [29] and the resource allocation based on exhaustive search. The optimal RB division approach is predicted using trained NN model on the received channel condition. The average sum rate performance for various schemes and UE are presented in Fig. 6.

Table 2. Channel Parameters

Sl. No	Parameter is	Value is	Parameter is	Value is
1	αLOS	69.80	Signal to Noise Ratio	0.20 dB
2	βLOS	2.0	Bandwidth	1.0 GHz
3	σLOS	5.80 dB	Backhaul	10.0 Gb/s
4	αNLOS	86.60	Number. of RBs	20.0
5	βNLOS	2.450	Count of UEs	4, 8, 12, 16, 19, 22
6	σNLOS	8.00 dB	mmWave link	1.0 GHz
7	Paths	4.0	M, N	2.0

In Fig. 6, it is clear that all of the systems' performance first increases with more slope, then as user numbers increase, performance increases with lower slope owing to the restricted backhaul capacity. As a result, BS is unable to serve some UEs. The exhaustive search strategy outperforms the RL and NN based approaches, however at the expense of a significant increase in computation time. It is clear that the recommended NN-based resource allocation outperforms the RL-based strategy and gets very near to exhaustive search in terms of performance.

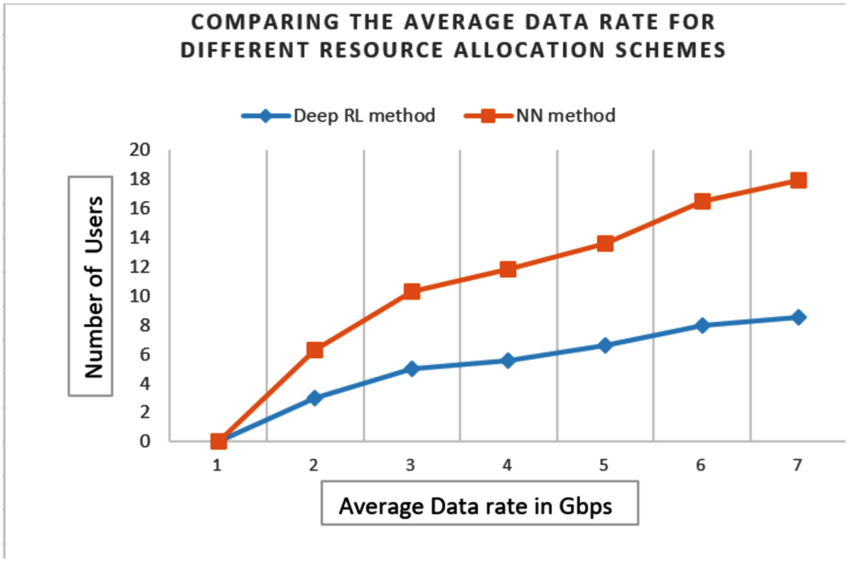

Fig. 6. Comparing the average data rate for Deep RL and NN method.

6 Conclusions

In conclusion, RL-based resource allocation methods like NN based, deep RL, have proven to be effective in optimizing resource allocation in 5G mmWave networks. Each method has its own strengths and weaknesses and the choice of method will depend on the specific requirements of the network. Deep RL and NN backhaul methods have been shown to achieve the best performance in terms of resource allocation in 5G mmWave networks. The results of simulations show that the proposed approach achieves better performance as compared with existing solutions.

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