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Minimization of Energy and Service Latency Computation Offloading using Neural Network in 5G NOMA System

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Abstract—**The future Internet of Things (IoT) era is anticipated to support computation-intensive and time-critical applications using edge computing for mobile (MEC), which is regarded as promising technique. However, the transmitting uplink performance will be highly impacted by the hostile wireless channel, the low bandwidth, and the low transmission power of IoT devices. Using edge computing for mobile (MEC) to offload tasks becomes a crucial technology to reduce service latency for computation-intensive applications and reduce the computational workloads of mobile devices. Under the restrictions of computation latency and cloud computing capacity, our goal is to reduce the overall energy consumption of all users, including transmission energy and local computation energy. In this article, the Deep Q Network Algorithm (DQNA) to deal with the data rates with respect to the user base in different time slots of 5G NOMA network. The DQNA is optimized by considering more number of cell structures like 2, 4, 6 and 8. Therefore, the DQNA provides the optimal distribution of power among all 3 users in the 5G network, which gives the increased data rates. The existing various power distribution algorithms like frequent pattern (FP), weighted least squares mean error weighted least squares mean error (WLSME), and Random Power and Maximal Power allocation are used to justify the proposed DQNA technique. The proposed technique which gives 81.6% more the data rates when increased the cell structure to 8. Thus 25% more in comparison to other algorithms like FP, WLSME Random Power and Maximal Power allocation.**

Keywords—**Mobile edge computing; Deep Q Network Algorithm; Latency Optimized; Computation Offloading; 5G**

I. INTRODUCTION

THE traditional mobile cloud computing systems would send the data from mobile devices to the cloud server in the core network for additional processing. However, this scheme cannot fit the future Internet of Things (IoT) era due to the explosively increasing amount of data generated by massive number of IoT wireless devices and the time critical requirements of new applications such as industrial monitoring, disaster early warning and healthcare. Recently, a new computing paradigm called edge computing for mobile (ECM) has emerged and drawn a lot of attention from both academia and industry. It pushes the computing capability from the core network to the network edge. New applications like augmented reality (AR), autonomous driving, and the Internet of things (IoT) have been made possible by fifth-generation (5G) cellular technologies.

9These applications need a lot of wireless devices (like sensors and actuators), in addition ultra-low-latency communication, computation, and control. The immediate time computation tasks that should be executed out in practice can be quite intensive, but wireless devices are typically small and only have limited communication, computation, and storage resources, so how to improve their computation abilities while decreasing computational latency is one crucial but challenging issue that must be addressed for making these 5G applications a reality. [1] Computation off-loading in edge computing for mobile (ECM) systems constitutes an efficient paradigm of supporting resource-intensive applications on mobile devices. The beneficial role of IRSs is investigated in MEC systems, where single-antenna devices may opt for off-loading a fraction of their analytical tasks to the edge computing node via a multi-antenna access point with the aid of an IRS. [2] Explains investigated system performance issues (energy consumption and execution delays) when task offloading from mobile devices to support services for sustainable IoT. Energy-efficient task allocation in a mobile cloud system (EETAMCS) algorithm which also considers execution delays. The algorithm manages to select an appropriate VM for the execution of the task while meeting deadline constraints. [3] Multi-access edge computing (ECM) has been proposed as an approach capable of addressing latency and bandwidth issues in application offloading of computation to extend the capabilities beyond the computational and storage limitations of mobile devices. [4] Adopted a heterogeneous network architecture where two edge servers are located at AP and BS, respectively. We created an energy minimization problem that takes heterogeneous computation resources, latency needs, power consumption at end devices, and channel states into account in order to provide optimal energy efficiency for all users. [5] To be able to increase the energy efficiency of the offloading system, this paper established a problem that decreases both the power using the communication process and which of the computation task execution.

Here we proposed an EECO scheme that better addresses the problem, which jointly optimizes the calculation offloading decisions and the radio resource allocation strategies a reduction in the system energy cost inside the delay constraints. [6] By taking into account user association, computing resource allocation, and power control together, the proposed NOMA-based ECM network's a challenge to minimizing energy

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consumption solved. [7] The hierarchical ECM network's computation offloading issue. In order to balance the workload across the entire network region, we propose topology independent offloading algorithms that generalize the assumption about the network layout. [8] Task segmentation and edge server cooperation are combined to significantly reduce the time and energy required for task processing. Introduced in recent years that provide abundant computing resource to mobile users in their close proximity, and mobile users can offload their tasks a single or multiple nearby ECM servers for processing. EEC thus has great potentials decrease the overall processing delay of computation-intensive tasks and to prolong the battery lifetime of mobile devices. It has attracted lots of attentions from both industries and academia. Mobile terminals, which include smart phones, tablet computers, laptops, and smart assistants, have become increasingly popular due to the rapid development of mobile Internet technology and the on-going advancement of mobile communication technology.

Lowering the overall energy consumption of the offloading process, large tasks can be split up and assigned to servers nearby in this work. [9] The joint computation offloading and resources optimization in a multi access ECM system. Mobile-edge computing (ECM) has been however, the mobile terminal is limited by things like volume, weight, performance, power, etc. Its working capacity is still in a dire and tiresome state, and it cannot satisfy the growing demand of people.

The following are the contributions made by this study:

- The increased cell structure is developed with multiple users at different time slots.
- The data rate of the 5G network is increased by introducing the DQNA technique and compared to the other techniques like FP, WLSME Random Power and Maximal Power allocation.
- The train histogram result also developed for more number of users.

The following describes the general organization of the paper: Information on edge computing for mobile in the 5G NOMA network is provided in Section 2. Section 3 clarifies the proposed DQNA-based allocation of power for 3 NOMA users at different time slots. The DQNA method's results and analysis are presented in Section 4. Section 5 of the foregoing work contains its conclusion.

II. RELATED WORKS

The existing system study the system performance of edge computing for mobile (ECM) wireless sensor networks (WSNs) using a multi antenna access point (AP) and two sensor clusters based on uplink non-orthogonal multiple access (NOMA). Due to limited computation and energy resources, the cluster heads (CHs) transfer their work to a multi antenna AP over Nakagami-m fading [10]. We proposed a combination protocol for NOMA-MECWSNs in which the AP selects either selection combining (SC) or maximal ratio combining (MRC) and each cluster selects a CH to participate in the communication process by employing the sensor node (SN) selection. [11] The existing system derive the closed-form exact the successful own words computation probability (SCP) to evaluate the system performance with both the latency and the energy use constraints of the considered WSN. A deep learning-based message-passing algorithm (MPA) for damped three dimensions (D3D). To learn the best D3D-MPA parameters, a feed-forward neural network is created, and a similar back propagation algorithm is created [12]. A joint radio communication, caching, and computing decision problem is developed to maximize the average tolerant delay while satisfying a specified transmission rate constraint to be able to optimize resource allocation at both mobile VR devices and fog access points (F-APs) [13, 14]. In a centralized computing network, traffic flows should be transmitted and processed, and they can be stopped by cutting off the resources needed for either communication or computation [15, 16]. Using the caching and cooperative communication abilities of the terrestrial Base Stations (BSs) and unmanned aerial vehicles (UAVs), a distributed heterogeneous computing platform (HCP) is created. We propose a 2-stage federated learning algorithm among UEs, UAVs/BSs, and HCP to jointly predict the content caching placement by taking traffic distribution, UE mobility, and localized content popularity into account. This will protect the privacy of the UEs' content [17, 18]. The offloading ratio and gearbox time are jointly optimized using an accelerated gradient algorithm that can find the ideal value quickly and accelerate convergence over conventional approaches [19]. To address the power allocation issues of the NOMA network, the multi-objective sum rate-based butterfly optimization algorithm (M-SRBOA) is suggested [20, 21].

III. SYSTEM DESIGN

Fig.1 explains about the main working of proposed system by assuming that in the BS complete knowledge of all user input data sizes, local computation power, and channel information. The BS calculates the gearbox power, the offloaded data, and the percentage of offloading time using this data. A suggested iterative technique that obtains closed-form expressions at each step to optimize time allocation or data offloading is based on the optimal conditions.

The following list includes the key actions in the system design architecture:

Module 1: Load Dataset the core functionality of the IoT (Internet of Things) data collecting, the detected information is sent from sensor nodes to the hub, with a timely style, allowing for the smart response to be done in an emergency. To improve system reliability and fault tolerance, multi-modal sensor data fusion seeks to acquire clear and precise data.

Module 2: The key performance indicators that control IoT are low latency and energy efficiency. Converge cast, a low-latency data gathering technique based on effective time division multiple access (TDMA), allows m packets to aggregate into a single packet from the output of each sensor node.

Module 3: Episode Development Phase to be able to optimize resource distribution among users, base stations (BSs), and sub-channels in keeping with the received power levels of users; we offer a multi-constrained clustering solution. To increase generality, appropriate bandwidth selection for the entire system at various traffic densities is also taken into account. We get a list of states and the related best actions after the exploration phase.

Module 4: Using a parametric function that must be created, the general rule of power allocation must then be learned from this data set. The function will be employed as a predictor after training to forecast the ideal course of action given an input state. Understanding the qualities of the training data is crucial to assist the predictor's design.

Module 5: The list of good actions in the training data, in particular, carries some randomness since it was created using the random acting procedure. The reality that there numerous distinct action vectors producing the identical reward for each state gives training data its randomization. As a result, two very identical states can be connected to very distinct action vectors, which lead to consistency issues and hinder learning. Phase of Evaluation Based on the forward and back propagation scheme, our networks is trained. The back propagation stage uses the derivative chain rule to assess the gradient of the error function based on weight set after the error has been calculated in the forward propagation stage. The weights can be updated in each training epoch by alternately performing forward and back propagation.

Module 6: Two types of loss are used to train our networks. Additionally, the optimization algorithm is utilized to reduce loss. The mean absolute error (MAE) between the target output vectors and the network outputs is the first type of loss function. Two terms compose the second type. The first phrase simply speaks of the discrepancy between desired outputs and network outputs. The average values calculated from the network outputs and target outputs are the second term. Network routing scenario, the agent can be rewarded for selecting paths with lower latency or for making decisions that prioritize low-latency communication.

A. NOMA SYSTEM MODEL

The combined signal, which is a superposition of the desired signals from various users with various allotted power coefficients, is transmitted by the BS to all mobile users from the transmitter side of the downlink NOMA network, as shown in Figure 2. Each user's receiver is assumed to undergo the SIC process in turn until the user's signal is recovered. Based on the channel conditions, users' power coefficients are distributed inversely proportionally. Each user decodes its own signal after treating users with lower power coefficients as noise. It is feasible to encode the transmitted signal in the following BS format:

$$z = \sum_{i=1}^{L} \sqrt{a_i P_b x_i} \quad (1)$$

The signal x_i is the message with unit energy, a_i is power allocation coefficient and P_b is the power which transmits from the base station. Input channel coefficient h_l with l^{th} users. The received signal w_l signal can be portrayed as

$$w_l = h_l s + n_l = h_l \sum_{i=1}^{L} \sqrt{a_i P_b x_i} + n_l \quad (2)$$

Where, n_l is Additive White Gaussian Noise with

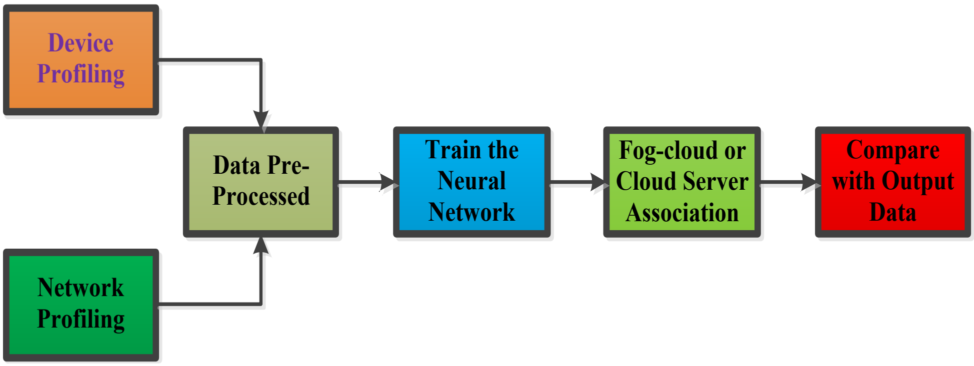

Fig.1. System Design Architecture

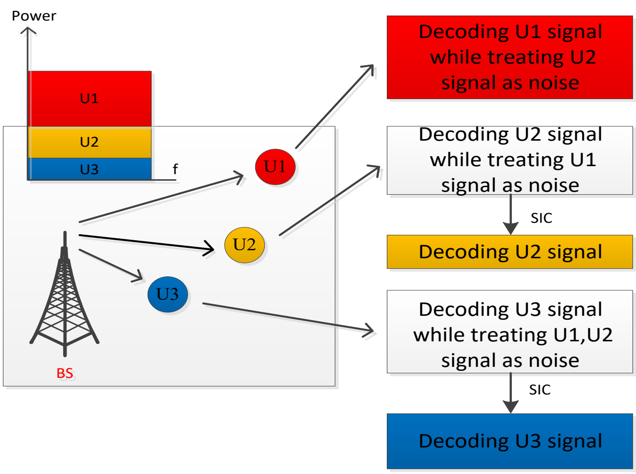

Fig.2. NOMA downlink scenario for 3 users

zero mean the noise variance $\frac{N_0}{2}$. With the aid of equation (2) the SINR can be indicated as below

$$SINR_{j\to l} = \frac{b_j\gamma|h_l|^2}{\gamma|h_l|^2\sum_{i=j+1}^{L} b_i+1} \quad (3)$$

The implementation of SIC procedures for the l^{th} user signal to locate the desired information of the user j$\leq i$. The l^{th} user can be represented as

$$SINR_l = \frac{b_l\gamma|h_l|^2}{\gamma|h_l|^2\sum_{i=l+1}^{L} b_i+1} \quad (4)$$

The SINR of the L^{th} can be represented as

$$SINR_L = a_L\,\gamma|h_l|^2 \quad (5)$$

The NOMA downlink from base station to the end user can be indicated as

$$R_l^{NOMA} = log_2(1+SINR_l)$$
$$R_l^{NOMA} = log_2\left[1+\frac{b_l\gamma|h_l|^2}{\gamma|h_l|^2\sum_{i=l+1}^{L} b_i+1}\right] \quad (6)$$

The data rate of the NOMA system can be indicated as

$$R_l^{NOMA} = \sum_{l=1}^{L} log_2(1+SINR_l)$$
$$= \sum_{l=1}^{L-1} log_2\left[1+\frac{b_l\gamma|h_l|^2}{\gamma|h_l|^2\sum_{i=l+1}^{L} b_i+1}\right] + log_2[1+b_L\gamma|h_L|^2]$$
$$= \sum_{l=1}^{L-1} log_2\left[1+\frac{b_l}{\sum_{i=l+1}^{L} b_i+{}^{1}/_{\gamma|h_l|^2}}\right] + log_2[1+b_L\gamma|h_L|^2] \quad (7)$$

For a high SNR value $\gamma\to\infty$, the NOMA downlink can be represented as

$$R_l^{NOMA} = \sum_{l=1}^{L-1} log_2(1+\frac{b_l}{\sum_{i=l+1}^{L} b_i})+log_2[\gamma|h_L|^2]$$
$$R_l^{NOMA} = log_2[\gamma|h_L|^2] \quad (8)$$

B. ALLOCATION OF POWER USING DQN ALGORITHM

In a 5G downlink scenario, the goal is to distribute transmit power to numerous users in a way that maximizes the overall performance within the system. In this case, the DQN algorithm can be employed to control power allocation.

Train a strategy to try and maximize the discounted, cumulative reward.

$$R_{to} = \sum_{t=t0}^{\infty} \gamma^{t-t0} rt \quad (9)$$

The return is another name forR_{to}. The reduction γ ideally, there should be a constant that converges the sum and is between 0 and 1. If we had a function, which is the central tenet of Q-learning.

$$Q^*: state \times Action \to R \quad (10)$$

We could easily develop a plan that maximizes our gains using the function mentioned above, which could estimate our return assuming that act in a specific state:

$$\pi^*(s) = argmax\big(Q^*(s,a)\big) \quad (11)$$

The result is, we lack access to Q^* information because we don't fully understand the world. Nevertheless, due to the universal nature of neural networks function approximations, we can easily make one and train it to look like Q^*.

We will use the observation that every Q function for some policy obeys the Bellman equation to formulate our training update rule:

$$Q^\pi(s,a) = r + \gamma Q^\pi(s^{|},\pi(s^{|})) \quad (12)$$

Known as the temporal difference error, the difference between the two sides of the equality

$$\delta = Q(s,a)\text{-}(r+\delta_{max}Q(s^{|},a) \quad (13)$$

We'll use the Huber loss to cut down on this error. The Huber loss is more resistant to outliers when the estimates of Q are highly noisy because it behaves like the mean squared error when the error is small and like the mean absolute error when the error is large. Over a number of transitions, we calculate this, B drawn from replay memory as samples.

$$L = \frac{1}{|B|}\sum_{(s,a,s^{|},r)\in B} L(\delta) \quad (14)$$

$$L(\delta) = \begin{cases} \frac{1}{2}\,\delta^2\,, for\ |\delta| \le 1 \\ |\delta| - \frac{1}{2}, otherwise \end{cases} \quad (15)$$

Table 1 describes the algorithm of the DQN algorithm initially constructs a setting that reflects the 5G NOMA system. To store the agent's experiences as tuples (state, action, reward, next state), create a replay buffer. Create a deep neural network (Q-network) from scratch that uses the system state as an input and outputs Q-values for various power allocation actions. The target network should be made as a duplicate of the Q-network. This adaptation describes how to use a 5G NOMA system's power allocation DQN algorithm. In a NOMA setting, it takes into account the particular goals and restrictions related to power distribution among users.

IV. RESULTS AND ANALYSIS

In this section, the DQNA's outcomes and analysis are presented. By successfully executing server code, establishing a server using python code, and creating a new server, this DQNA technique is implemented and simulated. Computer software that uses an i5 processor and 8 GB of RAM. This's primary goal is to DQNA is to increase the data rates for more umber of NOMA users at differ time slots.

A. PERFORMANCE EVALUATION

This study's creation of base station coverage and the number of users, as well as power allocation in cells at different locations. Here the performance is considered in terms of data rates to the 3 NOMA users when we are increases the cell size structure. Figure 3 explains the base station coverage and allocation of power the quantity of users in cells at different locations which gives higher throughput. Figure 4 gives the graphical explanation about bit rate of proposed system when the cells structured increases. Figure 5 gives the train histogram of the all the NOMA users. Figure 6 represents data rate of all the NOMA users at different time slots. Further table 2, 3, 5, and 5 explains the iterated Q values for the association of Fog cloud. As a way to sure in table 1, for the 1st user the iterated Q value for fog cloud association is obtained as 0.005 which indicates optimize resource allocation, reduce latency, improve energy efficiency, ensure the privacy less latency and increased computational speed and so on.

TABLE I
DQN ALGORITHM

1. Set the capacity of the replay memory D to N
2. Using weights that are random, initialize an action-value function Q
3. Make the target action-value function initialized Q~
4. In relation to the incident $\theta^{-}=\theta$
5. For episode=1
6. A sequence starting point $s_1 = \{x_1\}$ and sequence beforehand analyzing $\Phi_1 = \Phi(s1)$
7. For t=1
8. Probabilistically, select an arbitrary behavior a_t
9. Select $a_t = \mathrm{argmax}\, Q(\Phi(s_t))$
10. $S_{t+1} = s_t, a_t, x_{t+1}$ and
pre-processed $\Phi_{t+1} = \Phi(s_t + 1)$
$(\Phi_t, a_t, r_t, \Phi_{t+1})$ in D
$(\Phi_j, a_j, r_j, \Phi_{j+1})$
$y_j = \begin{cases} r_j, & j+1 \\ r_j + \gamma_{max} Q^{\sim}(\Phi_{j+1}, a:\theta), & \text{otherwise} \end{cases}$
$(y_j - Q(\Phi_j, a_j, \theta))^2$

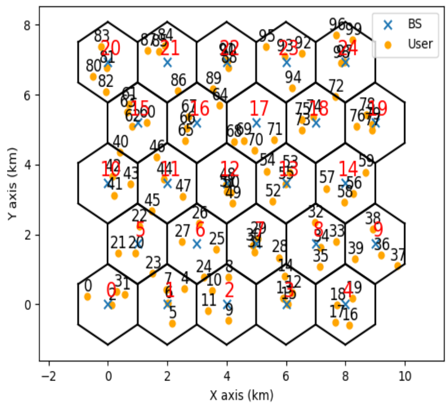

Fig.3. Base station establishment

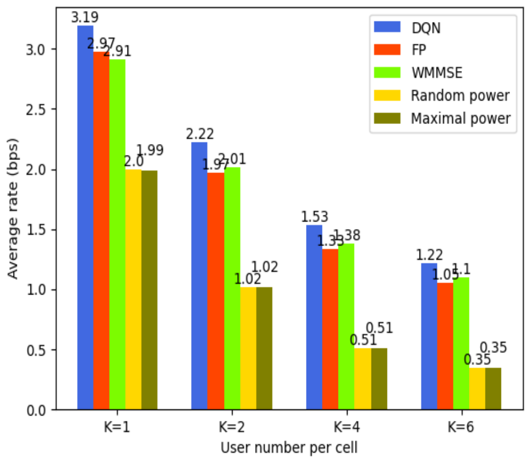

Fig.4. Data rates when trained with other power allocation techniques

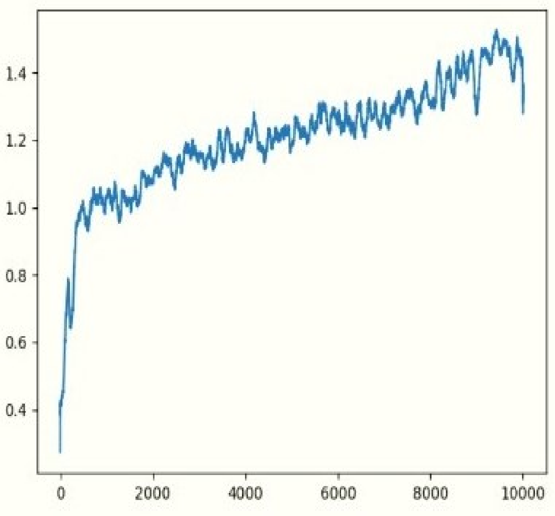

Fig.5. Trained Histogram report

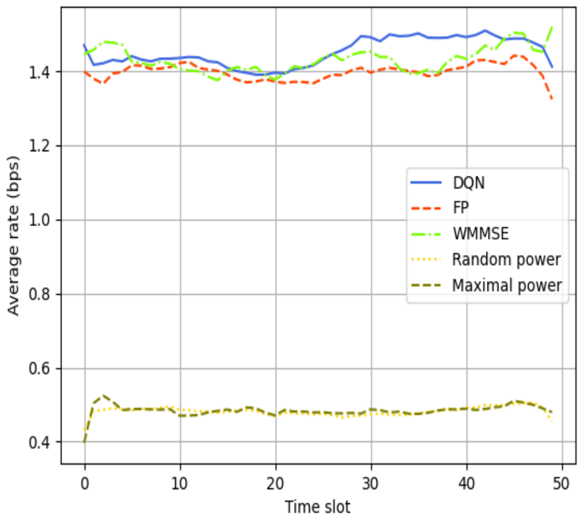

Fig.6. Data rate v/s different power allocation schemes

TABLE II
ITERATED Q VALUES FOR BASE STATION AT (5, 5)

Location of Users	Iterated Q values for association of Fog cloud				
(1,1)	5.656	0.839	1.083	0.157	0.111
(1,3)	4.721	0.491	2.000	0.290	0.111
(3,2)	3.602	0.503	3.000	0.965	0.111

TABLE 3
ITERATED Q VALUES FOR BASE STATION AT (-5, -5)

Location of Users	Iterated Q values for association of Fog cloud				
(-4,-1)	4.123	0.795	1.000	0.036	0.106
(-2,-4)	3.160	0.699	1.000	0.109	0.106
(-1,-2)	5.000	0.951	4.000	0.065	0.106

TABLE IV
ITERATED Q VALUES FOR BASE STATION AT (5, -5)

Location of Users	Iterated Q values for association of Fog cloud				
(-4, -1)	4.123	0.795	1.000	0.036	0.106
(-2, -4)	3.160	0.699	1.000	0.109	0.106
(-1, -2)	5.000	0.951	4.000	0.065	0.106

TABLE V
ITERATED Q VALUES FOR BASE STATION AT (-5, 5)

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(1,1)	5.656	0.839	1.083	0.157	0.111
(1,3)	4.721	0.491	2.000	0.290	0.111
(3,2)	3.602	0.503	3.000	0.965	0.111

TABLE VI
COMPARATIVE ANALYSIS OF THE DQN ALGORITHM

Algorithm	K=1	K=2	K=4	K=6
DQN	3.19 bps	2.22 bps	1.54 bps	1.22 bps
FP	2.97 bps	1.97 bps	1.33 bps	1.05 bps
WMMSE	2.91 bps	2.01 bps	1.18 bps	1.10 bps
Random Power	2.00 bps	1.01bps	0.51 bps	0.35 bps
Maximal Power	1.99 bps	1.02 bps	0.51 bps	0.35 bps

B. *COMPARATIVE ANALYSIS*

This section displays a comparison of the DQNA's data rate analysis when cell size structure changes. The DQN algorithm is compared to alternative power distribution techniques like FP, WMMSE, Random Power and Maximal Power are employed to assess how effective the DQNA technique. Table 6 provides the analysis of differences with all the different power allocation techniques. As a way to be sure for cell structure K=6 the DQN algorithm provides 1.22 bps which is higher the data rate when compare to FP, WMMSE, Random Power and Maximal Power. Due to DQN's potential for achieving fairness, faster convergence speed, and capacity to learn and adapt to changing channel conditions, it is a promising algorithm. The DQNA employed to distribute an optimal amount of power to the NOMA users, which increased the data rate, by using an appropriate objective function. The development of the NOMA network in this instance includes numerous users.

V. CONCLUSIONS

This study develops the DQNA method for distributing power among all NOMA network users. The performance of data rates is improved by using this DQNA-based power allocation for all NOMA users. With respect to performance and efficiency, DQN algorithm outperforms FP, WMMSE, and random power algorithms, and is a promising method for power allocation in wireless communication systems due to its flexibility in adapting to changing conditions, maximizing power allocation policies, and managing uncertainties. For each scenario, the energy consumption minimization problem is divided into more compact unit's issues, and low-complexity global optimal answers are given for the sub problems with the noted qualities. The proposed DQN algorithm provides 81.6% data rates which is 25% more compared to other techniques like FP, WMMSE, Random Power and Maximal Power. When the cell value K increases to 8 the data bit rate value is 1.22 bps which is higher than all other allocation techniques. Future power allocation over the NOMA network operations can be accomplished with the novel optimization algorithm.

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