วารสารวิชาการเทคโนโลยีอุตสาหกรรม (The Journal of Industrial Technology)
ISSN (online): 2697-5548
DOI: 10.14416/j.ind.tech.2024.04.003

บทความวิจัย

Optimal Power Allocation in NOMA System Based on Artificial Intelligence Methods

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Received: 13 June 2023; Revised: 29 November 2023; Accepted: 18 January 2024
Online Published: 18 April 2024

Abstract: This paper considers the Non-Orthogonal Multiple Access (NOMA) technique which is one of the core technologies in 5G and beyond. To distinguish users in the power domain, Superposition coding and Successive Interference Cancellation (SIC) are applied at the transmitter and receiver. Power allocation is shown to be significant in affecting the system performance. This work proposes an application of two Artificial Intelligence (AI) methods, Q-learning and Genetic Algorithm (GA), in order to optimize the power allocation in the NOMA system. Namely, the maximization of the minimum bitrate of the overall system as well as the transformation of the NOMA system into both Q-learning and GA components are obtained by setting and solving the power allocation optimization problem. Numerical results demonstrate that Artificial intelligence algorithms provide a higher minimum bitrate in comparison with the existing theoretical power allocation methods. Besides bitrate, the complexity of both methods is analyzed. It is concluded that Q-learning has an exponential, while GA has a linear complexity with the increase of the total number of users.

Keywords: NOMA; power allocation; Artificial Intelligence; Q-learning; Genetic Algorithm

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1. Introduction

Non-orthogonal multiple access (NOMA) is one of the candidates considered to be a core technology for future wireless communications. Many works prove that NOMA outperforms Orthogonal multiple access (OMA) in various aspects; for example, supporting multiple users and providing better spectral efficiency [1-4]. However, to enable NOMA, users should be operating in the same domain such as power or code. For power domain-NOMA, users are allowed to share some resources between each other, e.g., code, frequency, and modulation scheme, but they must stay separated in the power domain where Superposition coding is applied at the transmitter and receiver level. Received signal decoding is achieved by applying a Successive Interference Cancellation (SIC) method. Since users are separated by power, power allocation among them is of great importance. There are quite a huge number of existing works trying to optimize the power allocation in NOMA systems for various channel models and objectives presented in [5-8]. In [5], power allocation optimization problems were formulated in the manner of minimizing the transmission power and maximization of fairness rate. Minimizing the transmission power was also considered in [6] where power resource was allocated for multi-cell, multi-carrier NOMA system. In [7], power allocation algorithms for maximizing the sum of achievable rates and energy efficiency were proposed for millimeter wave (mm Wave) NOMA system. Also, NOMA system was applied for uplink with the Unmanned Aerial Vehicles (UAVs) system where the power allocation scheme was proposed to improve throughput and packet delay [8]. In addition to be standalone, power allocation is usually jointly optimized with other resources [9], [10]. Concretely in [9], power and time allocations were jointly optimized to minimize the system outage probability in bidirectional NOMA communications. Furthermore, power allocation and beamforming were considered to maximize the system reliability in multiple-input multiple-output (MIMO) NOMA channels [10].

Nowadays, Artificial intelligence (AI) is becoming an almost indispensable tool in solving a huge number of engineering problems, what necessitates its enormous demand and development [11]. Basically, an AI agent is trying to find an optimal environmental state through a trial-and-error process, receiving the reward where such depends on the objective value of the considered environmental state [12]. Therefore, AI agent moves through the n-dimensional state space, in general case, looking for the state in which it receives the highest possible reward. AI is also showing popularity in the field of wireless communication, particularly in solving optimization problems [13-15]. In [13], AI was applied to optimize uplink and

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downlink in decoupling system. Using AI to manage interference in the power optimization problem was considered in [14], where the objective was to maximize the sum of achievable rates. In [15], AI was applied to schedule transmission time slots in order to maximize the number of packets.

This paper considers a downlink power-domain NOMA system where a base station broadcasts signals to users. In order to maximize the minimum bitrate among users, the allocation of transmission power of all users to be achieved by applying two AI methods are proposed, Q-learning and Genetic algorithm. The mentioned problem was partially considered in [16], where only two users of NOMA system were taken into consideration. It is noted that AI was applied in resources allocation in NOMA channel with the difference in considered objectives [17], [18]. The equivalence between AI algorithms and NOMA system is successfully established. Precisely, the optimization problem in NOMA, which refers to an allocation of transmitting powers, was solved by AI algorithms whose components (e.g., population size and crossover probability in GA) were chosen in accordance with the problem formulation. Numerical results show that both AI methods provide higher minimum bitrate than the theoretical power allocation methods proposed in [19]. In addition to the bitrate, algorithm complexities are also considered. It can be concluded that the complexity of Q-learning increases with the total number of users while that of GA is linearly increasing.

This paper is organized as follows. Section 2 represents the introduction of a downlink NOMA system with a review of existing power allocation schemes. Power allocation problem formulation and AI algorithms (Q-learning and GA) application are presented in section 3. Performance comparison including minimum bitrate and algorithm complexity are shown in section 4. Finally, section 5 is devoted to the conclusion.

2. System Model

In this study, a single-cell discrete time downlink channel is considered. A single antenna is assigned to a base station and users. Regarding the NOMA advantages over the OMA system, the base forms a cluster with K users and assigns them the common bandwidth in frequency domain. This way, the base station is able to transmit data to all users sharing the same bandwidth by applying a Superposition coding method. Therefore, the transmitted signal is given by

$$x = \sum_{k=1}^{K} \sqrt{\alpha_k P_{\mathrm{tot}}} s_k \tag{1}$$

where α_k is the power allocation coefficient of user k, P_{tot} is a total budget of transmitted power and s_k is the symbol for user k. An additional assumption is that the user coefficients of transmitted power satisfy the following condition

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$\sum_{k=1}^{K} \alpha_k \leq 1$. The received signal for k-th user is given by

$$y_k = c_k h_k x + n_k \tag{2}$$

where h_k is a channel coefficient, n_k is Additive White Gaussian Noise (AWGN) with zero mean and variance σ_n^2 and c_k, $0 < c_k \leq 1$, is normalized degradation factor depending on the distance between the base station and the k −th user. Afterwards, the Successive Interference Cancellation method (SIC) is applied by each user separately on the received signal, so that each of them decodes their own signal. Therefore, the signal transmitted from the base station is jointly decoded by all users who are sharing the same bandwidth. The priority of decoding is given to user with lower channel quality and hence, the first decoded user must be fully interfered by other users. Each subsequent user signal is obtained by subtracting the prior decoded signals from the received signal. Hence, the current received Signal-to-Interference plus Noise Ratio (SINR) of user k is given by

$$\gamma_k = \frac{\alpha_k c_k^2 |h_k|^2}{c_k^2 |h_k|^2 \sum_{i=k+1}^{K} \alpha_i + \frac{\sigma_n^2}{P_{\text{tot}}}}. \tag{3}$$

Subsequently, the associated achievable rate can be computed as follows

$$R_k = log_2(1 + \gamma_k) \tag{4}$$

and the sum rate of overall system is given by

$$R_{\text{sum}} = \sum_{k=1}^{K} R_k \,. \tag{5}$$

By observing (3) it can be concluded that the overall system performance mainly depends on the set of allocated powers among users $\{\alpha_k\}_{k=1}^{K}$. What gives an opportunity to improve the system performance. According to reference [19], power equalization of received signals is obtained by applying a Channel inversion power allocation scheme. This strategy allocates power inversely with the channel quality. In this way, the transmission power of k-th user is given by

$$\alpha_k = \frac{1}{c_k^2 |h_k|^2 \sum_{i=1}^{K} \frac{1}{c_i^2 |h_i|^2}}. \tag{6}$$

In addition with Channel inversion, the same paper also proposes another method that can guarantee a minimum rate of one users per each frequency block. Furthermore, it is assumed the first decoded user is marked as l. Power allocated to this user, which also satisfies the desired SINR, is given by

$$\alpha_l = \frac{\gamma_l \left(c_l^2 |h_l|^2 + \frac{\sigma_n^2}{P_{tot}}\right)}{c_l^2 |h_l|^2 (1 + \gamma_l)}. \tag{7}$$

where γ_l represents desired SINR. The rest of power budget, $1 - \alpha_l$, will be uniformly allocated among others in the same group. However, in order to achieve a feasible power allocation, the desired SINR must be bounded by the next constraint

$$\gamma_l < c_l^2 |h_l|^2 \frac{\sigma_n^2}{P_{\text{tot}}}. \tag{8}$$

Although the power allocation schemes in (6) and (7) can maintain the performance of some users in

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the group, they do not cover the user with a minimum rate. Hence, the Quality of Service (QoS) of the overall system would be unreliable for both mentioned theoretical methods. Consequently, the goal of this paper is to maximize the minimum rate user performance to guarantee QoS of overall system.

3. Optimal Power Allocation with Q-learning and Genetic Algorithm

The overarching objective of this paper is to guarantee the overall system performance as described in the previous section. Namely, the individual information transmission quality for each user is evaluated by distributing the total available power among them. It turns out that (6) and (7) provide a significant difference in the information transmission quality between users. Accordingly, Q-learning and Genetic algorithm have that task of performing such a total power distribution among users, so the maximum similarity of their performance is ensured. This can be formalized with the following expression

$$\max_{\alpha_1,\alpha_2,\ \dots\ ,\alpha_K} \ min(\boldsymbol{\gamma})$$
$$\textit{subject to} \quad \alpha_1, \alpha_2, \dots \alpha_K \geq 0 \qquad (9)$$
$$\sum_{k=1}^{K} \alpha_k \leq 1$$

where γ is defined by (3) and $\alpha_1, \alpha_2, \dots\ , \alpha_K$ represent the parts of total power assigned to the users. It is also noted that the problem formulated by (9) can be solved using the classical optimization tools (e.g., Karush–Kuhn–Tucker or KKT theorem) if the channel distribution where the channel is described as a random variable is known. On the other side, if the channel distribution is unknown, the optimization technique can be learned through Artificial intelligence methods. Consequently, two Artificial intelligence methods, Q-learning and Genetic algorithm, are being applied in order to optimize the power allocation in NOMA channel.

3.1. Q-learning algorithm

Q-learning belongs to a group of algorithms called Reinforcement learning, which is a branch of Machine learning where agents learn optimal strategies through the method of unsuccessful attempts [12]. Q-learning algorithm can be formalized through 4 essential elements: state, action, reward, and Q value. State represents one of all problem solutions, regardless of whether that solution is physically achievable or not and whether it meets eventual limitations. Actions unambiguously define the transition from current to the next state and their number is arbitrary. Rewards represent the state's quality. It is usually measured as a distance from the goal state. Finally, Q values represent actions quality in the particular state, where number of actions and Q values has to be the same.

In the context of the problem exposed in this paper before, the relationship between NOMA

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system and Q-learning algorithm would be as follows:

- **Agent:** The base station that allocates the transmission power to each of the system users is an agent of this scenario.

- **State** (s_t) **:** A set of transmitting powers $\{\alpha_k P_{tot}\}_{k=1}^{K}$ is assumed to be the model state. In order to define a discrete state, all user coefficients α_k are quantized within the range $[0,1]$ with step Δ. Therefore, transmission power of each user is defined as a part of P_{tot} or overall P_{tot} power. However, the last user power must be equal to P_{tot} minus sum of all other user powers.

- **Action** (a_t)**:** A set of transmitting power coefficients $\{\alpha_k\}_{k=1}^{K}$, where subset of $k \in (0, K)$ coefficients are taking values from the range $[0,1]$ with step Δ and $\alpha_{k\in subset} \neq \alpha_{k-1} \wedge \alpha_{k\notin subset} = \alpha_{k-1}$, is considered to be an state action. In other words, increasing or decreasing power of user k is considered to be an action.

- **Model constraints:** All user powers must be positive numbers and their sum must be equal to total transmit power P_{tot}.

- **Reward** (r_t) **:** The main purpose of the state rewards is to incorporate the constraints introduced in advance. This way, the states which are not satisfying mentioned constraints are automatically receiving low rewards. Additionally, in order to maximize the minimum system SINR, the reward should be the total SINR difference among users. Accordingly, the state reward is defined as follows

$$r_t(s_t, a_t) = -\frac{2}{K(K-1)}\sum_{i=1}^{K-1}\sum_{j=i+1}^{K}\left|\gamma_i - \gamma_j\right| \quad (11)$$

- **Environment:** In accordance with the introduced Q-learning components, an environment of this system is described through **Algorithm 1**.

Algorithm 1: Environment: $Env(\cdot)$

1. Initialize current state s_t
2. Input action $a_t = \{\alpha_k\}_{k=1}^{K}$
3. Go to the next state $s_{t+1} = \{\alpha_k P_{tot}\}_{k=1}^{K}$
4. Find reward $r_t(s_t, a_t)$ using (11)
5. **IF** $r_t(s_t, a_t)$ is maximum **THEN**
6. $\quad terminal = T$ (true)
7. **ELSE**
8. $\quad terminal = F$ (false)
9. **END IF**
10. **RETURN** $s_{t+1}, r_t(s_t, a_t)$ and $terminal$

Algorithm 1 also represents one interaction between the agent and environment. This algorithm implies reaching the next state by executing an action in the current state. Therefore, the goal is to find an optimal action for each state that leads agent towards the maximum reward state. In order

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to satisfy this assumption, a Q value lookup table has to be created. Each slot in the table represents state and action pair Q value. "Learning" part of Q-learning algorithm refers to updating the Q values $\left(Q(s_t, a_t)\right)$ by using a Bellman equation with the temporal difference [12], which is given by

$$Q^{new}(s_t, a_t) \leftarrow Q^{old}(s_t, a_t) + \beta\left[r_t(s_t, a_t) + \mu \max_a Q(s_{t+1}, a) - Q^{old}(s_t, a_t)\right] \quad (12)$$

where β is a learning rate and μ is a discount factor. Finally, the entire Q-learning algorithm can be summarized by **Algorithm 2**.

Algorithm 2: Q-learning algorithm

1. Define number of episodes N, N_{lim}, β, μ and ε
2. **FOR** $episode = 1{:}N$ **DO**
3. Initialize starting state s_t , $terminal = F$ and $counter = 0$
4. **WHILE** $terminal = F$ **DO**
5. $counter = counter + 1$
6. **IF** $rand(\cdot) < \varepsilon$ **THEN**
7. Randomly select one action a_t
8. **ELSE**
9. Select the action $a_t = arg\ max_a Q(s_t, a_t)$
10. **END IF**
11. $s_{t+1}, r_t(s_t, a_t), terminal = Env(a_t)$
12. Use (12) to update Q-table
13. **IF** $counter \geq N_{lim}$ **THEN**
14. **BREAK**
15. **END IF**
16. **END WHILE**
17. **END FOR**

Where $\varepsilon \in (0,1)$ and $rand(\cdot)$ is a random variable uniformly taking the value between 0 and 1. Based on **Algorithm 2**, agent can either randomly choose an action or specify the action which maximizes the reward. This is directly related with the biological learning process which includes exploration and exploitation. Furthermore, once the execution of the **Algorithm 2** is finished, the agent or the base station will know the most appropriate action for each state. On the other side, by considering **Algorithm 1** and **Algorithm 2**. the conclusion can be drawn that the optimal power allocation based on the Q-learning algorithm performs a $(K-1)$ dimensional space searching. Accordingly, this method complexity depends on the number of state-action pairs what is a function of total number of users

$$comp\_Ql = \mathcal{O}((K-1)^2) \quad (13)$$

Equation (13) implies that the Q-learning complexity increases exponentially with the number of users in the system. This could be a serious problem when the base station needs to allocate power to many users at the same time. Basically, the complexity may refer to computation time or memory storage. Therefore, other Artificial intelligence methods which require less complexity than Q-learning algorithm are preferred.

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3.2. Genetic Algorithm

Genetic Algorithm (GA) is an optimization method for both constrained and unconstrained problems. The concept of this algorithm is based on natural selection. Algorithm starts by generating a random population of J individuals (chromosomes), where each of them will be coded with M bits. Afterwards, a new generation is formed by passing all J chromosomes through 4 essential GA components: Evaluation, Selection, Crossover and Mutation. Furthermore, the previous generation will be replaced with the next one and the overall process will be repeated until the stopping criterion is met [21].

Defining the first generation is one of the beginning steps of GA application in the power allocation domain. Namely, the set of J random chosen values from the range $[0, P_{tot}]$ represents initial population after coding. Each of J value is firstly rounded to the nearest of $(2^M - 1)$ quantization levels. Then each of them is binary coded with M bits. Therefore, the population of ith generation can be represented by $\boldsymbol{P}(i)$ matrix.

$$\boldsymbol{P}(i) = \begin{bmatrix} \boldsymbol{p}_{1,1}[M](i) & \cdots & \boldsymbol{p}_{1,K-1}[M](i) \\ \vdots & \ddots & \vdots \\ \boldsymbol{p}_{J,1}[M](i) & \cdots & \boldsymbol{p}_{J,K-1}[M](i) \end{bmatrix} \quad (14)$$

Where each row of $\boldsymbol{P}(i)$ matrix is a $(K-1)$ dimensional vector of power allocation coefficients $\{\alpha_k\}_{k=1}^{K-1}$ and $\alpha_K = 1 - \sum_{k=1}^{K-1} \alpha_k$. Then, all population members SINR (γ_k) per user is calculated using equation (3). This part directly leads to individuals evaluation or determining the fitness function value $f\big(chr_i(j)\big)$ which is constructed in accordance with the optimization problem in (9).

$$f\big(chr_i(j)\big) = e^{\left(-\sum_{t=0}^{K-2}\sum_{s=t+1}^{K-1}|\gamma_t - \gamma_s|\right)} \quad (15)$$

where i and j represent the $i-$th generation and the $j-$th individual, respectively. After each chromosome evaluation, the fitness function values are stored into the vector $\boldsymbol{f}$ defined by

$$\boldsymbol{f} = [f_1(i) \quad \dots \quad f_J(i)]. \quad (16)$$

The selection process is envisaged to be applied two times. Direct individuals transfer from the previous to the next generation, which refers to Generation gap [21], is the first application. The second time is during the crossover process while selecting the parental individuals. Basically, selection can be implemented through the several methods. However, Elitism and the “Roulette wheel” [22] are applied as the most frequent used selection methods. By Elitism, one individual with the highest criterion function value is directly transferred to the next generation, while “Roulette wheel” randomly chooses the rest of necessary number of individuals based on their fitness function values. Afterwards, the single-point crossover is applied on two parents selected by a “Roulette wheel” method, with the crossover probability of p_c. Therefore, if crossover occurs, two inheritances are formed by appending

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the first m representative bits of one parent and the rest $M - m$ bits of the other one and vice versa, otherwise parents are becoming the new generation members by themselves. The last step is mutation, performed by randomly choosing and inverting defined number of representative bits of randomly chosen chromosomes from $\boldsymbol{P}(i+1)$. The mutation process is extremely important because it provides a genetic diversity, but this is also in correlation with the number of mutation bits. In other words, large number of mutation bits leads to algorithm degradation. Finally, $\boldsymbol{P}(i)$ matrix is updated with $\boldsymbol{P}(i+1)$ and the process will be repeated until the individuals converge towards the optimal solution or maximum generation number is achieved. The entire GA can be summarized through **Algorithm 3**.

The complexity of this method mainly depends on the population size J, generation number N_g, and the number of representative bits M. Therefore, the complexity is given by

$$comp\_GA = O\big(N_g J(2M+1)\big). \quad (17)$$

Where N_g and M are constant values, while J depends linearly on the number of users K. Accordingly, GA complexity increases linearly with the number of users in NOMA system.

Algorithm 3: Genetic Algorithm

1. Define population size J, representative bits Number M, generations number N_g, crossover probability p_c, mutation probability p_m and generation gap G
2. Initialize first generation $\boldsymbol{P}(0)$, $terminal = F$, and $counter = 0$
3. **WHILE** $terminal = F$ **DO**
4. $counter = counter + 1$
5. Use (15) to calculate fitness function values
6. Store fitness function values in vector $\boldsymbol{f}$ from (16)
7. Use Elitism and “Roulette wheel” to perform Selection process of individuals number defined by G
8. Perform Crossover with p_c probability to produce the rest of individuals in population
9. Perform mutation with p_m probability
10. Update $\boldsymbol{P}(i) \leftarrow \boldsymbol{P}(i+1)$
11. **IF** $\boldsymbol{f}$ converges **OR** $counter = N_g$ **THEN**
12. $terminal = T$
13. **ENDIF**
14. **ENDWHILE**

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4. Numerical Results

To investigate the performance of all power allocation methods considered in this work, the Python programming language is used to implement simulations. Performances of all schemes are averaged over 1000 channel and noise realizations. Furthermore, the total number of users was set to be 2 and 3. Although that number could be greater than 3, it has been shown in [2] that there is a tradeoff between system performance and the number of users sharing frequency in NOMA group. The common parameters for each figure in continuation are $\Delta = 0.01, c_1 = 1, c_2 = 0.6, c_3 = 0.4$ and noise variance $\sigma_n^2 = 0.1$.

In Fig. 1, the sum of all user bitrates is demonstrated by using all power allocation schemes versus total transmission power P_{tot} in a 2-user NOMA system. As expected, the sum of bitrates increases with the total transmission power for each method. However, the QoS method clearly provides the highest performance while Channel inversion method referred as CSI provides the lowest. Performance of both AI methods (Q-learning and GA) are comparable, and their values are in between the QoS and CSI performance values. Therefore, AI methods do not provide the highest sum of bitrates.

In Fig. 2, the objective is changed to the minimum bitrate of the system. Consequently, GA achieves the highest minimum bitrate while Q-learning is the second best. This approach improves the system quality of service in the way that the minimum performance user is maximized while others maintain optimal (maximum) values.

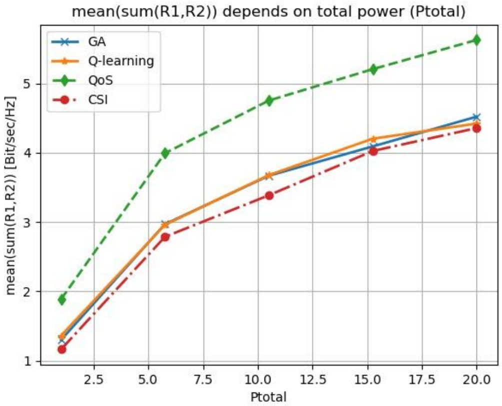

Fig. 1 Average sum of user bitrates for all power allocation methods in a 2-user NOMA system with total transmit power P_{tot}

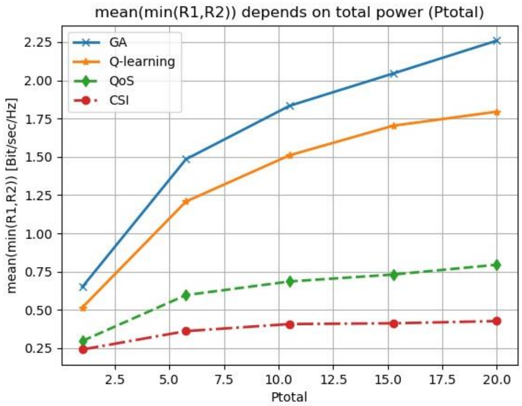

Fig. 2 Average minimum of user bitrates for all power allocation methods in a 2-user NOMA system with total transmit power P_{tot}

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In Fig. 3 and Fig. 4, the results are extended when 3 users are considered. Similar to a 2-user system, the same trend is provided by all power allocation methods. However, Q-learning is not taken into consideration due to its exponential time complexity, however; the same performance trend as the 2-user system is expected.

Fig. 5 shows individual user bitrates obtained by GA and CSI methods in a 3-user NOMA system. This figure emphasizes the advantages of Artificial intelligence methods over the theoretically based methods. Namely, bitrates computed by GA are almost the same, what was the initial goal. On the other side, that is not the case for the CSI method, where the bitrate of one user is extremely high while of the other one is extremely low. Mentioned fact is of great importance while maintaining the overall quality of the system.

Fig. 6 represents the complexities of Artificial intelligence algorithms with the total number of K users in NOMA system. As expected, the complexities of both methods increase with the number of system users. However, Q-learning provides less complexity than GA when the number of users is less than or equal to 3. Moreover, as the number of users grows Q-learning is becoming more complex what explains its exponential complexity nature, while GA maintains its complexity in the linear domain as described in Section 3.

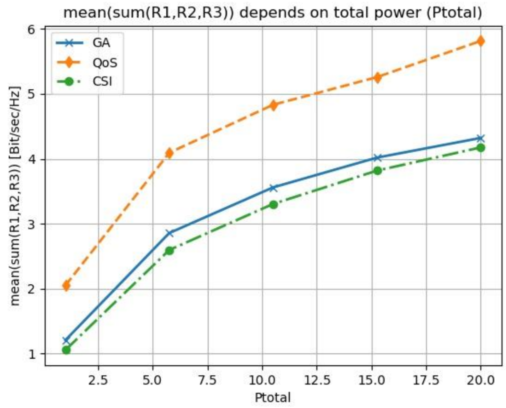

Fig. 3 Average sum of user bitrates for GA, QoS and CSI power allocation methods in a 3-user NOMA system with total transmit power P_{tot}

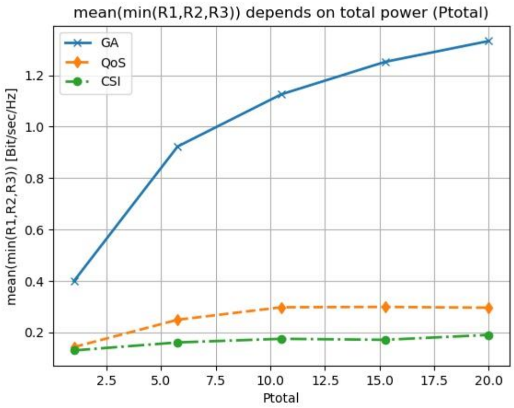

Fig. 4 Average minimum of user bitrates for GA, QoS and CSI power allocation methods in a 3-user NOMA system with total transmit power P_{tot}

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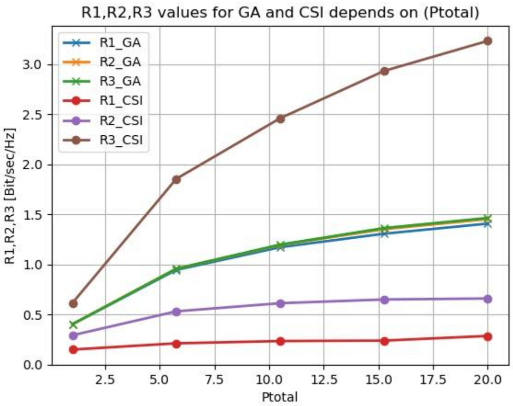

Fig. 5 Individual rates of all users for 3-user NOMA system performed by GA and CSI with total transmit power P_{tot}

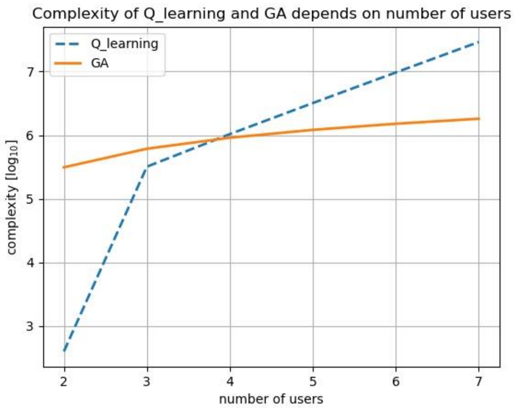

Fig. 6 Genetic algorithm and Q-learning complexities with the total number of system users

5. Conclusions

The allocation of transmission powers among users in the downlink NOMA system has been considered. Consequently, the power optimization problem is formulated to maximize the minimum bitrate of overall system. Apart from the theoretical methods, Q-learning and Genetic algorithm are applied in order to solve the appointed problem. Firstly, the transformation steps from NOMA system to GA and Q-learning components are described. Simulation results demonstrate that the Artificial intelligence methods outperform the existing theoretically based power allocation methods. Furthermore, the algorithm complexities are also considered, and it turns out that GA has less complexity in comparison with Q-learning algorithm with the increase in total number of users. Therefore, it can be concluded that GA is more suitable over Q-learning in optimal power allocation application since it provides less complexity and better performance.

In this work, a simple model is considered since NOMA system is assumed to be a single-cell and single-antenna. Therefore, power allocation is the only parameter to be optimized. Thus, the future work should consider more complex systems as well as AI algorithms improvement in order to achieve better performance.

วารสารวิชาการเทคโนโลยีอุตสาหกรรม (The Journal of Industrial Technology)
ISSN (online): 2697-5548
DOI: 10.14416/j.ind.tech.2024.04.003

6. Acknowledgement

I. Jovanovic was supported by the IAESTE scholarship to join the Department of Electronic Engineering Technology, KMUTNB as a visiting scientist during September to October 2022.

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ISSN (online): 2697-5548
DOI: 10.14416/j.ind.tech.2024.04.003

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