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Joint Channel and Power Allocation Based on Generalized Nash Bargaining Solution in Device-to-Device Communication

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ABSTRACT In this paper, a new generalized Nash bargaining framework is proposed for joint channel and power allocation in device-to-device (D2D) communication underlying cellular networks. In the considered system, cellular users (CUs) must jointly determine to share radio resources with D2D users (DUs) and to charge the DUs accordingly. The proposed framework aims to maximize the overall throughput of the communication system by guaranteeing the minimum rate of each CU and proportional fairness and efficient power allocation among the CUs and DUs. To make this NP-hard problem more tractable, it is decomposed into two sub-problems: channel assignment and power allocation. First, an optimal channel assignment strategy is derived using a max-weighted max-flow algorithm. Then, the optimal power allocation strategy for both DUs and CUs is analyzed using the Lagrangian multiplier method. Numerical results are presented to show the throughput performance characteristics of different resource allocation solutions. Comparisons between the proposed and traditional policies show the significant effect of fairness on the transmission performance.

INDEX TERMS D2D communication, channel assignment, power allocation, generalized Nash bargaining solution.

I. INTRODUCTION

The ongoing growth in bandwidth-intensive wireless applications has been motivating the deployment of novel wireless cellular technologies [1]–[4]. Device-to-device (D2D) communication underlying cellular networks, which emerged in the 3GPP LTE standardization process, is gaining significant research attention as a promising solution for boosting the capacity of tomorrow's cellular systems [5]. D2D communication supports direct communication between two adjacently located cellular users, known as D2D user pairs (DUs), while bypassing the base station (BS). Such DUs must efficiently co-exist with conventional cellular users (CUs) who are directly served by the BS. D2D communications can significantly improve network throughput, spectrum efficiency, and reduce transmission delay [6]. However, in order to benefit from D2D, one must overcome many technical challenges in terms of resource management, mode selection, and interference mitigation [7]–[13].

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In particular, D2D communication suffers from intra-cell interference due to spectrum sharing between DUs and other CUs, as shown in Fig. 1. When a pair of DUs communicate with one another using cellular down-link resources, they can cause significant interference to nearby CUs. Meanwhile, a pair of DUs communicating with each other using cellular up-link resources will experience interference from the simultaneous up-link transmission between BS and CUs. To overcome this obstacle, there have been a significant number of recent works that devise resource allocation algorithms (see [14], [15] for a detailed survey).

A. RELATED WORKS

In [16], the authors analyze the throughput optimization over the shared D2D resources while meeting prioritized cellular service constraints. However, this work is based on a centralized approach. In [17], joint resource allocation and power control in a D2D network are investigated using fractional programming, and a tractable iterative solution is proposed which can improve the energy and resource usage efficiency. The authors in [18] integrate D2D communication with the

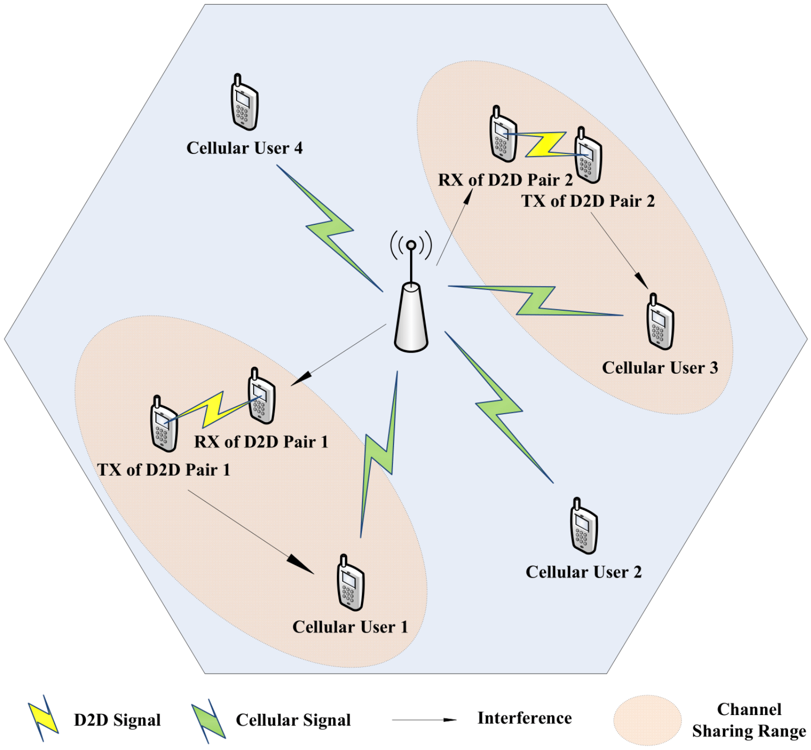

FIGURE 1. D2D communication underlying a down-link cellular network.

mobile edge computing to further enhance the computation capacity of the cellular system. Reference [19] has recourse to the deep reinforcement learning and a distributed spectrum allocation framework is devised, which requires only the neighbor users' information. In [20], the authors utilize the mean-field game theoretic framework and propose a power control policy based on the Lax-Friedrichs scheme and the Lagrange relaxation. Reference [21] formulates the data communication problem as a mixed-integer non-linear program. Considering the difficulty of the original problem, it is relaxed to a convex one and a heuristic method based on greedy task assignment is then developed. Aimed at maximizing the utility of all D2D pairs, [22] models the system as a combinational optimization problem, which is solved by a learning framework based on Markov chain.

Resource allocation in D2D networks has also attracted significant recent attention using game theory [23]–[28]. For instance, in [24], an efficient auction algorithm is proposed to improve the performance of D2D communications, in which DUs are viewed as players competing for channel resources. A joint scheduling and resource allocation scheme is proposed by developing a Stackelberg game model for D2D communication in [25]. A combinatorial auction-based resource allocation mechanism is developed to improve system performance for D2D communication [26]. A Bayesian coalitional game framework is developed to analyze the spectrum sharing problem between multiple D2D links and a cellular network with multiple operators [27]. In these existing models [24]–[27], the commonly used fairness criterion for wireless resource allocation is max-min fairness, in which the performance of the user with the worst channel condition is maximized. However, this criterion penalizes the users with channels of good condition, which can be detrimental to the overall system performance.

It is well known that efficiency and fairness are two important yet somewhat contradictory indices in the game theory. Apparently, while ensuring fairness, the max-min fairness criterion can cause a decline in efficiency, which is not desirable. To overcome this drawback, one can adopt the notion of the Nash bargaining solution (NBS) [29] to determine the contribution of the user resources and allocate the service capacity to each user efficiently and fairly. In the NBS, which can yields an outcome of Pareto efficient and fair, the minimal requirements for all users have been satisfied first, then the rest of the resources are allocated proportionally to users according to their channel characteristics (e.g., fading) and traffic characteristics (e.g., delay requirements). Considering the disagreement performance of each player, the NBS ensures that all participating users will receive a outcome not worse than his/her standalone performance. Due to these advantages, the NBS has been used to analyze the spectrum access and sharing problems [30]–[32], and mobile Internet access problem [33]. For instance, in [34], the authors utilize NBS to decide the service deployment so as to meet the Quality of Service (QoS) of the fog computation in Internet of Things. In [35], NBS is applied to the power control in distributed multiple-radar architecture underlying wireless communication system. The authors propose an algorithm with low computational complexity and prove its convergence to a Pareto-optimal equilibrium. Reference [36] studies the D2D communication in 5G network using NBS. The D2D pairs are divided into two groups based on their pairwise distances. The NBS are introduced to allocate resource blocks (RBs) to D2D pairs whose pairwise distances are longer than some threshold to improve the utilization of cellular up-link spectrum.

Despite the delicate balance NBS can achieve between efficiency and fairness among many players, there is still a disadvantage. In the NBS, each player is treated equally, that is, the same decision on different players will bring about the same outcome. However, in some actual situations, the players can have different impacts on the results. Take the D2D communication in cellular networks as an example, the CUs, which communicate with the base station, usually enjoy higher priority in communication than D2D pairs, which transmit data to each other directly. This means that the limited resources should be allocated to the CUs first while meeting the basic constraints of all users. To model this characteristic, Generalized Nash Bargaining Solution (GNBS) can be introduced, which employs bargaining factors to distinguish players with different priorities. In the GNBS, a player having a higher bargaining factor will be a candidate to obtain an advantage in the final outcome of resource allocation. As a variant of the NBS, the concept of a GNBS can further improve the fairness and efficiency by assigning different bargaining factors to different players [37]. The work in [38] uses the GNBS for allocating the bandwidth between applications with general concave utilities. The authors study the impact of concavity on the allocation and present computational methods for obtaining fair allocation in a general topology, based on a dual Lagrangian approach and on semi-definite programming. The authors in [39] adopt the GNBS to analyze the multimedia resource management. It is shown that a significant improvement in the system performance is achieved by the choice of the bargaining factors, which allow more importance to be given to some users. In [40], the authors propose a bargaining game scheme that is used to achieve an optimal rate control solution for spatial scalable video coding.

B. OUR CONTRIBUTIONS

Although CUs occupy higher levels of priority in the spectrum resource than D2D users, little work has been done to analyze how the GNBS can be utilized to improve the outcome of resource allocation in D2D communication. We study the channel assignment and power allocation mechanism in D2D communication underlying the cellular network using GNBS. To be more specific, the main contribution of this paper is summarized as follows:

- We formulate the resource allocation in D2D communication with the help of GNBS in which the CUs are the players that must decide on how to share the resource with the DUs. Such resource sharing is done in a way to maximize a payoff function that captures the overall throughput of the entire cellular system by introducing a bargaining factor.
- We show that the problem can be cast as a mixed integer optimization problem, which is known to be NP-hard. To make it more tractable, we divide the original optimization problem into two sub-problems: channel assignment and power allocation.The first sub-problem is posed as a pairing process of CUs and DUs, which is solved using the max-weighted max-flow algorithm. Based on the assigned channels, a Lagrangian multiplier method is applied to optimize power allocation. We prove that the result obtained from the two sequential algorithms is exactly the optimal solution for the original problem.
- We present extensive numerical results to illustrate the corresponding characteristics of our proposed joint channel assignment and power allocation scheme.

The rest of this paper is organized as follows. Section II introduces the considered D2D system model and formulates the corresponding optimization problem based on GNBS. The design and analysis of algorithms for channel assignment and power allocation are described in Section III. The numerical results are presented in Section IV. Finally, we conclude this paper in Section V.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. SYSTEM MODEL

Consider the down-link of a wireless cellular network with a single BS b located at the center of the cell. In this network, C CUs and D DUs are uniformly distributed in the cell, and we have $C \geq D$. The sets of the CUs and the DUs are denoted by $\mathcal{C} = \{1, 2, \ldots, C\}$ and $\mathcal{D} = \{1, 2, \ldots, D\}$ respectively. We consider a fully loaded cellular network scenario such as in [28], [41], in which there exists C orthogonal down-link channels that can be shared by CUs and DUs. In other words, C active CUs occupy the C orthogonal channels in the cell and there exists no additional available spectrum. Let $\boldsymbol{p}_C = [p_1, p_2, \ldots, p_C]$ be the vector of downlink power allocation strategies of all CUs. Let $\boldsymbol{P} = [p_{ij}]$ be the $C \times D$ power allocation matrix of DUs, where p_{ij} denotes the allocated transmission power of DU j on the channel that belongs to CU i. In addition, we assume the BS has the perfect channel state information (CSI) of all the links, and both CUs and DUs have their minimum quality-of-service (QoS) requirements in terms of the signal-to-interference-plus-noise-ratio (SINR).

If two DUs communicate directly by reusing the channel of an existing CU, which is known as the reuse mode, spectrum efficiency can be further improved [10]. However, interference between the D2D pair and its co-channel CU will occur. To reduce the interference to the CUs, each DU can only occupy at most one existing CU's channel. Meanwhile, one CU's channel can be shared at most by one D2D pair. To indicate whether a DU occupies a single channel, a binary indicator c_{ij} is defined as follows: If CU i shares its channel with DU j, $c_{ij} = 1$; otherwise, $c_{ij} = 0$. The channel assignment strategy is captured by a $C \times D$ matrix $\boldsymbol{C} = [c_{ij}]$. In the reuse mode, the SINR of CU i when it experiences interference by D2D pair j can be given by:

$$\xi_i = \frac{p_i g_{bi}}{\sigma_N^2 + p_{ij} g_{ij}^I}, \tag{1}$$

where g_{bi} is the channel gain between BS b and CU i, and g_{ij}^I denotes the channel gain between the transmitter of D2D pair j and CU i. σ_N^2 is the power of the additive white Gaussian noise (AWGN). Meanwhile, the SINR of D2D pair j when reusing the down-link channel of CU i can be given by:

$$\xi_{ij} = \frac{p_{ij} g_j}{\sigma_N^2 + c_{ij} p_i g_{bj}^I}, \tag{2}$$

where the channel gain between D2D pair j is g_j, and g_{bj}^I is the channel gain between BS b and the receiver of D2D pair j. The transmission rate of CU i, $i = 1, 2, \cdots, C$, is then given by:

$$r_i = \log_2 (1 + \xi_i), \tag{3}$$

while the transmission rate of DU pair j on channel i, is then given by:

$$r_{ij} = c_{ij} \log_2 \left(1 + \xi_{ij}\right). \tag{4}$$

For clarity, we let vector $\boldsymbol{r_C} = [r_1, r_2, \ldots, r_C]$ and matrix $\boldsymbol{R} = [r_{ij}]$ be the transmission rate of CUs and DUs, respectively. Based on (4), the total transmission rate of DU j is given by:

$$r_j = \sum_{i=1}^{C} r_{ij}. \tag{5}$$

B. PROBLEM FORMULATION BASED ON GNBS

As has been noted, in the reuse mode, the spectrum efficiency of the total communication system can be further improved [5]. To strike a balance between efficiency and fairness, we use the GNBS to formulate the problem of resource allocation in cellular networks. But first, a mathematical description of GNBS is necessary.

In the primary settings of GNBS, there are more than one player competing for limited resources. Each player has a flexible need and some satisfaction with the acquisition of resources. Given an allocation strategy, each player will get certain amount of resources and a corresponding payoff, measuring its satisfaction. For this problem, the basic need or constraint of each player must be satisfied, which reflects the fairness, and the solution should aim to maximize the total utility - the sum of payoffs of all players, which shows the efficiency.

Considering the specific problem studied in this paper, take each CU as a player, so there are C players competing for communication resources altogether. The payoff of each player is modeled as its transmission rate attained by negotiation among players $U_i(c_{ij}, p_i, p_{ij}) = \sum_{j=1}^{D} c_{ij} \log_2 \left(1 + \frac{p_i g_{bi}}{\sigma_N^2 + p_{ij} g_{ij}^I}\right)$. Our goal is to maximize the total utility of the cellular links while satisfying the QoS constraints by properly matching each D2D link with a CU and coordinating their power on the associated RB. In the actual communication system, there is usually a minimal transmission rate for each CU, denoted by μ_i^0. Then, the optimization problem using GNBS is given by

$$\max_{\boldsymbol{C},\boldsymbol{P}} \sum_{i=1}^{C} \alpha_i \ln \left(\sum_{j=1}^{D} c_{ij} \log_2 \left(1 + \frac{p_i g_{bi}}{\sigma_N^2 + p_{ij} g_{ij}^I}\right) - \mu_i^0 \right) \tag{6}$$

$$\text{s.t.} \sum_{j=1}^{D} c_{ij} \leq 1, \ \sum_{i=1}^{C} c_{ij} \leq 1, \quad \forall i, j, \tag{6a}$$

$$\sum_{j=1}^{D} \sum_{i=1}^{C} c_{ij} p_i \leq P_{CU}, p_i > 0, \quad \forall i, j, \tag{6b}$$

$$0 \leq p_{ij} \leq P_{max}, \ \forall i, j, \tag{6c}$$

$$\frac{p_i g_{bi}}{\sigma_N^2 + p_{ij} g_{ij}^I} \geq \epsilon \beta_i, \quad \forall i, j, \tag{6d}$$

$$\frac{p_i g_{ij}}{\sigma_N^2 + c_{ij} p_{ij} g_{ij}^I} \geq \beta_i, \quad \forall i, j, \tag{6e}$$

$$c_{i,j} \in \{0, 1\}, \quad \forall i, j, \tag{6f}$$

where bargaining factor α_i, $i \in \{1, 2, \cdots, C\}$ is a normalized weighting factor, i.e., $\alpha_i \geq 0$, $\sum_{i=1}^{C} \alpha_i = 1$. Note that if $\alpha_i = 1, i = 1, 2, \cdots, C$, then the GNBS is reduced to the traditional Nash bargaining solution (NBS), which provides a unique and fair Pareto-optimal operation point under the Nash axioms [29], [42]. As previously mentioned, bargaining factors are introduced to assign different players with different priorities. The higher the bargaining factor, the higher the payoff achieved by a game player, which denotes that it allows the maximization to become more biased towards the player having a higher bargaining factor. In general, the priority of CUs' communication requirement is higher than the DUs', which means that the limited communication resource should preferably be allocated to the CUs to satisfy their communication quality. As for the meaning of the constraints, (6a) ensures that the resource of an existing CU can be shared by at most one D2D pair, and meanwhile it indicates that a D2D pair shares at most one existing CU's resource. P_{CU} and P_{max} denote the maximum transit power of D2D pair and CUs respectively. Constraints (6b) and (6c) guarantee that the transmit powers of D2D pairs and CUs are within the maximum limit, which are used for reducing the complicated interference environment brought by the D2D communications. We assume that the minimal SINR requirement of CUs is β_i, $i = 1, \ldots, C$. We set a constant ϵ as the interference margin threshold, which can be decided for specific situations. Constraints (6d) and (6e) represent the QoS requirements of CUs and D2D pairs respectively. Constraints (6f) means c_{ij} are binary 0–1 discrete variables. Further, p_i and p_{ij} are continuous variables, thus the problem (6) is a mixed integer optimization problem, which is NP-hard.

Based on [10], the optimization problem (6) consists of two layers. The inner one is power allocation, denoted by p_i and p_{ij}, $\forall i \in C, j \in D$, and determines the optimal transmit powers of CUs and DUs. The outer one is channel assignment, denoted by binary variables c_{ij}, $\forall i, j$, and determines the optimal channel matching. Fortunately, the two layers can be decoupled. Therefore, we can decompose the problem into two sub-problems and then solve them respectively to obtain the optimal solution.

III. OPTIMIZATION ALGORITHMS OF CHANNEL AND POWER ALLOCATION

In this section, we solve the two sub-problems derived from the original problem (6) individually. First, the channel assignment problem is solved by a max-weighted max-flow algorithm to decide which channel each DU should share with the CUs. After that, the Lagrangian multiplier method is used to find the power allocation of CUs. Finally, we show that the solution obtained by these two sequential algorithms is the optimum of the original problem.

A. CHANNEL ASSIGNMENT ALGORITHMS

For the channel assignment sub-problem, we first introduce two concepts: unit earnings and system earnings. Based on (1), a unit earning is denoted as $\varphi_{ij} = \frac{g_{bi}}{g^I_{ij}}$, which reflects that a larger φ_{ij} leads to a higher transmission rate for the CUs, with fixed powers p_i and p_{ij}. Here, we construct the $C \times D$ unit earnings matrix $\mathbf{\Phi} = [\varphi_{ij}]$. The system earnings are then given as

$$\sum_{j=1}^{D} \sum_{i=1}^{C} c_{ij}\varphi_{ij}, \tag{7}$$

which is the aggregation of the unit earnings. Unit earnings reflect whether the occupied channel condition is good for every DU. Therefore, maximizing system earnings (7) implies optimizing the channel assignment, which is the objective function of the channel assignment sub-problem satisfying the constraint (6a).

From constraint (6a), we can see that every CU can share channels with no more than one DU and every DU can occupy only one channel. Thus, we transform the channel assignment sub-problem into a user matching problem. CUs are allocated in the exclusive channel. DUs have a corresponding weight on every channel that reflects the channel condition, called the unit earnings, and search for the optimal CU match to maximize the total weight, called the system earnings. Here, we solve the channel assignment sub-problem using a max-weighted max-flow algorithm, which is shown in Algorithm 1. In order to maximize system earnings, the algorithm constantly selects the maximal unit earnings and updates the unit earnings matrix, which results in optimal channel assignment because it constantly seeks the current optimal solution.

Algorithm 1 Channel Assignment Algorithm

```
Initialization : Let C, D, g_bi, g^I_ij, set the matrix C = 0,
    Φ = [φ_ij], where φ_ij = g_bi/g^I_ij.
Construct a weighted bipartite graph Φ
if no augmenting chain exists then
    while ∀j ∈ N(i) do
        Find out the maximal value φ'_ab in Φ = [φ_ij]
        Set corresponding element c_ab = 1 in the channel
            assignment matrix C = [c_ij]
        Update the unit earnings matrix Φ = [φ_ij] by setting
            φ_aj = 0, j = 1, ··· , K and φ_ib = 0, i = 1, ··· , C
    end while
else
    Find the one that has the minimum weight;
    Add it to the initial flow and treat the new flow as a
        new initial flow;
end if
Obtain the optimal channel assignment policy C* = [c*_ij]
```

B. POWER ALLOCATION ALGORITHM

For the power allocation sub-problem, we need to consider not only the minimal transmission rate requirement, which is satisfied by the QoSs of CU, but also the channel condition. Then, the power allocation of all users can be divided into two parts: DU power allocation and CU power allocation. For DUs, their power is restricted by the maximum transmit power. There is no interactional influence among all DUs because these channels are the orthogonal channels in the cell. However, DUs will cause interference to CUs sharing the same channel, which results in the performance degradation of CUs. Hence, considering the minimal transmission rate of CUs, we set the interference margin threshold for the power of the DUs, described in (6d) and (6e). For the CUs, their powers are allocated by the BS. These CUs compete for power, as to improve the transmission rate on their channels as much as possible. Based on the allocated channel, the Lagrangian multiplier method is applied to allocate power for the underlying CUs.

Based on the optimal assigned channel strategy obtained from Algorithm 1, the optimal power allocation strategy of DUs is derived as follows: the optimal power allocation strategy of DUs is $\boldsymbol{P^*} = [p^*_{ij}]$, where $p^*_{ij} = \min\{p^{max}_{ij}, P_{max}\}$, and $p^{max}_{ij} = \frac{(\epsilon-1)\sigma_N^2}{g^I_{ij}}$, $\forall i, j$. Then, we can see that DUs infinitely improve their transmission power if there are no power constraints. Therefore, considering the minimal transmission rate of CUs, an interference margin threshold ϵ needs to be introduced to manage the interference, which could determine the maximal transmission rate of DUs given the

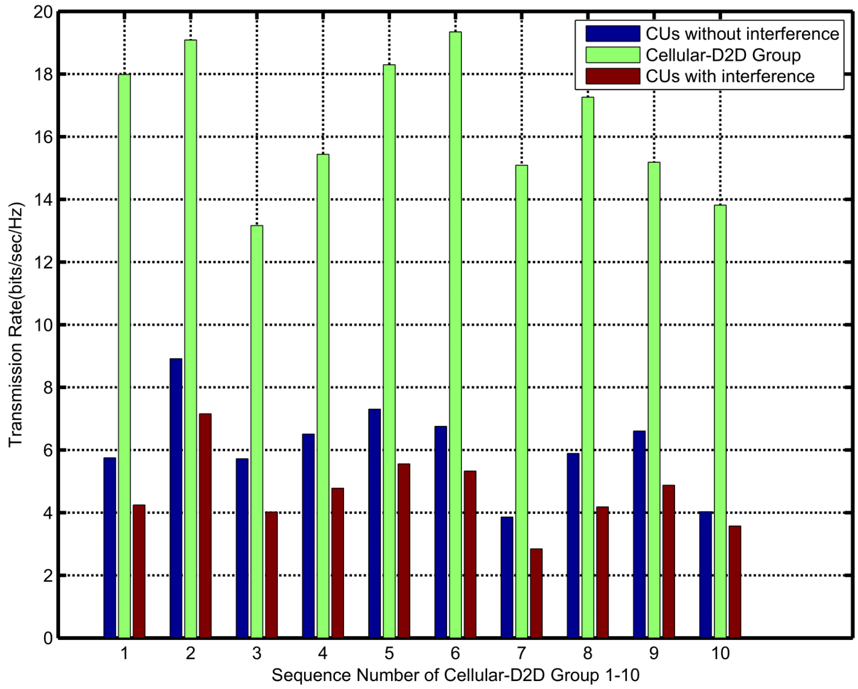

FIGURE 2. Transmission rate of CUs sharing the channels with and without DUs, and the cellular-D2D group.

requirements of the minimal CU transmission rate. Based on the assigned channel and power allocated to the DUs, the Lagrangian multiplier method is used to solve the optimal CU power problem, which is shown in Algorithm 2. In the following, we define DU j and the corresponding CU as cellular-D2D group j. The following result is given as:

Theorem 1: The optimal power allocation strategy of the underlying CUs is $\boldsymbol{Q}^* = [q_j^*]$, where q_j^* given by:

$$q_j^* = \Lambda\left(c_{ij}^*, p_{ij}^*, \alpha_j\right). \tag{8}$$

Here, Λ denotes an implicit function given by (13), (14) in Appendix A with parameters $c_{ij}^*, p_{ij}^*, \alpha_j$.

Proof: The proof is presented in Appendix A. ∎

According to the above analysis, the optimal transmission rate of CUs and DUs are given by, respectively:

$$r_i^* = \log_2\left(1 + \frac{p_i^* g_{bi}}{\sigma_N^2 + \sum_{j=1}^{D} c_{ij}^* p_{ij}^* g_{ij}^I}\right), \quad \forall i; \tag{9}$$

and

$$r_j^* = \sum_{i=1}^{C} c_{ij}^* \log_2\left(1 + \frac{p_{ij}^* g_{ij}}{\sigma_N^2 + p_i^* g_{bj}}\right), \quad \forall j. \tag{10}$$

C. JOINT ANALYSIS OF THE TWO ALGORITHMS

As has been discussed, the origin optimization problem (6) is NP-hard and thus it is not desirable to solve it directly. We notice that, its three kinds of optimal variables – $c_{i,j}$ indicating the channel assignment of DUs, p_i deciding the power allocation for CUs, $p_{i,j}$ representing the power allocation for DUs – can be decoupled into two groups.

Algorithm 2 Power Allocation Algorithm Based on Lagrange Multipliers Method

Initialization : let C, D, set $\boldsymbol{P} = [p_{ij}] = \mathbf{0}$, and $\boldsymbol{Q} = [q_j] = \mathbf{0}$, $\boldsymbol{C}^* = [c_{ij}^*]$ is the optimal channel assignment matrix based on Algorithm 1, and ϵ is the interference margin threshold.
if $c_{ij} = 1$ **then**
  if $P_{\max} \leq \frac{(\epsilon-1)N_0}{g_{ij}^I}$ **then**
    $p_{ij}^* = P_{\max}$
  else
    $p_{ij}^* = \frac{(\epsilon-1)N_0}{g_{ij}^I}$
  end if
end if
if $c_{ij} = 1$ **then**
  $q_j^* = \Lambda\left(c_{ij}^*, p_{ij}^*, \alpha_j\right)$ by Lagrange multipliers method with Kuhn-Tucker's Theorem (KKT conditions).
end if
Obtain optimal power allocation of DU p_{ij}^* and CU q_j^*.

Then, the optimization problem is solved by two algorithms – channel assignment with variables $c_{i,j}$ and power allocation with variables $p_i, p_{i,j}$. Although this approach can give a solution, it is natural to ask whether the result obtained by these two algorithms is the optimal solution of the origin problem. We have the following theorem.

Theorem 2: The proposed solution of the joint channel assignment and power allocation is the optimization solution of problem (6).

Proof: The proof is presented in Appendix B. ∎

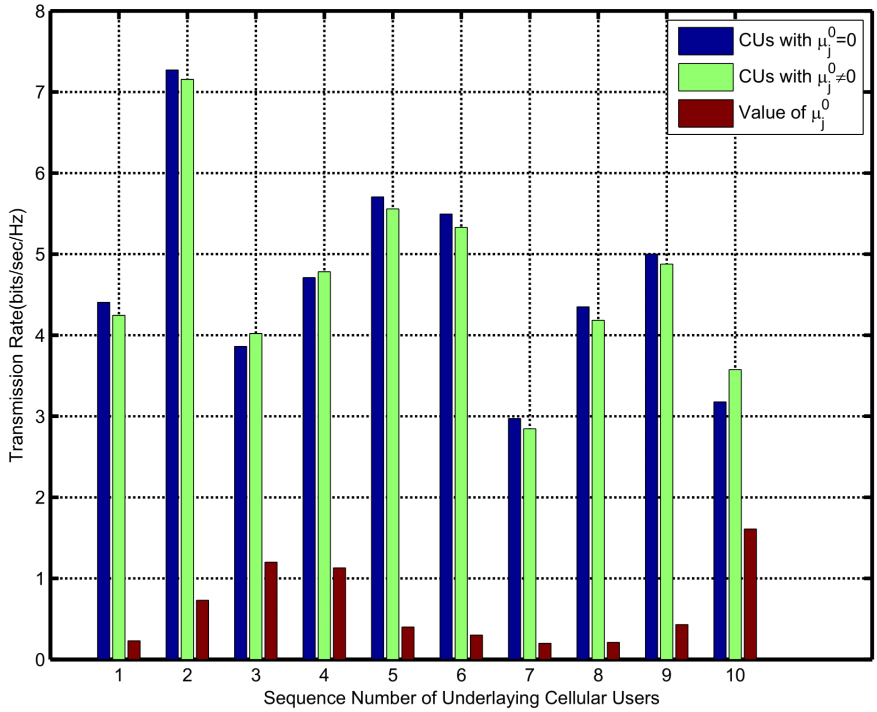

FIGURE 3. Transmission rate comparison for different weighting factors.

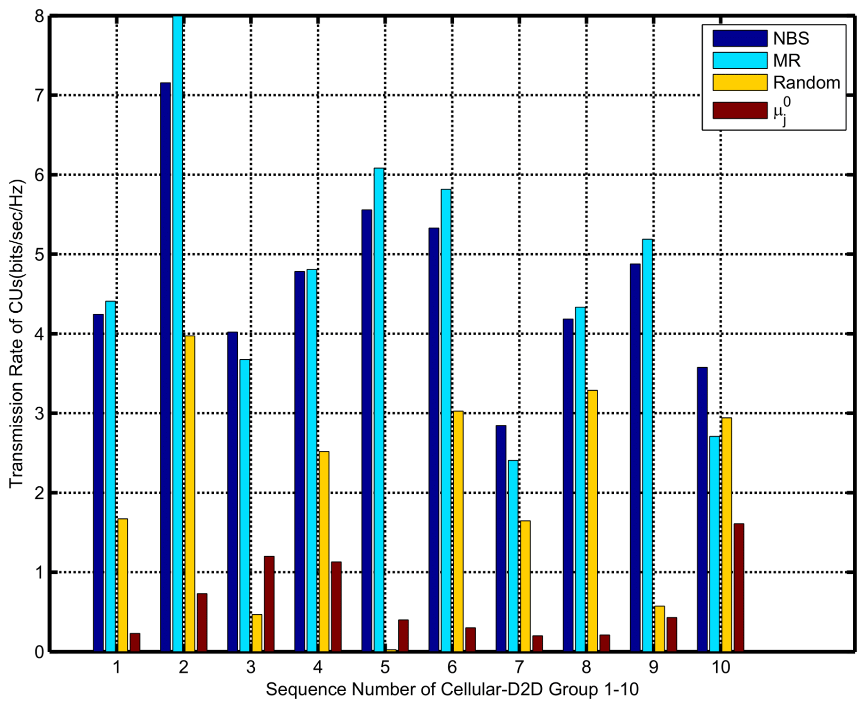

FIGURE 4. Transmission rate of CUs based on GNBS, MR, and random allocation algorithms.

IV. NUMERICAL RESULTS

A. SIMULATION SETTINGS

In this section, we consider a single cell communication system with a coverage radius of 500 m. Let $D = 10$, $C = 15$, and the CUs and DUs be randomly distributed in the cell. The distance between the D2D transmitter and its receiver is less than 50 m. Let the channel bandwidth be 180 kHz. The total power of the underlying CUs is 33 dBm. The maximal power of the D2D links is 23 dBm, and the noise spectral bandwidth is -174 dBm/Hz. As different weighting factors can effectively induce different payoffs for the players, we select three types of weighting factors for different preferences in

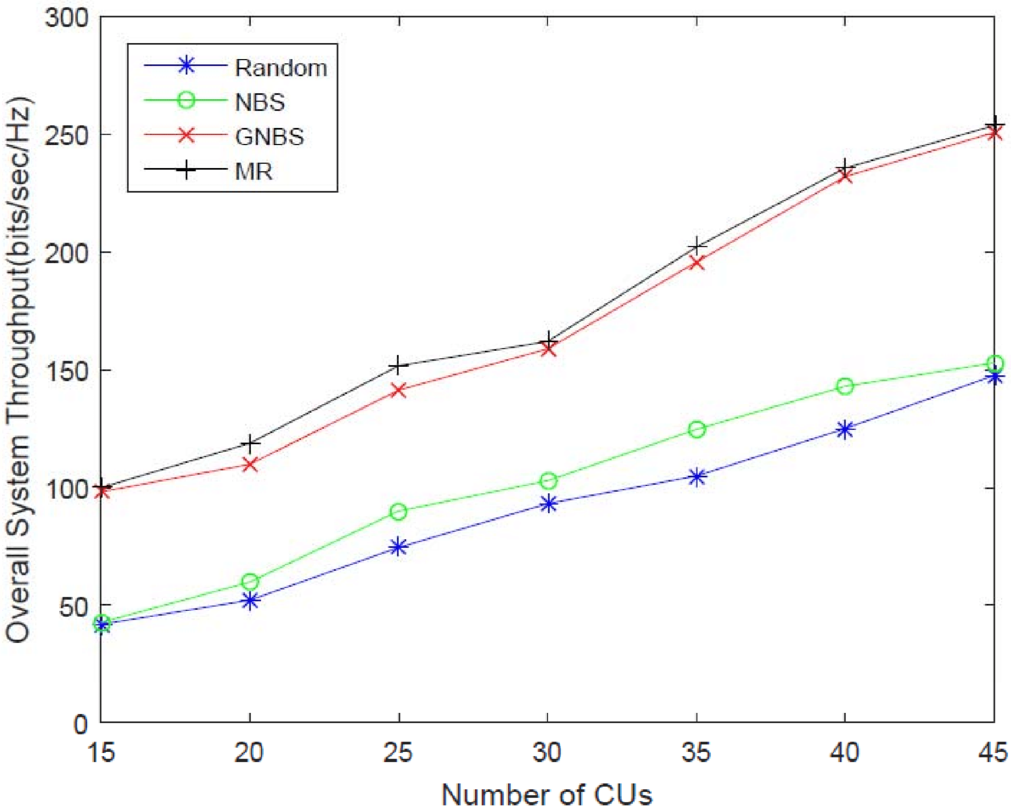

FIGURE 5. Sum rate comparison of the GNBS, NBS, and random algorithms.

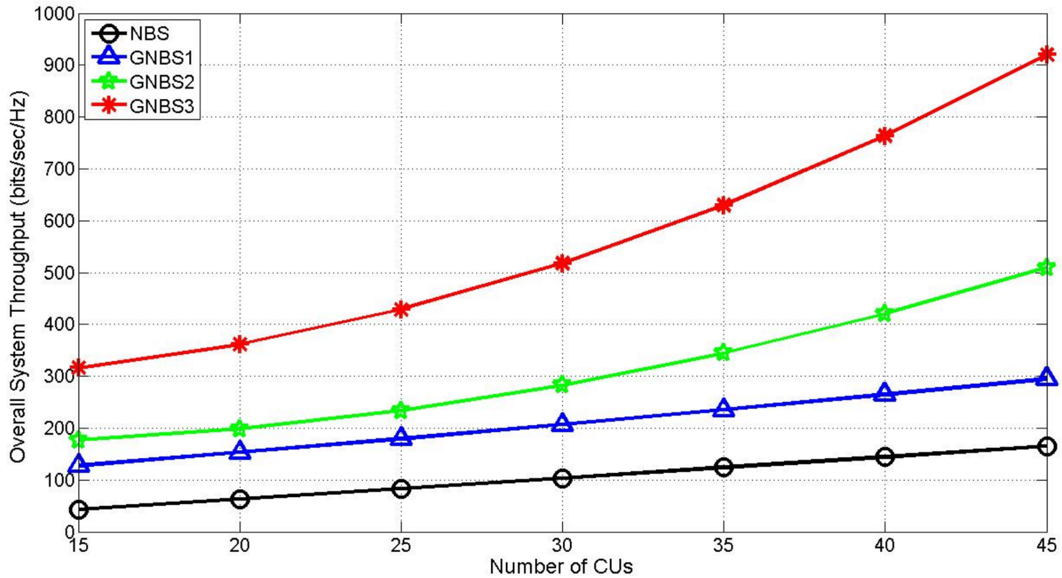

FIGURE 6. The total throughput for the different weighting factors.

the following simulations: i) $\alpha_j = 1/D$, i.e., the traditional bargaining problem emphasizing fair resource allocation; ii) $\alpha_j = \frac{u_j^0}{\sum_{j=1}^{D} u_j^0}$, which allocates more resources to the player who is eager for more transmission bandwidth, thus achieving more payoff; and iii) $\alpha_j = \frac{\sum_{i=1}^{C} c_{ij} \frac{g_{ei}}{g_{ij}^I}}{\sum_{j=1}^{D} \sum_{i=1}^{C} c_{ij} \frac{g_{ei}}{g_{ij}^I}}$, which indicates that game players who own better channel conditions can obtain a greater payoff.

B. SIMULATION RESULTS

Fig. 2 shows the transmission rate of CUs sharing the channels with and without DUs, and the transmission rate of cellular-D2D group. Here, the CUs and DUs sharing the

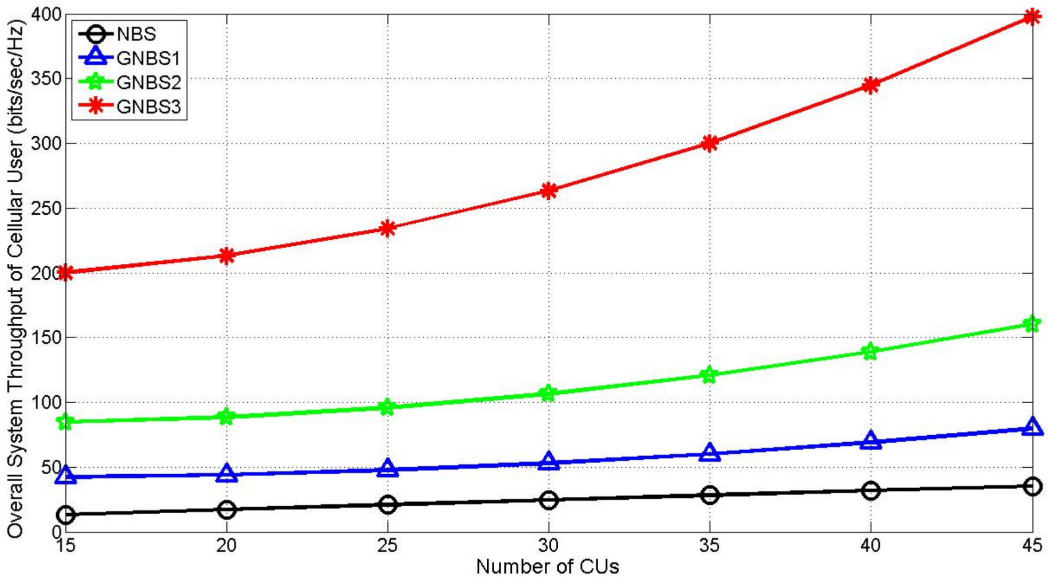

FIGURE 7. The total throughput of the CU for the different weighting factors.

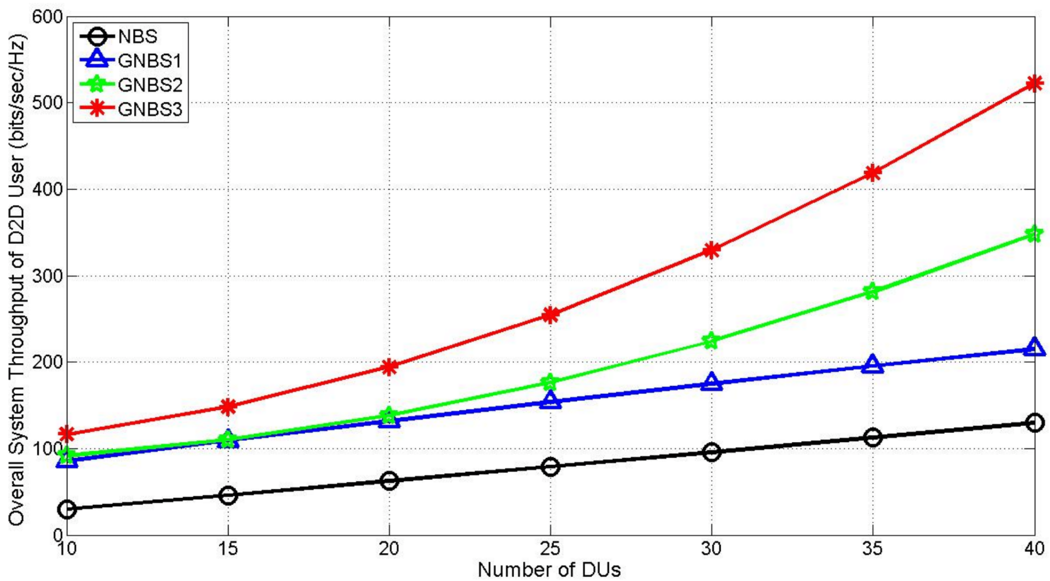

FIGURE 8. The total throughput of the DU for the different weighting factors.

channels under the fixed total power of CUs and maximal power constraints of DUs, i.e., $P_{max} = 23$ dBm and $P_{CU} = 33$ dBm. In the figure, it is clear that when DUs share the channels with CUs, the transmission rate of the CUs degrades because of the interference of DUs (red and blue bars shown in Fig. 2). However, the results of the cellular-D2D group imply that D2D communication can improve the transmission rate significantly; the total sum rate of the communication system (green bar) is shown in Fig. 2.

The effects of weighting factors in the proposed GNBS algorithm are shown in Fig. 3; here, μ_j^0 denotes the minimal transmission rate requirement of CUs $j = 1, 2, \cdots, 10$. Fig. 3 shows that traditional NBS returns relatively fair resource allocation results. These are nearly the same as the results based on GNBS with minimal transmission rate constraints. Considering the channel conditions, the GNBS obtains a better sum rate performance, but with the loss of fairness.

In Fig. 4, we compare the transmission rate of the proposed algorithm with other related allocation mechanisms, such as maximal rate (MR) and random allocation, based on the same channel and CU power constraints. The results show that the proposed GNBS algorithm achieves better fairness than the MR algorithm, which denotes that the gap between

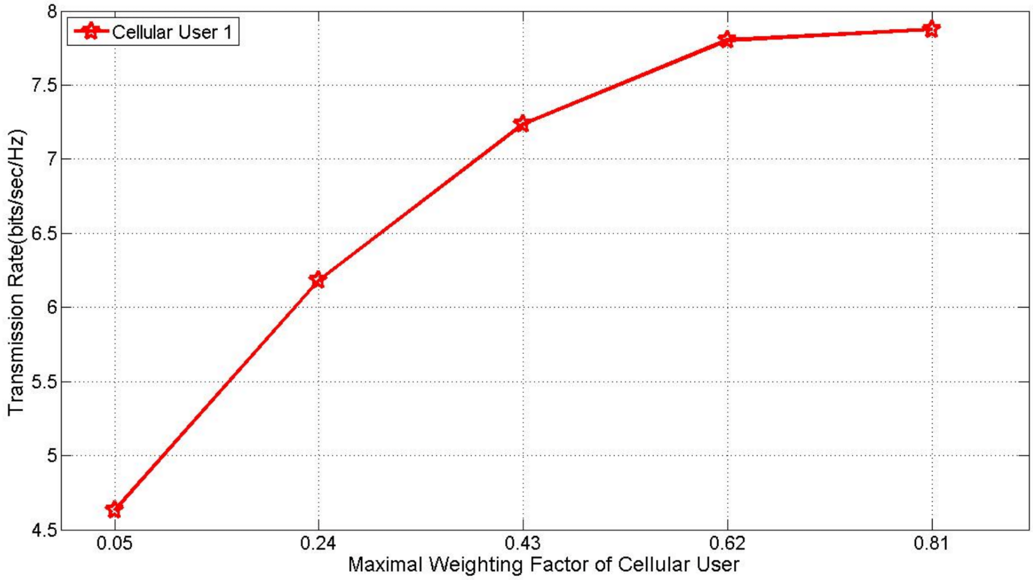

FIGURE 9. The throughput of CU1 with the maximal weighting factors.

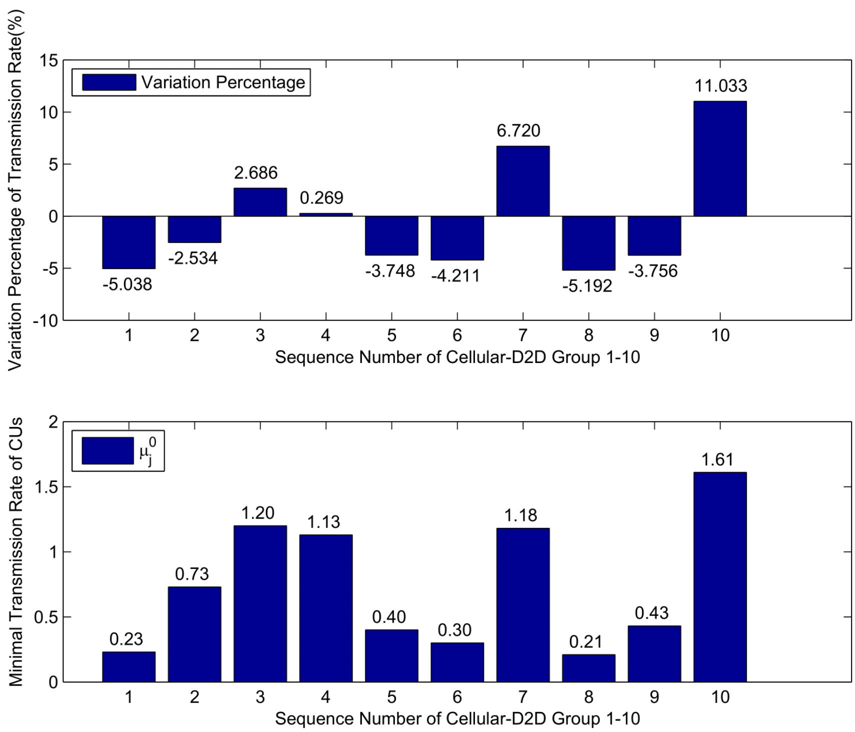

FIGURE 10. Performance variation percentage of CUs, as shown in the upper image, under the minimal transmission rate requirement u_j^0, as shown in the lower image.

the different cellular-D2D groups in the proposed algorithm is smaller than that in MR algorithm. Moreover, these two algorithms have nearly the same sum rate. However, it is evident that the random allocation algorithm is the worst in comparison; for this algorithm, the transmission rates of some CUs approach zero because the minimal transmission rate requirement (such as for groups 3, 8, and 10) has not been considered. The CUs in group 2 obtains a considerably high transmission rate.

Fig. 5 shows the sum rate comparison among GNBS, NBS, and random allocation algorithms. The results show that the GNBS algorithm has a better sum rate than traditional NBS and random allocation algorithms, which verifies that the GNBS algorithm can maintain fairness while also improving the sum rate.

Figs. 6-8 compare the throughput resulting from the proposed approach, under different weighting factors. Here, the weighting factors of NBS, GNBS1, GNBS2, and GNBS3 are $\frac{1}{D}$, $\frac{\sum_{i=1}^{C} c_{ij} \frac{g_{ei}}{g_{ij}^I}}{\sum_{j=1}^{D}\sum_{i=1}^{C} c_{ij} \frac{g_{ei}}{g_{ij}^I}}$, $\frac{\sum_{i=1}^{C} c_{ij} \frac{g_{ei}}{g_{ij}^I}}{\sum_{j=1}^{D}\sum_{i=1}^{C} c_{ij} \frac{g_{ei}}{g_{ij}^I}}$, and $\frac{\sum_{i=1}^{C} c_{ij} \frac{g_{ei}}{g_{ij}^I}}{\sum_{j=1}^{D}\sum_{i=1}^{C} c_{ij} \frac{g_{ei}}{g_{ij}^I}}$, respectively. Although the different weighting factors have all better sum rate than traditional NBS, the improvement is not very high. This verifies that the GNBS algorithm can only maintain the fairness of all users, with no emphasis on improving the overall throughput. This result also has been further verified in the following figures.

To highlight the role of the weighting factors, we considered a scenario in which only one user's weighting factor is increased while the other users' weighting factors are all equal. For example, suppose that the number of the CU equals to 20, the weighting factors of user 1 are 0.05, 0.24, 0.43, 0.62, 0.81. The weighing factors corresponding to the other users are 0.05, 0.04, 0.03, 0.02, 0.01. The result is shown in Fig. IV-B. From this figure, we can see that the throughput of the user increases as the weighting factor increases. Different from the NBS algorithm, the GNBS algorithm not only improves the overall throughput, but also maintains the fairness of all of the users by the weighting factors.

Fig. 10 shows the direct effect of the minimal transmission rate requirement u_j^0 on the CU transmission rate. The positive percentage of the upper image in Fig. 10 corresponds to the higher minimal transmission rate of CUs, while the negative percentage corresponds to the lower minimal transmission rate of the CUs, according to the minimal transmission rate requirement shown in the lower image in Fig. 10. Furthermore, a higher absolute percentage value reflects a more adjustable effect, as cellular-D2D group 10 shows.

V. CONCLUSION

In this paper, we propose a joint channel assignment and power allocation algorithm between the CUs and DUs in D2D communication underlying cellular networks. The cooperation between the CUs and DUs is modeled as a GNBS such that each DU is expected to benefit from cooperating with the CUs that have a minimal transmission rate, which is a NP-hard problem. To make the problem more tractable, we decompose it into two sub-problems: channel assignment and power allocation. Furthermore, we propose a matching framework to assign channels. In addition, the optimal power allocation scheme is developed using the Lagrangian multiplier method. Our numerical results show that the proposed scheme achieves good performance on the sum of the system rate. For future work, we will evaluate the performance of the proposed scheme in a more generalized scenario with multiple cells.

APPENDIX A
PROOF OF THEOREM 1

Based on the optimal channel assignment $C_{C\times K}^* = [c_{ij}^*]$, there is an optimal channel i^* for any DU j. With the allocated channel and power of DUs, the CU power allocation problem is given by:

$$V(q_j) = \sum_{j=1}^{K} \alpha_j \ln\left(\log_2\left(1+\frac{q_j g_{bi^*}}{\sigma_N^2 + p_{i^*j}^* g_{i^*j}^I}\right) - \mu_j^0\right),$$

$$s.t. \sum_{j=1}^{K} q_j \le P_{CU}; \quad p_i \ge 0, \quad \forall i,j, \tag{11}$$

The Lagrangian function of problem (11) is then given by:

$$L(q_j,\nu) = \sum_{j=1}^{K} \alpha_j \ln\left(\log_2\left(1+\frac{q_j g_{bi^*}}{\sigma_N^2 + p_{i^*j}^* g_{i^*j}^I}\right) - \mu_j^0\right) - \nu\left(\sum_{j=1}^{K} q_j - P_{CU}\right), \tag{12}$$

where $\nu \ge 0$ is a Lagrange multiplier. Based on the Lemma 1 in ref. [33], and using KKT conditions, for the identified c_{ij}^* and p_{ij}^*, we have

$$\frac{\delta L}{\delta q_j} = \alpha_j \cdot \frac{g_{bi^*}}{\ln 2 \times \left[\log_2\left(1+\frac{q_j g_{bi^*}}{\sigma_N^2 + p_{i^*j}^* g_{i^*j}^I}\right) - u_j^0\right]} \cdot \frac{1}{\sigma_N^2 + p_{i^*j}^* g_{i^*j}^I + q_j g_{bi^*}} - \nu = 0. \tag{13}$$

Meanwhile,

$$\frac{\delta L}{\delta \nu} \to \sum_{j=1}^{K} q_j = P_{CU}. \tag{14}$$

Based on (13) and (14), we can obtain q_j^*, ν^*. Thus, we finally obtain the optimal power allocation strategy $Q_K^* = [q_j^*]$.

This completes the proof of **Theorem 1**.

APPENDIX B
PROOF OF THEOREM 2

Let c_{ij^*} be the optimal channel assignment solution for CU i. Namely, DU j^* is the optimal match for CU i while maximizing the payoff of game players, which is satisfied with the following formulation:

$$V(p_i) = \sum_{j=1}^{K} \alpha_j \ln\left(\sum_{i=1}^{C} c_{ij} \log_2\left(1+\frac{p_i g_{bi}}{\sigma_N^2 + p_{ij} g_{ij}^I}\right) - \mu_j^0\right) \tag{15}$$

Further, $\varphi_{ij} = \frac{g_{bi}}{g_{ij}^I}$ is the maximal unit earnings of CU i. Based on the optimal channel and power allocation strategy, the payoff of game player i is U_{j^*}. An apagoge is used to prove the conclusion, as follows.

Let us suppose that there is an global optimal solution $c_{ij'}$ that is different from c_{ij^*}, where $j^* \ne j'$. Furthermore, global optimal power solution p_i' is derived from the utility function in formula (15) relative to global optimal channel solution $c_{ij'}$. Therefore, $U_{j^*} < U_{j'}$. Because the power allocation of DUs is independent in manner, the optimal DU transmission power is $p_{ij}^* = \min\{p_{ij}^{max}, P_{max}\}$. We next discuss the optimal CU solution in two different cases, $p_{ij}^* = p_{ij}^{max} = \frac{(\epsilon-1)\sigma_N^2}{g_{ij}^I}$ and $p_{ij}^* = P_{max}$.

When $p_{ij}^* = P_{max}$, to the optimal solution $c_{ij'}$ and p_i', the payoff of player i is given by $U_{j'} = \log_2\left(1 + \frac{p_i' g_{ei}}{\sigma_N^2 + P_{max} g_{ij'}^I}\right)$. In addition to optimal solution c_{ij^*} and p_i^*, the payoff of game player i is given by $U_{j^*} = \log_2\left(1 + \frac{p_i^* g_{ei}}{\sigma_N^2 + P_{max} g_{ij*}^I}\right)$. Furthermore, for optimal solution c_{ij^*} and p_i', the payoff of game player i is given by $U_{j^*}' = \log_2\left(1 + \frac{p_i' g_{ei}}{\sigma_N^2 + P_{max} g_{ij*}^I}\right)$.

Based on the joint channel and power allocation algorithm, for CU i, there is maximal unit earnings $\varphi_{ij^*} = \frac{g_{bi}}{g_{ij^*}^I}$, and $g_{ij^*}^I > g_{ij'}^I$. Hence, $U_{j^*}' > U_{j'}$. It is obvious that $U_{j^*} \geq U_{j^*}'$. We then have $U_{j^*} \geq U_{j^*}' > U_{j'}$, which contradicts $U_{j^*} < U_{j'}$. Therefore, there is no other optimal solution except for the one derived from the joint channel and power allocation algorithm used to achieve greater payoff of the game player, where $p_{ij}^* = P_{max}$.

For the global optimal solution $c_{ij'}$ and p_i', c_{ij^*} and p_i^*, and c_{ij^*} and p_i', when $p_{ij}^* = \frac{(\epsilon-1)\sigma_N^2}{g_{ij}^I}$, the payoff of player i is given by $U_{j'} = \log_2\left(1 + \frac{p_i' g_{ei}}{\epsilon\sigma_N^2}\right)$, $U_{j^*} = \log_2\left(1 + \frac{p_i^* g_{ei}}{\epsilon\sigma_N^2}\right)$, and $U_{j^*}' = \log_2\left(1 + \frac{p_i' g_{ei}}{\epsilon\sigma_N^2}\right)$, respectively. Hence, $U_{j^*} \geq U_{j^*}' = U_{j'}$, which contradicts $U_{j^*} < U_{j'}$.

Therefore, there is no other optimal solution except for the solution derived from the proposed algorithm to achieve a greater payoff for a game player when $p_{ij}^* = \frac{(\epsilon-1)\sigma_N^2}{g_{ij}^I}$.

This completes the proof of **Theorem 2**.

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