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Interference Management Based on Meta-Heuristic Algorithms in 5G Device-to-Device Communications

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Abstract: Device-to-Device (D2D) communication is an emerging technology that is vital for the future of cellular networks, including 5G and beyond. Its potential lies in enhancing system throughput, offloading the network core, and improving spectral efficiency. Therefore, optimizing resource and power allocation to reduce co-channel interference is crucial for harnessing these benefits. In this paper, we conduct a comparative study of meta-heuristic algorithms, employing Genetic Algorithms (GAs), Particle Swarm Optimization (PSO), Bee Life Algorithm (BLA), and a novel combination of matching techniques with BLA for joint channel and power allocation optimization. The simulation results highlight the effectiveness of bio-inspired algorithms in addressing these challenges. Moreover, the proposed amalgamation of the matching algorithm with BLA outperforms other meta-heuristic algorithms, namely, PSO, BLA, and GA, in terms of throughput, convergence speed, and achieving practical solutions.

Keywords: 5G; bee life algorithm; bio-inspired algorithms; device-to-device communication; genetic algorithm; particle swarm optimization; power control; resource allocation

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1. Introduction

Over the past decade, there has been a significant increase in the number of mobile users, resulting in a substantial burden on the cellular network core [1,2]. To keep pace with advancements in cellular networks, extensive research is being conducted to drive the evolution toward the next generation of cellular networks, commonly referred to as the fifth generation (5G) and beyond (5GB) [3,4]. These technologies aim to alleviate network strain, improve energy and spectral efficiency, reduce latency, and increase throughput. One promising solution to achieve these benefits is Device-to-Device (D2D) communication [5,6]. D2D communication technology enables direct communication between devices without involving the Base Station (BS) [7,8]. It is characterized by three primary modes, as illustrated in Figure 1: relay mode, controlled direct mode, and uncontrolled direct mode. In relay mode, User Equipment (UE) extends the coverage of the BS by acting as a relay between a receiver and the BS or between two devices [9]. In controlled direct mode, the transmitter and receiver communicate directly, but under the control of the BS. Conversely, in uncontrolled direct mode, the transmitter and receiver communicate directly without any intervention from the BS or other devices [10].

The classification of D2D communication is based on the spectrum utilized, as depicted in Figure 2. The first category is the licensed class, also known as in-band, where the communicating devices operate in either overlay or underlay mode using licensed spectrum

resources. The second category is the unlicensed class, or out-band, which can be further divided into two types depending on the involvement of the Base Station (BS): controlled by the BS or operating without BS control [11].

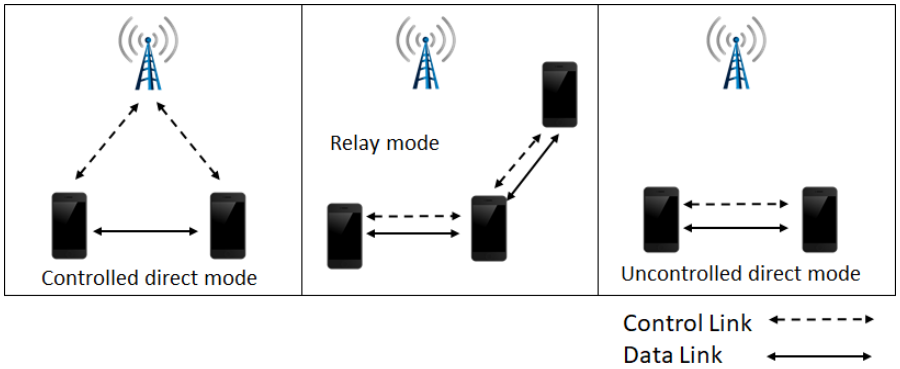


Figure 1. D2D communication modes.

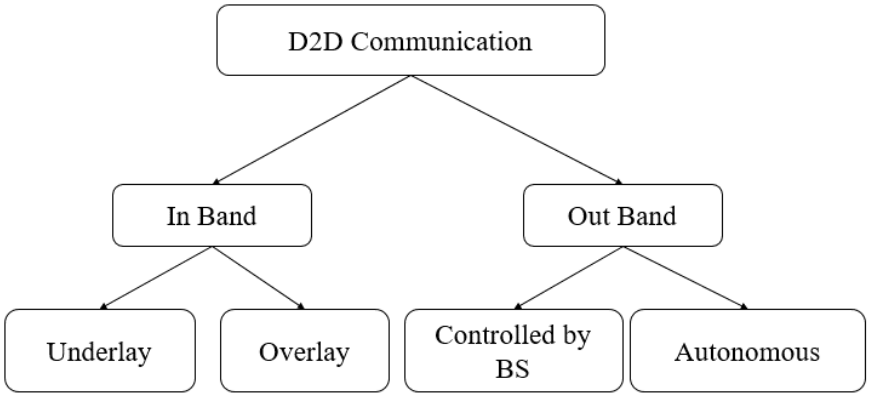


Figure 2. Classification of D2D communication.

D2D communication technology encounters numerous challenges, including interference mitigation, mode selection, resource allocation, and power control. Another critical issue is ensuring security, especially in the exchange of sensitive information [12,13]. The effective allocation of resources and adept power management are key to reducing interference and maximizing overall network throughput [14]. This research investigates the application of meta-heuristic algorithms to address the challenges of channel allocation and power control in 5G cellular networks.

The field of D2D communication technology confronts several challenges, including interference mitigation, mode selection, resource allocation, and power control [15,16]. A significant concern is the aspect of security, especially when exchanging sensitive information [13,17]. Efficient resource allocation and effective power management lead to reduced interference and maximized overall throughput [14,18]. This research investigates the efficacy of meta-heuristic algorithms in addressing channel allocation and power control challenges in 5G cellular networks.

In practical scenarios, uplink spectra are often less utilized compared to downlinks. Therefore, optimizing channel utilization can be achieved by sharing uplink resources [19,20]. Additionally, the Base Station (BS) can more effectively manage interference from D2D pairs when they reuse the uplink. This led us to consider dividing uplink channels between D2D and cellular communications.

In this paper, we focus on D2D communication underlaid within cellular networks, where multiple D2D users can communicate over uplink channels concurrently used by a single cellular communication in each Block of Resource (BR). Consequently, the interference is primarily between CUs and D2D users, as well as among D2D users sharing

the same channel. The objective of this study is to explore the effectiveness of various bio-inspired methods for channel and power allocation, with the goal of reducing interference and enhancing overall network throughput.

Overall, the main contributions of this study are summarized as follows:

- Focusing on Device-to-Device (D2D) communication as a key component in the advancement of cellular networks, including 5G and beyond.
- Highlighting D2D communication's potential in improving system throughput, offloading network cores, and increasing spectral efficiency.
- Emphasizing the importance of optimizing resource and power allocation to minimize co-channel interference and maximize the benefits of D2D communication.
- Conducting a comparative analysis of meta-heuristic algorithms, such as Genetic Algorithms (GAs), Particle Swarm Optimization (PSO), and Bee Life Algorithm (BLA).
- Introducing a novel combination of matching techniques with BLA for joint channel and power allocation, enhancing the optimization process.
- Demonstrating that the combined matching algorithm and BLA outperform PSO, BLA, and GA in terms of throughput, convergence speed, and practicality.
- Investigating the use of D2D communication within cellular networks, particularly over uplink channels shared with cellular communications.
- Aiming to reduce interference between Cellular Users (CUs) and D2D users, as well as among D2D users sharing the same channel.
- Seeking to enhance overall network throughput by effectively managing channel and power allocation.

1.1. Related Work

In their study, Austine et al. [14] proposed a combined algorithm integrating Genetic Algorithm (GA) and Adaptive Bat optimization for resource allocation. This algorithm outperforms other approaches, such as Ant Colony optimization and game theory, in achieving more effective solutions. The researchers in [21] introduced a solution for channel allocation using GA and Binary Particle Swarm Optimization (PSO). Their simulation results highlight GA's superiority over PSO for this specific issue. Xia et al. [22] suggested a hybrid approach combining the Simulated Annealing algorithm with PSO to avoid local optima in power control problems. The study in [23] focuses on optimizing resource efficiency in D2D communication by introducing a sharing optimization algorithm based on PSO. In [24], a PSO-based algorithm is proposed for data transmission between high-speed devices, such as Unmanned Aerial Vehicles (UAVs) [25], energy systems [26,27], indoor monitoring [28,29], smart cities [30,31], healthcare [32,33], indoor localization [34,35], etc., aiming to minimize energy consumption while maintaining minimum Quality-of-Service (QoS) requirements. Mehdi et al. [36] applied an algorithm inspired by bee flight patterns to find optimal resource allocation solutions for D2D communication. To enhance network throughput, the authors of [37] employed the Bee Life Algorithm for channel and power allocation in D2D communication. A novel approach called E-BLAD2D, which combines the Bee Life Algorithm with simulated annealing, was proposed in [38] to address the joint problem of spectral and power allocation. The research in [39] focuses on minimizing interference between D2D and cellular users to maximize network throughput, with Shamaei et al. utilizing the Poisson Point Process (PPP) to model user spatial positions and proposing a many-to-many matching approach for resource allocation. In [40], a many-to-many matching method was proposed to solve the joint power and channel allocation problem in non-orthogonal multiple-access cellular networks (NOMAs) underlaid with orthogonal multiple-access D2D communication, aiming to maximize the downlink network sum-rate. Most research on interference mitigation addresses the resource allocation and power allocation problems separately. Our approach aims to concurrently solve the channel allocation and power allocation issues, iterating between the two to find the most effective combination of allocated channels and transmission power.

1.2. Main Contribution

This paper delves into the application of meta-heuristic paradigms to the challenge of channel and power allocation in D2D communication. Our primary aim is to diminish or manage interference between cellular users and D2D pairs, thereby enhancing network throughput and accommodating a greater number of D2D users. We have formulated the problem as one of joint channel and power allocation for D2D communication and approached its resolution through various meta-heuristic paradigms. The bio-inspired algorithms employed in our study include Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Bee Life Algorithm (BLA), and a novel combination of BLA with matching theory.

The structure of this paper is outlined as follows: Section 2 introduces the system model and outlines the problem formulation. Section 3 details the joint channel allocation and power control algorithm for each of the bio-inspired methods. In Section 4, we present the emulation of these meta-heuristic algorithms along with the results obtained. Finally, Section 5 concludes the study, summarizing our findings and discussing potential avenues for future research.

2. System Model and Problem Formulation

This study examines a system comprising one BS, a certain number of communications (including 'nbC' cellular User Equipment (UE) and 'nbD' D2D pairs), as illustrated in Figure 3. We assume that D2D communications utilize uplink resources. Despite using uplink channels, D2D users encounter interference from cellular UE. In such underlay systems, D2D pairs have the capability for direct communication, while the BS oversees channel allocation and facilitates the establishment of connections between devices [20]. We represent the communications (both cellular and D2D) as follows:

$$U = [UE_1,\ UE_2,\ \ldots,\ UE_{nbC,\ UE_nbC+1},\ \ldots,\ UE_{nbr}] \tag{1}$$

In this context, UEi denotes the i-th communication among the collective of CUs and Device-to-Device (D2D) users. The spectrum is divided into K of BRs, and the set of these BRs is represented as follows:

$$BR = [br_1,\ br_2,\ \ldots,\ br_K] \tag{2}$$

We designate $A \in \{0,1\}\ nbr,\ K$, the allocation matrix, where, when $A_{i,r}$ contains 1, it signifies that the r-th resource block is being used by the i-th communication, while, when $A_{i,r} = 0$, it signifies that r-th resource block does not belong to i-th communication.

In accordance with Shannon's equation [41], we expressed the throughput on the r-th BR while used by the i-th communication as:

$$Thput(i\text{-th}) = B \log_2(1 + SINR_{ir}) \tag{3}$$

The available bandwidth is designated by B, and the signal-to-interference and noise ratio is identified by $SINR_{ir}$. The $SINR_{ir}$ is expressed as follows:

$$SINR_{ir} = \frac{G_{ii}\ P_i\ A_{ir}}{WGN + \sum_{j \in E,\ j \neq i} G_{ji}\ P_j\ A_{jr}} \tag{4}$$

where A_{ir} equals 1 if a communicating device is using a BR equal to 1 if that device (i-th) utilizes that BR (r-th) and 0 otherwise. The power of transmission used by the i-th communication is Pi. Additionally, we symbolize the White Gaussian Noise using WGN. As used in [42], we opt to use a Urban Micro System (UMi). The UMi exhibits a single small cell that contains high traffic loads and great user density in dense urban space [43],

in which the path loss model adopted is Rayleigh fading [44]. The model of path loss is expressed as:

$$PL = 36.7\log_{10}(d) \ + 22.7 + 26\log_{10}(F) \tag{5}$$

We consider i-th and j-th as transmitter and receiver, respectively. The distance between i-th and j-th is d (in meters) and F (in GHz) symbolizes the medium of the communication frequency. Thus, between the two users, the channel gain is $G_{i,j}$, expressed as [42]:

$$G_{i,j} = 10^{-PL/10} \tag{6}$$

Therefore, the expression for the throughput of cellular devices is the sum of all cellular devices:

$$CThput = \sum_{i=1}^{nbC} \sum_{r=1}^{K} B\log_2(1 + SINR_{ir}) \tag{7}$$

The throughput of every D2D user is the sum of all D2D pairs, it can be written as follows:

$$DThput = \sum_{i=nbC+1}^{nbr} \sum_{r=1}^{K} B\log_2(1 + SINR_{ir}) \tag{8}$$

The sum of (7) and (8) is the overall throughput. Thus, it is expressed by the following equation:

$$Thput = CThput + DThput \tag{9}$$

If we replace each entity with its equivalent and simplify the expression, we obtain the following equation:

$$Thput = \sum_{i=1}^{nbr} \sum_{r=1}^{K} B\log_2(1 + SINR_{i_r}) \tag{10}$$

By efficiently allocating resources and adjusting the transmission power of devices, we target the maximization of overall network throughput. The maximization problem of joint power and channel allocation is mathematically expressed as follows:

$$Max\ Thput = Max \sum_{i=1}^{nbr} \sum_{r=1}^{K} B\log_2(1 + SINR_{ir}) \tag{11}$$

Subject to:

$$P_i \leq P_{dmax}\ \forall\ i = nbC + 1 \ldots nbr \tag{12}$$

$$P_i \leq P_{cmax}\ \forall\ i = 1 \ldots nbC \tag{13}$$

$$SINR_{i,r} \geq SINR_{min} \forall\ i = 1 \ldots nbC,\ \forall r = 1 \ldots K \tag{14}$$

$$A_{i,r} \leq 1\ \forall\ i = 1 \ldots nbc,\ \forall\ r = 1 \ldots K \tag{15}$$

Constraints (12) and (13) ensure that the transmission powers P_i for both CUs and D2D pairs do not exceed their respective maximum limits, P_{cmax} and P_{dmax}. Constraint (15) stipulates that the value of $A_{i,r}$ must be either 0 or 1, signifying that each BR can be allocated to no more than one CU at a time. This is because the primary recipient of cellular communication is the BS, and if a BR is allocated to two CUs, the BS would be unable to differentiate their signals. However, a single BR can be allocated to multiple D2D pairs, as they have different receivers. Constraint (14) establishes a minimum SINR limit ($SINR_{min}$) for CUs while also allowing multiple D2D communications to share the same BR, provided that the SINR constraint is satisfied.

Finding an optimal solution to the optimization problem posed in (11), which involves numerous constraints, may not be feasible through exhaustive search due to the immense search space. To address the constrained problem of resource and power allocation, which

aims to enhance overall network throughput, we propose using bio-inspired methods. These methods have shown promising results in previous works [37,45–48]. In the following section, we will detail the bio-inspired algorithms and their application in optimizing channel and power allocation for D2D communication within cellular networks.

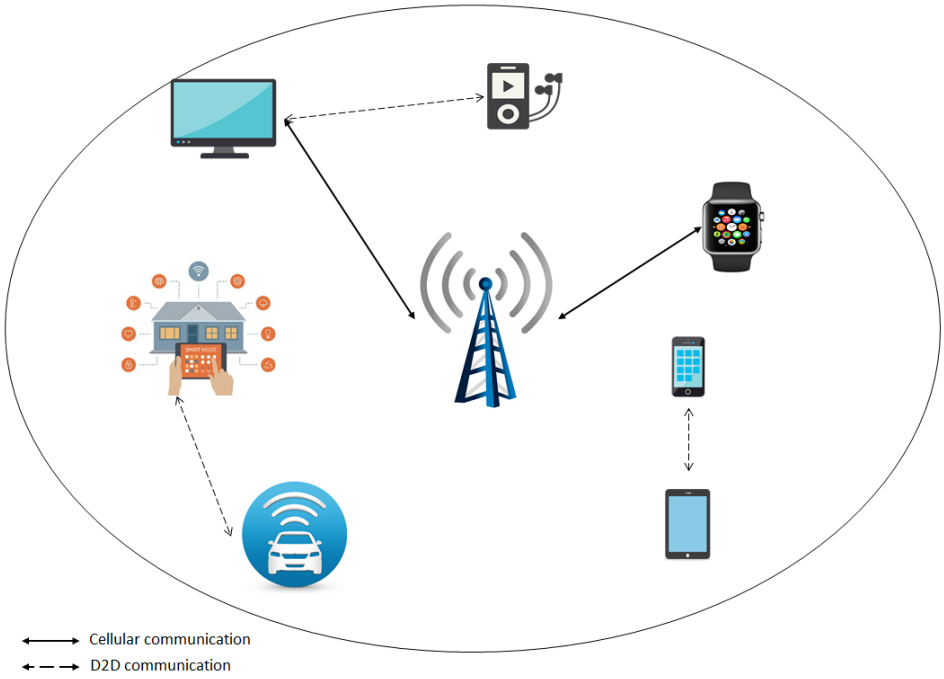


Figure 3. System illustration.

3. Bio-Inspired Algorithms

In this section, we first outline the individual representation and its corresponding fitness evaluation. Subsequently, we delve into the specifics of each bio-inspired algorithm and their implementation in optimizing power and channel allocation for Device-to-Device (D2D) communication underlaying a cellular network.

3.1. Individual Representation and Fitness

In optimization tasks, the concept of fitness refers to a mathematical function used to evaluate the performance of each candidate solution within a population. In our context, an individual is conceptualized as a specific solution encompassing a set allocation of channels and a regulated transmission power, as detailed in Table 1. Therefore, the fitness of an individual in relation to our problem is quantified based on their throughput, which can be calculated using the following formula:

$$Fitness(Bees) = \sum_{i=1}^{nbC+nbD} \sum_{r=1}^{K} B\log_2(1+SINR_{i,r}) \quad (16)$$

Table 1. Individual representation.

BR#	User Equipment (UE)	Power (P)
BR1	UE4	P4
	UE2	P2
	UE5	P5
BR2	UE1	P1
	UE6	P6
BR1	UE7	P7

3.2. Genetic Algorithm (GA)

A genetic algorithm is a method of optimization that mimics Darwin's theory of the survival of the fittest across a population of competing individuals evolving from one generation to the next. To simulate the evolutionary process of the genetic algorithm, we employ two primary operations: Crossover and Mutation [49].

3.2.1. Crossover Operation

This operation is crucial for mimicking the reproductive behavior and ensuring the diversity of solutions. Crossover involves combining genetic information from two individuals—each representing a portion of the solution—to produce offspring with novel genetic traits. The crossover threshold is denoted as Th_C. In our study, we propose an algorithm employing a two-point crossover technique. The points for slicing the chromosomes of the two parent individuals are randomly determined by selecting two communications from the total number of communications (ranging from 1 to *nbr*).

$$Individual_1 = \{UE_1, UE_2, UE_3, UE_4, UE_5, \ldots, UE_{nbr}\} \tag{17}$$

$$Individual_2 = \{UE_1, UE_2, UE_3, UE_4, UE_5, \ldots, UE_{nbr}\} \tag{18}$$

In this scenario, we randomly select the third and fifth communications for the crossover process. Consequently, the offspring will comprise three segments, potentially incorporating one or two parts from one parent and the remaining segments from the other parent. This is further elucidated as follows:

$$offerspring_j = \{UE_1, UE_2, UE_3, UE_4, UE_5, \ldots, UE_{nbr}\} \tag{19}$$

where j = 1:6.

3.2.2. Mutation Operation

Genetic mutations occasionally occur in the genes of offspring. The likelihood of such mutations is determined by a probability known as the mutation threshold (Th_M). For instance, the mutation process can be exemplified as follows: two communications within the offspring's chromosome are randomly selected, and their respective Block of Resource (BR) allocations are interchanged. This mutation process is illustrated below [50]. It is important that the two chosen communications are of the same type. If a D2D pair is selected, the counterpart with whom the BR will be exchanged should also be a D2D user, and similarly, for cellular users [51].

For our example, we select the fifth communication. The offspring will maintain the same communications, except for U_5, which will undergo the mutation process:

$$\text{Brood } = \{UE_1, UE_2, UE_3, UE_4, \boldsymbol{UE}_5, UE_6, \ldots, UE_{nbr}\} \tag{20}$$

3.3. Particle Swarm Optimization (PSO)

The notion and construction of the PSO algorithm were inspired by perceiving the social comportment of birds gathering and fish schooling. Originally in nature, a group of birds hovers in the space behind a leader who has the nearby position of nourishment. The social conduct of birds can be interpreted into algorithmic processes, as in PSO, to decipher optimization problems where the horde of birds is taken as a swarm of particles and each particle symbolizes a contender solution. The swarm of particles explores the space in certain dimensions and discovers the best way out of an optimization problem [52]. Figure 4 depicts the PSO algorithm function for the channels and power allocation in 5G D2D communication.

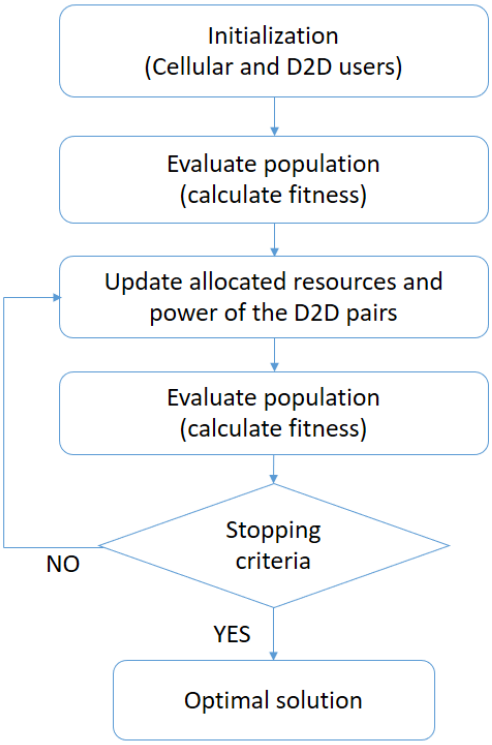


Figure 4. Particle Swarm Optimization diagram.

3.4. Bee Life Algorithm (BLA)

3.4.1. Bees in Nature

Bees engage in a very precise kind of communication characterized by two distinct forms of dances, employed during their foraging activities. The first dance, known as the circular dance, is utilized when a food source is in close proximity. Conversely, the second dance, like the symbol for infinity (∞), is performed when the food source is situated at a considerable distance. The reproductive process of bees is facilitated by the queen. The female engages in several copulations during flight, until her spermatheca becomes replete. According to the cited source [53], unfertilized eggs have the potential to develop into drones, whereas fertilized eggs have the capacity to give rise to either a worker in the hive or a queen, depending on the food quality.

3.4.2. The Bee Life Algorithm

The Bee Life Algorithm was proposed as an advanced method for optimization that has been applied to job scheduling, resource allocation, and routing optimization, and it has given good results in previous work [37,38,54]. The composition of BLA is constructed from two distinct components that are inspired by the fundamental behaviors exhibited by bees during their lifespan. The first behavior consists of reproduction in which the queen mates with many drones while hovering. Basically, this behavior is coupling, which can be modeled through a Genetic Algorithm, with Crossover and Mutation as optimization operators and that is the first part of BLA. Food foraging is the second behavior, where worker bees search the neighborhood for a source of nourishment based on two criteria: merit and amount of nutrition. This second behavior is modeled with a local search algorithm. We adopted the same Crossover and Mutation methods used in GA for reproduction. Thus, in the following, we will discuss in detail the food foraging method used in BLA for the problem at hand whereas the its pseudo code for power and resource allocation is shown in Appendix A.

3.4.3. Food Foraging

The laborers engage in a process of exploration within the local vicinity in order to identify and locate food sources of sustenance. In the context of BLA, a greedy local search strategy is employed for each worker bee (solution) to determine whether a more optimal solution exists within its local vicinity, resulting in the identification of local optimal solutions. Local search is employed to ensure the attainment of the optimal solution inside a certain region, hence mitigating the risk of overlooking superior solutions due to a failure to fully explore the vicinity surrounding a satisfactory answer. In order to achieve this objective, a random D2D pair link is selected and enhances the power of transmission to the highest level. The better-found individuals are kept; if not, we disregard them as follows:

$$\begin{array}{ll} worker = & [CU_1, CU2_2, \ldots, D2D_1, \ldots, D2D_i \\ with & P_i = x_i dBm, \ldots, D2D_n] \end{array} \quad (21)$$

$$\begin{array}{ll} Neighbor_i = & [CU_1, CU2_2, \ldots, D2D_1, \ldots, D2D_j \\ with & P_i = y_i dBm, \ldots, D2D_n] \end{array} \quad (22)$$

Figure 5 presents a diagram of the proposed algorithm based on the life of bees in nature:

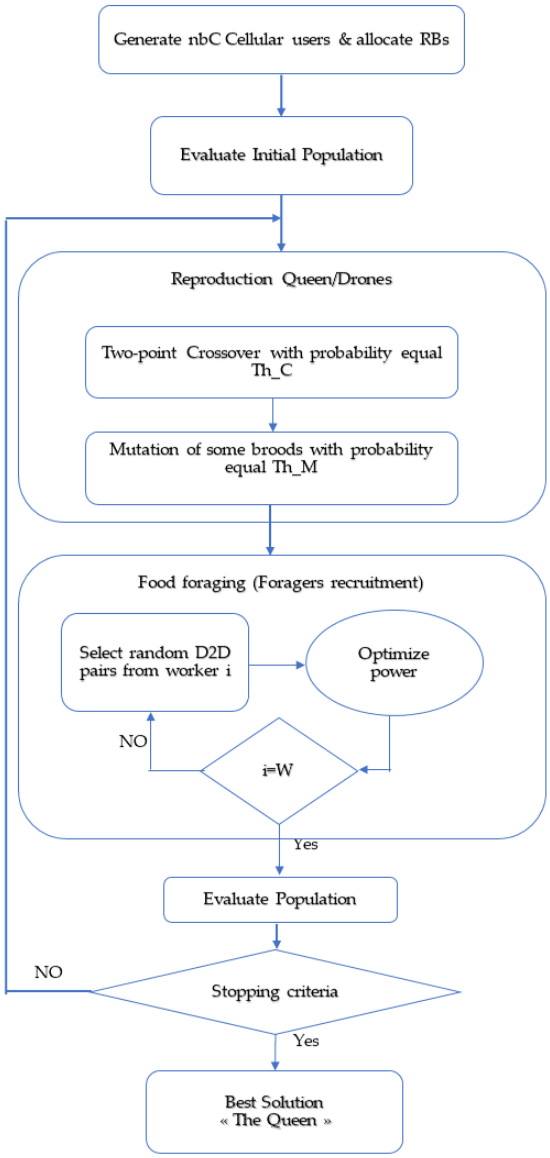


Figure 5. BLA diagram.

4. The Matching Bees Algorithm (MBA)

The algorithm utilized in this study is derived from a modified version of the BLA that incorporates enhancements to its optimization procedures. Techniques from matching theory are employed to enhance the performance of BLA [55]. The enhancement process begins by applying a one-to-many matching approach, which includes externalities in the allocation of channels. This step is specifically aimed at effectively serving D2D couples. A resource block is exclusively allocated to a D2D communication only if this allocation results in superior throughput. The MBA pseudo code for power and resource allocation are presented in Appendix B.

After establishing an improved initial population, the iterative BLA process begins, following enhancements to reproductive capabilities and food-foraging strategies. This improvement in the initial population through matching theory involves selecting a resource block that demonstrates a higher improvement in throughput compared to the initially allocated BRs.

The throughput for each pair of D2D users is calculated for every Resource Block (BR). These computed throughputs are then sorted, and the pair comprising a D2D user and BR that achieves the highest throughput is selected. This process is executed iteratively for each D2D pair. If multiple pairs achieve the maximum throughput, the selection prioritizes the resource block with the fewest D2D pairs sharing it. If more than one BR has an equal number of D2D pairs, the BR selection is made randomly. Figure 6 illustrates the Matching Bees Algorithm, incorporating comprehensive optimization operators.

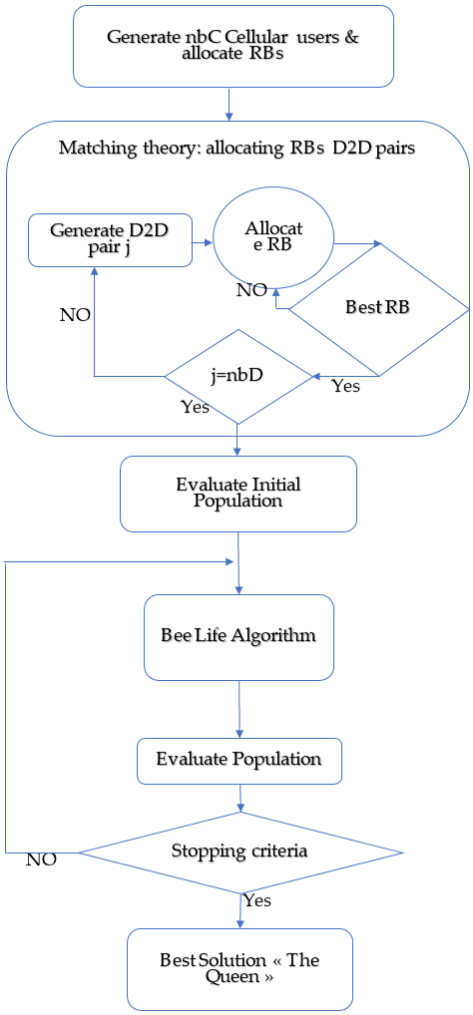


Figure 6. The MBA diagram for channel and power allocation in 5G D2D communication.

5. Simulation and Discussion

This section presents the validation of the proposed algorithms through simulation. The objective of this study was to perform a comparison analysis of the MBA algorithm and several other meta-heuristic algorithms, including GA, PSO, and BLA. The network analyzed in our simulations consists of a single cell, as illustrated in Figure 7, which provides a snapshot of the simulated system. In this depiction, D2D users are represented by red and blue stars, while cellular users are indicated by black triangles. The circle represents the macro cell, with the BS positioned at its center.

In general, the macro cell radius is commonly set at 1 km [56], as set in our simulation. The typical distance between the transmitter and receiver in a pair of Device-to-Device (D2D) users, frequently cited in numerous academic articles [57], is 50 m. The cell center acts as the central hub for our base station, which accommodates both cellular and D2D users. Additionally, with the simulation utilizing a centralized technique, the Base Station (BS) provides channel state information. A radio frequency of 2.4 GHz was employed, with the power for both communication types adjusted to be less than or equal to 23 dBm. The optimization operators and number of D2D pairs of used algorithms have been summarized in Table A1 (Appendix C).

In our simulations, the system parameters are detailed in Table 2. The population size is set at 20 individuals for all algorithms. For the BLA and MBA, the population consists of 12 Workers, 7 Drones, and 1 Queen. The Crossover operation used in this study is a two-point crossover for the MBA, BLA, and Genetic Algorithm (GA). Consequently, the number of broods produced in each mating event is 6, resulting in a total of 42 offspring in each generation.

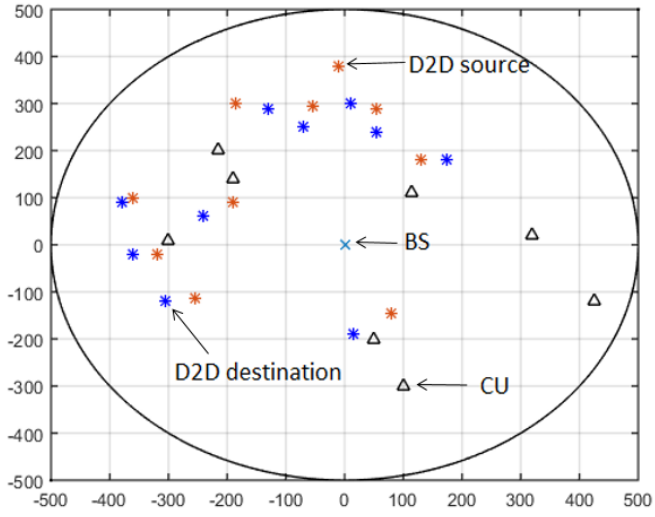


Figure 7. Snapshot of system simulation.

Table 2. Simulation parameters.

Parameters	Values
Radius of the cell	1000 m
Coverage of D2D users	50 m
WGN	−174
Max power (CU and D2D)	23 dBm
B	1 MHz
F	2.4 GHz
nbC	8
Y	42
X	20
D	7
W	12

Our findings are compared to those obtained via MBA, BLA, Particle Swarm Optimization (PSO), and GA using the same metrics as cited in [58], which are based on PSO.

5.1. Convergence of the Algorithms

The algorithms employed are characterized by their iterative nature, highlighting the importance of achieving rapid convergence. Consequently, we assess the convergence of all algorithms in two different scenarios. The first scenario involves a total of eight cellular users and ten pairs of D2D users. Moreover, the second scenario consists of twenty pairs of D2D users, while maintaining eight CUs. Each user is required to have a minimum data rate of 250 kilobits per second (kbps).

Figure 8 demonstrates that the total network throughput is lower in the first scenario compared to the second, indicating that an increase in the number of D2D pairs enhances network throughput. The Matching Bees Algorithm (MBA) achieves higher throughputs in both scenarios compared to the Biogeography-Based Algorithm (BLA), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA), and does so within a reasonable timeframe; while BLA, GA, and PSO tend to converge to local optimal solutions, MBA manages to escape these local optima and searches for a globally better solution with higher throughput.

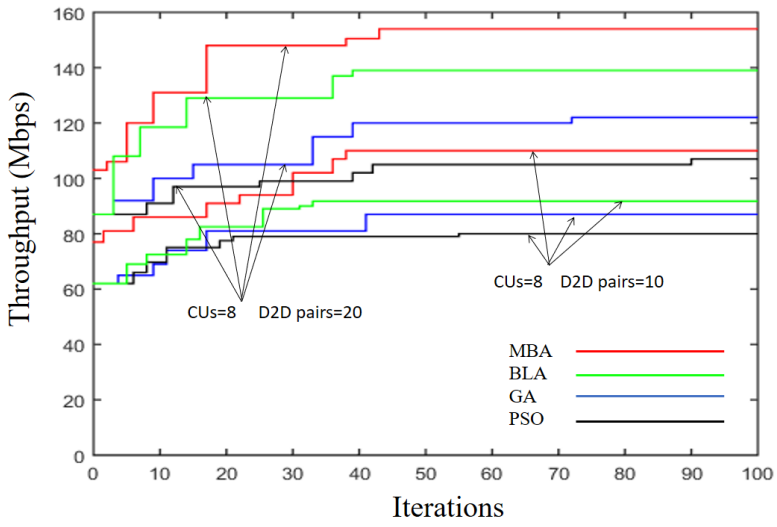


Figure 8. Convergence evaluation of simulated algorithms.

5.2. Network Performance Based on D2D Pairs Number

To understand the impact of D2D communications on network throughput, we analyzed the throughput as the ratio of D2D pair to Cellular User (CUs) increases. The number of CUs was fixed at eight, and the ratio was varied from 1 to 5 in increments of 0.5. Consequently, one to five D2D pairs share the same Resource Block (BR) for each CU. For each configuration, the simulations were conducted 50 times. Figures 9 and 10 display the throughput (cellular, D2D, and total network) achieved by the algorithms. In Figure 9, no rate requirements are established for each individual user. Moreover, as depicted in Figure 10, every user is assigned a minimum rate requirement of 250 kilobits per second (kbps).

According to Figure 9, there is a positive correlation between the number of D2D pairs and both D2D communication and network throughput. Moreover, there is a decrease in cellular throughput in relation to the increasing number of Device-to-Device pairings. The rise in the number of D2D pairs leads to a corresponding increase in interference in cellular communications. The MBA attains better throughput of all types (cellular, D2D, and network) compared to the other algorithms.

In Figure 10, it can be shown that the network throughput D2D and CUs, experiences a decline when the number of D2D to cellular communication ratio increases starting at 1.5 to

5. The primary factor contributing to this phenomenon is the imposition of a minimum rate requirement for each user, which restricts the ability of algorithms to enhance throughputs.

In the next scenario, the number of cellular users is held constant at eight throughout the next simulation, while the number of D2D pairs grows from two to four to eight to sixteen.

Figure 11 illustrates that with an increase in the number of D2D pairs, there is a corresponding rise in both network and D2D throughputs for each of the four techniques evaluated. However, as the number of D2D communications increases, the cellular throughput achieved by these techniques decreases. This decline is attributed to the enhanced interference on cellular users resulting from the higher density of D2D pairings. Notably, the MBA demonstrates a clear advantage in achieving higher throughput for cellular communications compared to the other algorithms. This advantage is also evident in the throughput for D2D communications.

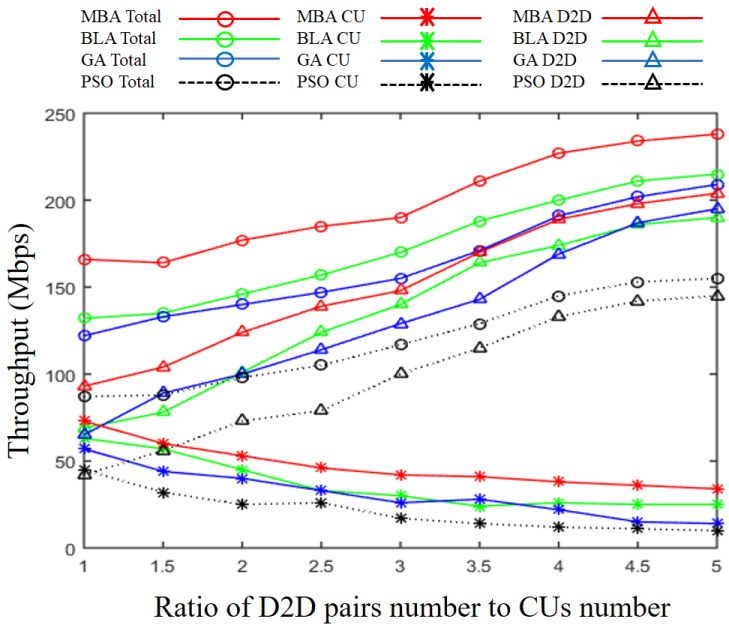


Figure 9. Effect of D2D pair number on cellular throughput. There is no rate requirement.

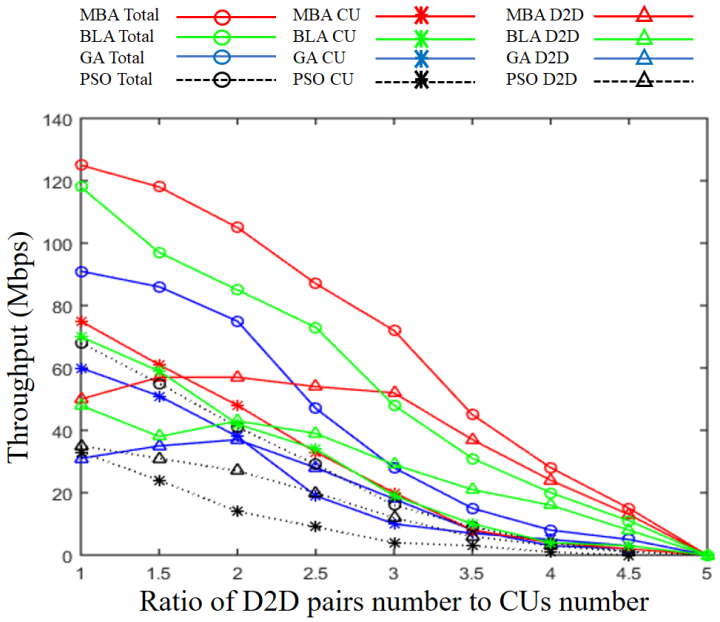


Figure 10. Effect of D2D pair number on cellular throughput with 250 Kbps as rate requirement.

In Figure 12, the MBA's throughput remains consistent when the number of D2D pairings is less than the number of cellular communications. It shows an increase when the number of D2D pairings is less than 12. A comparison of the network throughput in both scenarios (with and without a rate constraint) using the MBA reveals that when the number of D2D pairs exceeds sixteen, the throughput drops below 164 Mbps in scenarios without rate constraints and falls to 118 Mbps when rate constraints are imposed. As demonstrated in both Figures 11 and 12, the MBA consistently achieves higher overall throughput than the GA and BLA, as well as PSO, thus outperforming them in these metrics.

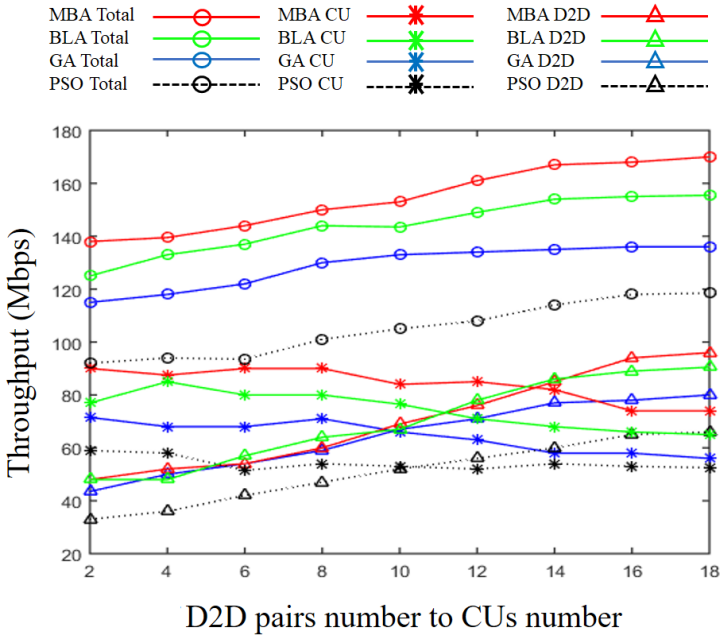


Figure 11. Changing number of D2D pairs with no rate condition.

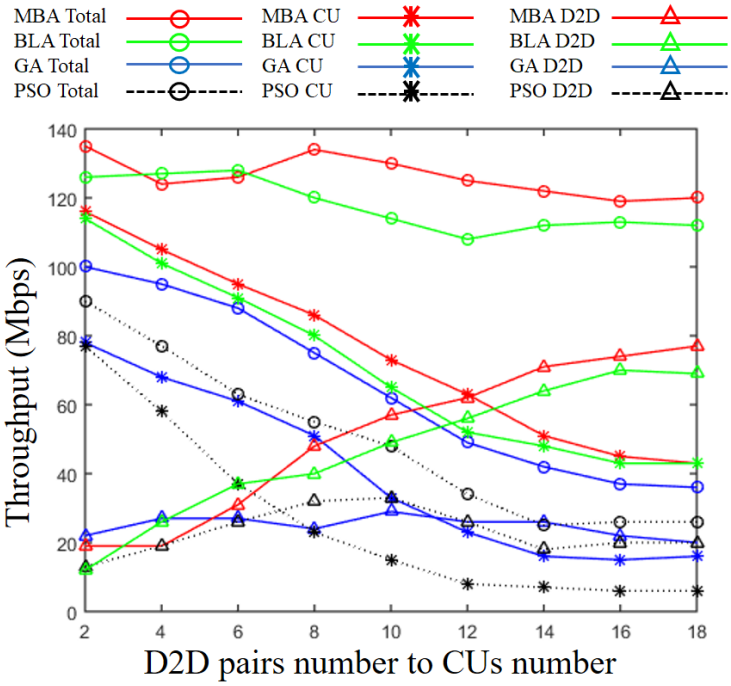


Figure 12. Changing number of D2D pairs with 250 Kbps as rate requirement.

5.3. Effects of Rate Restrictions on Acceptance Ratio

We analyze how the four algorithms fare when their acceptance rate is constrained. After time T of the simulation, if the method converges to a feasible solution P times, we can determine the algorithm's acceptance ratio like in [58]:

$$Acceptance\ ratio = \frac{P}{T} \tag{23}$$

The simulation results presented above were achieved using a configuration wherein the number of CUs was set to 8, and the number of D2D pairs was set to (10, 20). The algorithms were executed fifty times to determine the acceptance ratio. By increasing the rate by 125 kbps, the initial rate of 250 kbps increased to 1250 kbps.

Upon comparing Figures 13 and 14, it becomes evident that the acceptance ratios depicted in the former exhibit a greater magnitude than those presented in the latter. The underlying cause can be attributed to the number of users, as an increased number of D2D users results in heightened mutual interference. Upon comparing the two figures, it becomes evident that the acceptance ratios are higher in Figure 13 compared to those of Figure 14.

Subsequently, we proceed to examine the impact of the rate condition on the acceptance ratio in the presence of a comprehensive minimum constraint on the rate of cellular users. For this investigation, we establish a scenario wherein the number of cellular users is fixed to eight, while the number of D2D user pairs amounts to twenty. The acceptance ratios of all algorithms are depicted in Figure 15.

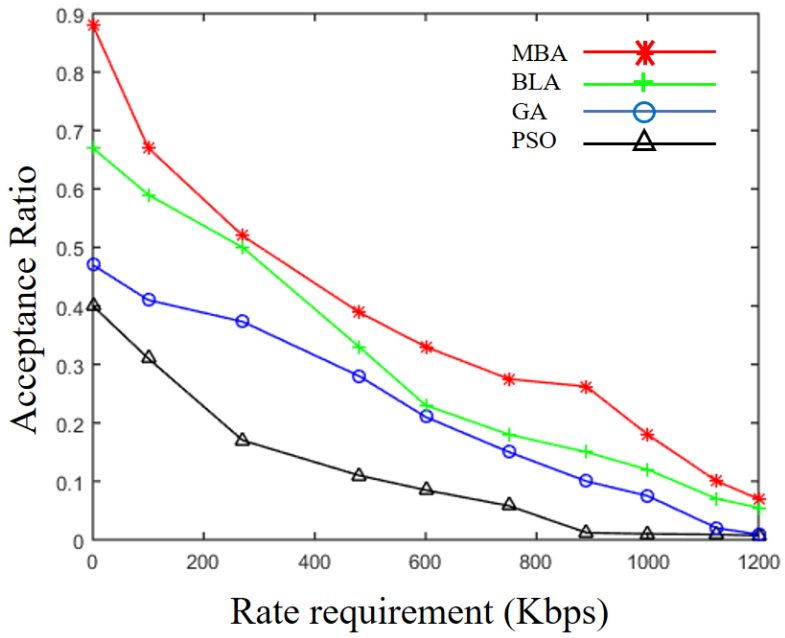


Figure 13. Acceptance ratio with rate constraint. Cellular communication equals 8 and 10 D2D communication.

Based on the data presented in Figure 15, it is evident that the acceptance ratios attained by the MBA algorithm exhibit a higher level of performance when compared to other methods.

Through simulation results, we conclude that the best bio-inspired algorithms for the joint channel and power allocation are the MBA algorithms in terms of speed of convergence, network throughput, number of served D2D pairs, and converging to feasible solutions. However, the complexity of the MBA algorithm is higher compared to BLA, GA, and PSO.

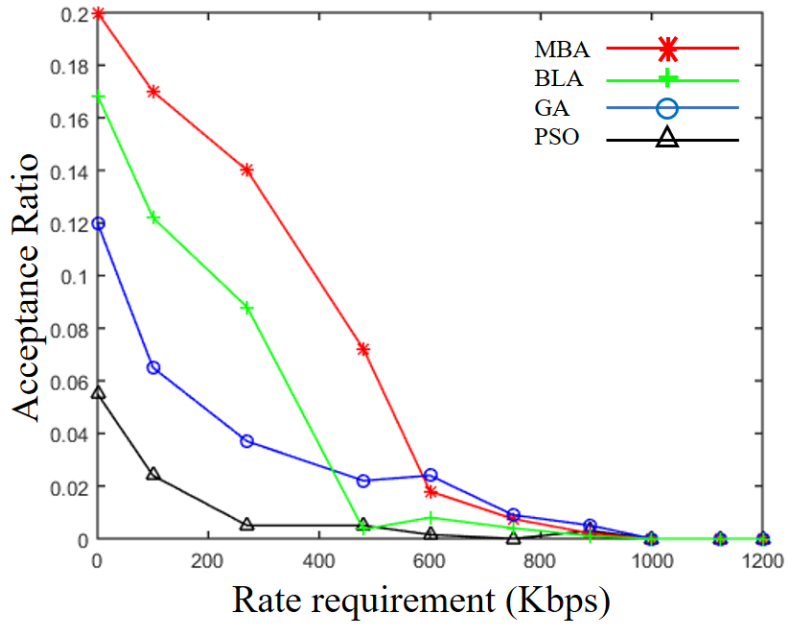


Figure 14. Acceptance ratio with rate constraint. Cellular communication equals 8 and 20 D2D communication.

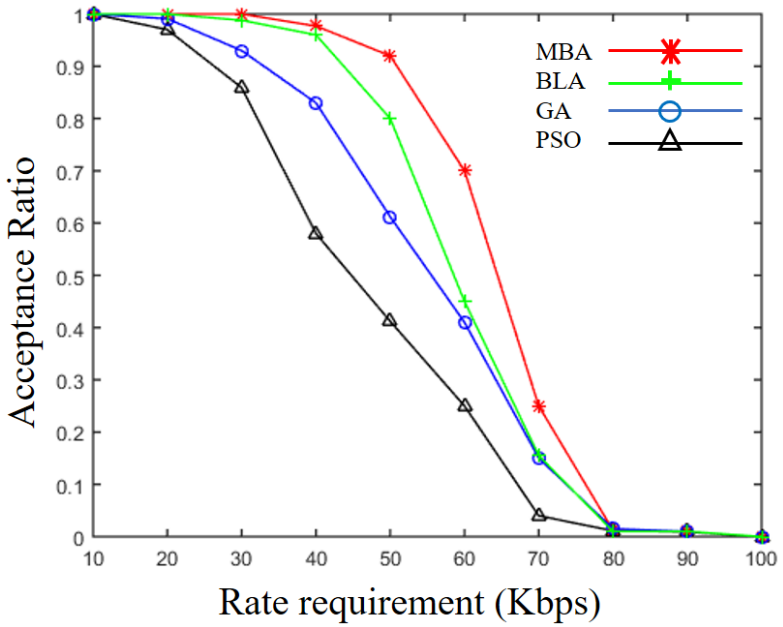


Figure 15. Impact of total rate requirement for cellular communication on acceptance ratio.

6. Conclusions

In this study, we delved into the efficacy of bio-inspired optimization algorithms for channel and power allocation in 5G cellular networks with Device-to-Device (D2D) communication underlays. The setup involved multiple D2D user pairs sharing a resource block with a cellular user, with the primary goal of maximizing overall network throughput while ensuring a minimum rate for cellular communications. The Modified Bee Algorithm (MBA) was utilized to avoid infeasible solutions, using a fitness value defined by rate constraint. Our simulation results demonstrate that the MBA outperforms BLA, GA, and PSO across various scenarios, particularly in terms of convergence speed, solution quality, and the realization of practical solutions. Following the MBA, BLA exhibited the next best performance, succeeded by GA, and then PSO.

For future work, we propose further enhancing the MBA approach by incorporating the impact of interference from adjacent cells in resource allocation and power control strategies. This paper's scope was limited to users within a single cell and did not account for interference from neighboring cells. However, in practical scenarios, this external interference can significantly influence the Signal-to-Interference-plus-Noise Ratio (SINR) of users. Therefore, an extended study that includes this aspect could offer a more comprehensive understanding and a robust solution applicable in real-world multi-cell environments. Additionally, exploring the application of MBA in various network topologies and user densities could yield valuable insights into its adaptability and effectiveness in diverse network settings.

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Abbreviations

The following abbreviations are used in this manuscript:

U	The set of users
$UEnbC/UEnbD$	CU and D2D pairs number, respectively
BR	Resource blocks set
K	Resource blocks number
A	Matrix of allocation
$Thput, CThput, DThput$	Throughput
$SINRmin$	CUs minimum SINR
Gij	Gain between UEi and UEj
PL	Path Loss model
B	Bandwidth
$Pcmax$	CUs maximum power
$Pdmax$	D2D pairs maximum power
Th_C	Crossover threshold
Th_M	Mutation threshold
WGN	White Gaussian Noise
F	Carrier frequency
X	Population account
D	Number of drones
W	Number of workers
Y	Number of broods
5GB	Fifth Generation and Beyond
PPP	Poisson Point Process
BLA	Bee Life Algorithm
PSO	Particle Swarm Optimization
BR	Block of Resource
QoS	Quality of Service
BS	Base Station
SINR	Signal-to-Interference-plus-Noise Ratio
CU	Cellular User
UAV	Unmanned Aerial Vehicle
D2D	Device to Device
UE	User Equipment

GA	Genetic Algorithm
UMi	Urban Micro System
kbps	Kilobits per second
MBA	Matching Bees Algorithm

Appendix A

BLA pseudo code for power and resource allocation:

1. Generate X random bees: Initialization
2. Calculate Fitness (X bees): Evaluation
3. Categorization: One Queen, W workers, D drones // Reproduction: first optimization operator (ending$_c$ criteria not met)
4. do
5. Crossover (Queen, Drone) // Queen and Drones mate with probability ThC
6. while (there is a drone who did not mate with Queen)
7. for (some broods)
8. Mutation (brood) // The broods mutate with probability ThM
9. end for // Food Foraging: second optimization operator
10. for (all workers)
11. Random selection (D2Dpair)
12. Transmission power optimization (D2Dpair)
13. end for
14. Calculate Fitness (broods, new workers): Evaluation
15. Keep X best bees: Selection
16. end while
17. Best Solution (Queen) BLA

Appendix B

MBA pseudo code for resource and power allocation

1. for (*i* 1 to X) do
2. for (*r* RB1 to RBK) do
3. if (Best fitness < fitness (*i*-th, *r*-th)) then
4. Best fitness (*i*-th, *r*-th)
5. end if
6. end for
7. end for // end of initialization of X bees with matching theory
8. while (not (stopping criteria)) do
9. Evaluation: calculate fitness (X bees)
10. Categorization: One Queen, W workers, D drones
11. Reproduction
12. Crossover
13. Mutation
14. Food Foraging
15. Optimize transmission power D2Dpair
16. Calculate fitness (broods, new workers): Evaluation
17. Keep X best bees: Selection while
18. Best Solution (Queen)
19. End MBA

Appendix C

Table A1. Bio-inspired algorithms for channel and power allocation.

	GA	PSO	BLA	MBA
Source	Genetics	Particle Swarms	Bees	Combination of bees and matching theory
Optimization operators	Crossover and Mutation	Updating power and resource allocated to D2D pairs	Reproduction (Crossover and Mutation) and food foraging (Local search)	Matching theory to optimize first population and BLA (reproduction and food foraging) to enhance the optimized first population
Number of D2D pairs supported	Multiple			

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