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Original Article

Advanced Resource Allocation in Multicell D2D Communication through Archimedes Optimization

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Abstract *- The transition to 5G networks challenges managing resources for Device-To-Device (D2D) communication within cellular systems. While D2D offers efficiency benefits, D2D communication can improve spectrum efficiency, increase system capacity, and reduce base station communication. Interference problems are the most challenging area in D2D communication. Efforts in research have intensified to address interference concerns and optimise the allocation of shared cellular resources. The focus is on devising strategies and algorithms that strike a balance between enabling the benefits of D2D communication and minimising interference to an acceptable level. This paper introduces a new algorithm to resolve co-channel interference issues and optimise energy efficiency within a Long-Term Evolution (LTE) network. The increasing difficulty and complexity of real-world numerical optimisation problems require highly efficient optimisation methods. While numerous metaheuristic approaches exist, only a select few have gained recognition in the research community. In this research work, a novel metaheuristic algorithm, the Archimedes Optimisation Algorithm (AOA), is analysed and designed to solve optimisation problems using a fuzzy clustering method that divides D2D users into groups based on minimising outage probability. This approach aims to enhance system throughput and mitigate interference among users. The overall sum rate of 12.20bps/Hz is achieved by the AOA-based D2D resource allocation mechanism. Compared with Particle Swarm Optimisation (PSO), the system achieves the highest sum rate in low SNR regions.*

Keywords *- Resource Allocation, Sum rate, Archimedes Optimization Algorithm (AOA), Device-To-Device (D2D), Particle Swarm Optimisation (PSO).*

1. Introduction

1.1. Key Concepts of D2D Communication

In modern wireless networks, a paradigm known as Device-To-Device (D2D) communication offers a direct connection between devices without requiring traffic to be routed via a base station. It improves network performance, minimizes latency, and enhances spectrum efficiency. However, to ensure smooth operation and compatibility with cellular users, effective implementation requires addressing several key aspects [1]. Among the basic concepts of D2D communication is:

- Device Discovery: finding nearby devices with direct communication capabilities, which the network can help with or the devices can do on their own.
- Mode Selection: Depending upon link quality, interference levels, and network conditions, a device may communicate directly (D2D mode) or through the cellular network (cellular mode).
- Resource Allocation: Efficiently distributing spectrum and power among D2D and cellular users to maximize throughput while minimizing interference.
- Interference Management: Co-channel interference occurs when D2D users and cellular users occupy the same frequency, which is a significant problem in D2D communication. In order to maintain network performance and ensure the smooth coexistence of D2D and traditional cellular communication, effective interference.

1.2. Overview of Resource Allocation in D2D Communication

In D2D communication, resource allocation refers to effectively managing and distributing network resources (such as power, spectrum, and time slots) among devices to guarantee outstanding performance. D2D communication resource allocation is critical for several reasons;

- Enhancing the Spectrum Efficiency
- Improving Capacity and Throughput of the Network
- Latency Reduction
- Mitigating Interference

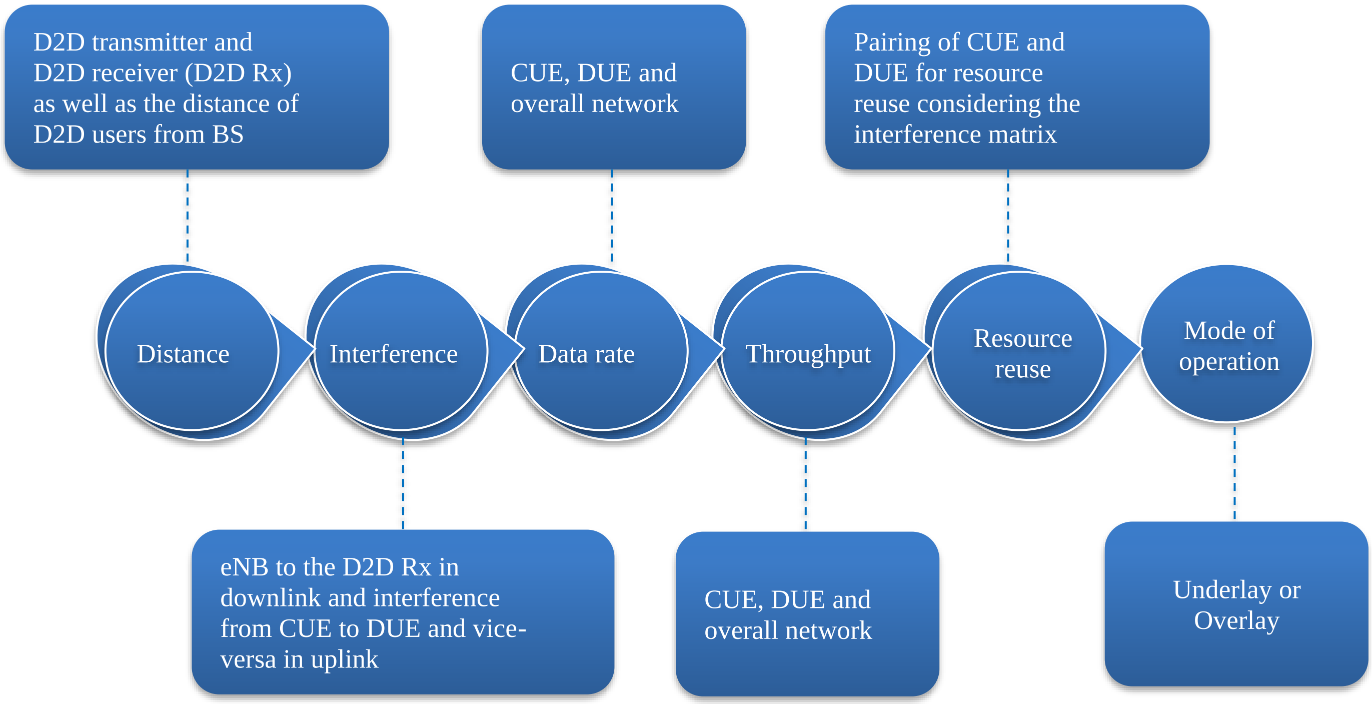

Fig. 1 Resource allocation aspects

Device-to-device communication presents promise for enhancing spectrum and energy efficiency in 5G cellular networks. Nevertheless, challenges arise due to constrained user power and co-channel interference, making the design of energy-efficient D2D communication complex. This paper introduces a new framework aimed at optimizing the energy efficiency of D2D communication within a Heterogeneous Network (HetNet) during downlink transmission. The optimization problem is formulated mathematically, considering mode selection, power control, and resource allocation [2]. Ensuring enhanced Quality-of-Service (QoS) is imperative in modern wireless communication, particularly for multimedia applications that demand elevated data rates. This necessitates the creation of robust resource management strategies that deliver high throughput and optimize the utilization of existing resources effectively [3]. In [4], the challenge of allocating multiple D2D pairs within each sub-channel in a multi-cell environment featuring numerous sub-channels is addressed. They represent the subchannel allocation issue as a generalized assignment problem and suggest a locally greedy algorithm with low complexity to address it. In [5], the optimization challenge of allocating spectrum resources for D2D communication across various microwave and millimeter-wave bands within HCNs. [6] This paper introduces an innovative algorithm aimed at tackling co-channel interference and optimizing energy efficiency in a long-term evolution network. The algorithm utilizes a fuzzy clustering method, employing minimal outage probability to categorize D2D users into multiple groups, enhancing system throughput while minimizing interference. Additionally, an efficient power control algorithm, grounded in game theory, is proposed to optimize user transmission power within each group, ultimately enhancing user energy efficiency. Genetic Algorithms (GAs) represent a crucial category within Evolutionary algorithms. They initiate their search with a randomly generated population, evolving it through successive iterations. GAs employs biological operations like selection, crossover, mutation, and reproduction to advance the population from one generation to the next. On the other hand, Swarm Intelligence (SI) techniques emulate the collective behavior observed in organisms living in groups, fostering cooperation among themselves. Examples of SI algorithms encompass Particle Swarm Optimization (PSO), among others [7]. Salp Swarm Algorithm (SSA), Grey Wolf Optimizer (GWO) and Ant Colony Optimization (ACO) are among the prominent algorithms in the field.

Notably, PSO stands out as the predominant Swarm Intelligence (SI) algorithm extensively employed in the literature. These algorithms were initially developed to address problems involving continuous variables. Among several highly effective metaheuristic algorithms, certain algorithms have demonstrated a consistent history of resolving various optimization problems, while others are undergoing effective adaptations to enhance their search capabilities. Many problems occur with all these metaheuristic algorithms, and many problems occur, like modeling imperfect CSI and allowing a D2D pair to simultaneously transmit on multiple sub-channels [4], Scheduling problems between cellular and D2D users [8] Interference Problems. Device-To-Device (D2D) communication boosts energy efficiency and spectrum. Its implementation is complicated by issues, which include co-channel interference and limited user power. Mode selection, power control, and resource allocation have all been addressed in previous research; nevertheless, important problems, including dynamic spectrum allocation, interference mitigation, and inadequate CSI modeling, were not addressed. Combining D2D users, a fuzzy clustering technique lowers the chance of an outage while improving throughput and lowering interference.

In addition, optimization is being studied using metaheuristic algorithms like Genetic Algorithms (GA) and Swarm Intelligence (SI) approaches, such as PSO, SSA, GWO, and ACO. Although these algorithms work well, they have difficulty assigning subchannels and scheduling between D2D and cellular users. The proposed approach includes innovative optimization techniques to fill these gaps, ensuring appropriate resource allocation and enhanced network performance.

In order to solve the mentioned issues, a new resource allocation algorithm is presented in this paper. The contributions of this paper can be outlined as follows.

- D2D users are categorized into user groups. Subsequently, the optimal cellular user resources are allocated for each group to enhance system throughput and minimize co-channel interference.
- Regarding spectral and energy efficiency, our method utilizing Fuzzy clustering within a D2D network proves more effective than conventional cellular transmissions.
- We introduce an adaptable resource allocation scheme for Sum rate maximization.
- We evaluate the performance of the proposed algorithm by comparing it with other metaheuristic algorithms used for Resourse allocation in D2D communication.

The rest of the paper is organized as follows: Section 2 covers related work, Section 3 introduces the system model and problem formulation, Section 4 provides the proposed algorithm, Section 5 presents numerical outcomes and performance analysis, and Section 6 draws conclusions from this investigation.

2. Related Work

Various resource allocation techniques have been presented recently to improve spectral efficiency, sum rate, and interference mitigation. For Resourse allocation in [9], a hybrid GA-PSO is proposed for power control and cooperative subcarrier allocation in a D2D multicast underlay network. The power control problem is solved using the continuous conventional PSO, while the GA handles the discrete allocation for subcarriers. The Simple Particle Swarm Optimization (SPSO) technique for RB allocation to increase D2D communication throughput and improve system capacity performance was evaluated in [10]. N. Taşpınar [11] assigns a comprehensive numerical description of the system's achievement with resources to a D2D communication where they use the Grey Wolf Optimization (GWO) algorithm. The joint-greedy method is described in this research as a greedy-based resource allocation mechanism for D2D users to use in the communications process. The Join-greedy algorithm chooses the optimal resource for each D2D user through two sorting phases. Identifying the best resource for each D2D user is the first step in the sorting process; the best solution found from the first process result in the second step is suggested by V. S. W. Prabowo [12, 13]. This paper presents a novel approach to resource allocation for the D2D user density identification problem in a 5G network.

The method first defines an optimization function with the D2D users' QoS and system throughput as its inputs. Furthermore, the IWOA is used to solve the optimization function. The relationship between transmission power and serial interference cancellation decoding order is examined in [14]. They suggest three feasible frameworks based on the Differential Evolution (DE) algorithm to improve the sum rate of D2Ds. In order to encode the RB allocation and power allocation into the same individual for evolution, researchers initially decided on a co-evolution DE-based resource allocation (CDRA) framework. Second, they provide a two-step DE-Based Resource Allocation (IDRA) methodology that combines iterations. At last, the DE-based Resource Allocation (PDRA) framework for power restoration.

A joint interference management and resource allocation scheme tailored for D2D communications within decoupled heterogeneous networks. By optimizing interference and resource allocation strategies, it enhances spectral efficiency and supports seamless integration of D2D communication alongside conventional cellular networks is proposed in [15]. In [16], the author introduces an adaptive D2D resource allocation approach within 2-tier heterogeneous cellular networks, aiming to optimize spectrum utilization and enhance network performance through dynamic resource allocation strategies. It addresses the complexities of integrating D2D communication efficiently within existing cellular infrastructures.

In [4], they analyze the issue of assigning numerous Device-To-Device (D2D) pairs per subchannel in a multi-subchannel scenario where the inter-D2D and inter-cell interference are unknown. In [12], a greedy-based allocation technique called the joint-greedy algorithm was proposed in the work to assign resources to D2D users for the communications process. The Join-greedy algorithm finds the optimal resource for each D2D user through two sorting phases. In [17], this research work states that the Lagrangian dual optimization approach is used to estimate the appropriate power for every D2D user. The developed power control maximization technique effectively balances the D2D sum rate and total transmission power.

Several gaps have been identified in the existing literature and comparative analyses of resource allocation schemes.

- Computational Complexity: Many existing metaheuristic algorithms exhibit high computational complexity, hindering real-time implementation and scalability in large-scale networks.
- Real-Time Constraints: It is challenging to meet real-time constraints while maintaining optimal resource allocation performance, particularly in dynamic environments.
- Scalability Issues: Current approaches may struggle to scale effectively when applied to large networks or scenarios with numerous devices, impacting their practical deployment.
- Interference and QoS Challenges: Ensuring minimum sum-rate due to interference and addressing Quality of Service (QoS) requirements remain significant challenges affecting resource allocation schemes' performance.
- Focus on Single-Cell Scenarios: Most research in D2D resource allocation has primarily focused on single-cell scenarios, limiting insights into multi-cell environments where interference and resource allocation complexities are more pronounced.

We used a new metaheuristic algorithm called Archimedes Optimization Algorithm (AOA) to address these challenges comprehensively. AOA is designed to deliver rapid convergence speeds while maintaining a balanced approach between local and global search capabilities. Additionally, our research extends beyond single-cell scenarios to encompass multi-cell environments, enhancing our understanding and optimization of interference dynamics and resource allocation strategies. These advancements are pivotal for achieving superior performance, scalability, and real-time applicability in D2D communication systems.

3. System Model and Problem Formulation

The proposed methodology is divided into two sections: network scenario initialization and Implementation of the proposed algorithm to maximize the throughput and sum rate.

3.1. Network Scenario

The proposed work focuses on maximizing the system throughput through an optimization problem that controls transmission power and manages interference. The fitness function aims to maximize the sum rate, which depends on minimizing distance, interference, and power requirements and ensuring robustness to noise.

Let C-1 be a cellular user, and D1 to D3 are D2D users in a cell, and these devices are working as transceiver devices; equation 1 states that the SINR of C-1 at base station B-1 is given as

$$\gamma_{C-1} = \frac{P_C h_{C1-B1}}{N_0+\sum_1^d x_D^c P_D h_{D2B1}^c} \quad (1)$$

$$X^c_D = \{1 \text{ if D2D pair reuse the resources of C1,else } 0 \quad (2)$$

X^c_D is an indicator variable of cellular resources allocated to D2D users. P_c and P_D are transmitted power of C-1 and D2D of D3 and D2, respectively.hc1-b1 is channel gain from cellular C-1 to base station B-1 and is channel gain of D-2 to B-1 when using cellular resources. SINR at D2D of D3-D2 h^c_{D3D2} Is the channel gain between D-3 and D-2 using the RR of cellular.

$$\gamma_D = \frac{\sum_1^d x_D^c P_D\ h_{D3D2}^C}{N_0+\sum_1^d x_d^c P_C\ \ h_{C1D3}} \quad (3)$$

The throughput can be calculated both for cellular users and D2D users using the Shannon capacity model. This is an optimization problem to maximize the system throughput by controlling transmission power and interference. Mathematically, this optimization problem can be solved as,

$$= \max_{x_D^c \geq 0, P_D \geq 0} \sum_1^d R_D + \sum_1^c R_C \quad (4)$$

where $Rc \geq R_{c,\ min.}$

From the above equations, it can be observed that D2D users should reuse the RR of cellular users of the largest gain $h^d{}_{c;}$ therefore, D2D users have the best SINR. Cellular users should allow D2D users to channel reuse, which has the smallest gain h_{DB}.When the uplink resources of cellular user c_1 are multiplexed by multiple D2D user pairs, the interference occurs between the cellular user and any given D2D user and D2D users. At this time, the D2D user pair that reuses the uplink resources of the cellular user c_1 is called a D2D user group. The SINR at the base station is then

$$\gamma_{l,b} = \frac{P_c\ |h_{c2b}|\ d_{c2b}^{-a}}{\sum_{D\epsilon Gi} P_D\ |h_{d2b}| d_{d2b}^{-a} + N_0} \quad (5)$$

The SINR received by the D2D user pair is represented by

$$\gamma_{l,b} = \frac{P_{cD}\ |h_{T_x 2R_x}|\ d_{T_x 2R_x}^{-\partial}}{\sum_{D\epsilon Gi} P_D\ |h_{d2b}| d_{d2d}^{-\partial} + P_c\ |h_{c2d}|\ d_{c2d}^{-\partial} + N_0} \quad (6)$$

Where P_c and P_D are the transmit power of cellular users and D2D users to the transmitter, respectively; d_{c2b},d_{c2d}, d_{d2d}, d_{d2b}, and $d_{T_x 2R_x}$ are the distances from the cellular user to the base station, from the cellular user to ith D2D pair to Rx, between different D2D links, from jth D2D to the base station, and from T_x to R_x; h_{c2d}, h_{c2b}, h_{d2d}, h_{d2b}, and $h_{T_x 2R_x}$ are the channel fading coefficients from the cellular user to the base station, from the cellular user to jth D2D pair, between different D2D links, from ith D2D user to the base station and of any D2D user from T_x to R_x; ∂ is the path loss factor; and N0 is the Gaussian white noise with a mean of 0 and a variance of σ.

3.2. Fuzzy Clustering Method

In D2D communication, fuzzy clustering is a useful technique for controlling interference and allocating resources as efficiently as possible. Fuzzy clustering enables devices to have membership in numerous clusters to differing degrees, which makes it more flexible to changing network conditions than traditional hard clustering, which places each device in a single cluster. Devices can belong to various clusters with different membership levels according to the Fuzzy C-Means (FCM) algorithm, which is usually the foundation of fuzzy clustering in D2D communication. The following is a formulation of the mathematical model:

$$Jm = \sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^{m} \left\|x_i - c_j\right\|^2 \tag{7}$$

where

N = Total number of D2D users

C = number of clusters

x_i = feature vector of the i D2D user

c_j = center of cluster j

u_{ij} = membership value of xi in cluster j$(0 \leq u_{ij} \leq 1)$

m = fuzziness coefficient

The membership values are updated as:

$$u_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\frac{\left\|x_i - c_j\right\|}{\left\|x_i - c_k\right\|}\right)^{\frac{2}{m-1}}} \tag{8}$$

Cluster centers are updated iteratively as:

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^{m}\, xi}{\sum_{i=1}^{N} u_{ij}^{m}} \tag{9}$$

This ensures that the cluster centers are dynamically adjusted based on D2D users' characteristics. The algorithm iterates until the difference between consecutive cluster centers is satisfied.

$$\left\|{c_j}^{(t+1)} - {c_j}^{t}\right\| \tag{10}$$

4. Proposed Algorithm

Archimedes Optimization Algorithm (AOA)steps are in Figure 2. It is a population-based algorithm where the objects submerged in the population are the individuals. Similar to previous population-based metaheuristic algorithms, AOA starts the search process with a starting population of objects (candidate solutions) that have arbitrary accelerations, densities, and volumes. At this point, the initial position of each object in the fluid is similarly random. When the starting population's fitness is assessed, AOA continues in iterations until the termination condition is satisfied. AOA updates the volume and density of each item in each iteration. Based on the circumstances surrounding any collisions with nearby objects, the object's acceleration is adjusted.

Step1:
Initialize the network scenario
N: Population size (no of materials)
Iter_max: maximum iterations
C1,C2.C3,C4: random variables
Step 2:
Initialize random population (Possible D2D allocation) with random positions
Initialize densities and volumes
Evaluate the fitness for initial population based on total sum rate
Select object with best fitness
Step 3:
while iter < iter_max
for each object i do
update density and volume of every object
update transfer and density decreasing factor (TF, d)
if TF < 0.5 then // Exploration phase
Update acceleration and normalize acceleration update positions
else //Exploitation phase
Update acceleration and normalize acceleration
Update direction flag
update positions
end if
end for
compute fitness of each object
select object with highest fitness value
set iter-iter+1
Step 4:
Allocate the resources for best D2D pairs

Fig. 2 Proposed algorithm

An object's updated position is determined by its volume, acceleration, and density. It has the advantages of fast convergence speed and balance between local and global search ability when solving continuous problems. [Archimedes optimization algorithm: a new metaheuristic algorithm for solving optimization problems]. It offers exploration and exploitation. Exploration is the process of looking into unexplored areas within a feasible zone, whereas exploitation is the process of looking into the area around a promising region.

5. Experimental Results and Discussions

Table 1 provides the simulation and network parameters used in implementing the proposed system, which is designed for a multi-cell scenario illustrated in Figure 2. In Figure 3, the multi-cell scenario includes a central BS surrounded by seven hexagonal cells. Across these cells, 15 pairs of D2D Transmitters (Tx) and Receivers (Rx) are distributed arbitrarily. The system emphasizes higher inter-cell interference over intra-cell interference considerations.

Table 1. Simulation and network parameter

Parameter	Specification
No of D2D pairs	10, 20,…100
Maximum threshold for D2D pairs	40 m
Radius of cell	250m
Base station position	Centralized
Base station transmits power	46 dBm
Cellular users transmit power	21 dBm
D2D user transmit power	21 dBm
Gaussian white noise density	-174 db/Hz
Path loss index	3
Number of cellular users	10
System bandwidth	10 MHz

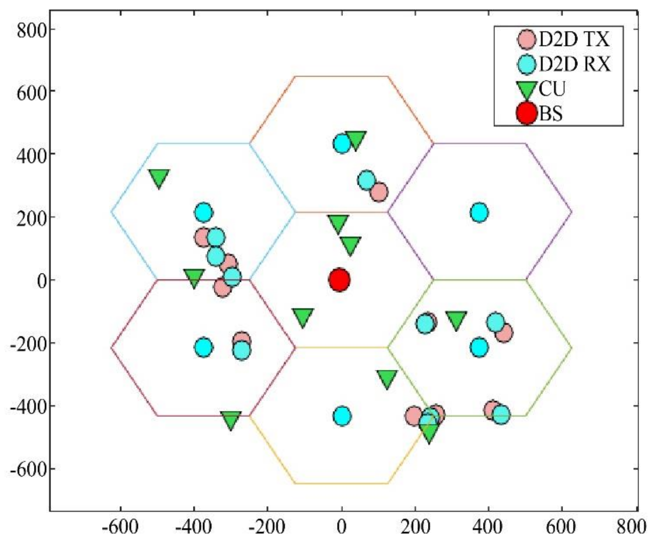

Fig. 3 Multi-cell simulation scenario

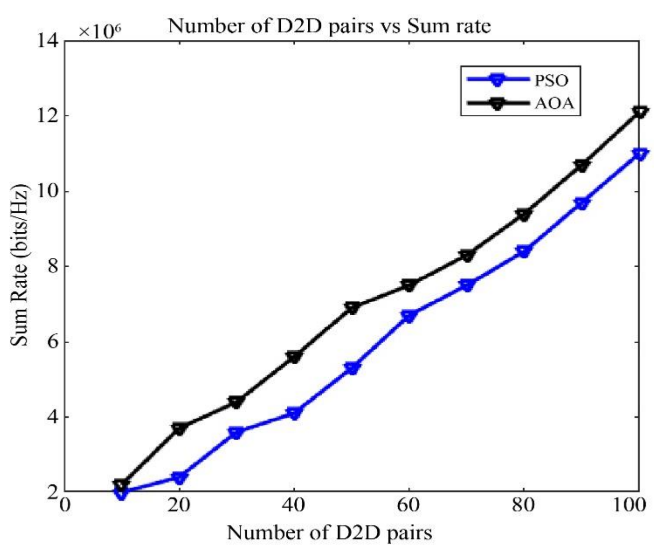

Fig. 4 Performance of D2D pairs vs Sum Rate

The proposed AOA based D2D resource allocation approach is compared with the traditional Particle Swarm Optimization (PSO) algorithm based on metrics such as sum rate and throughput. Figure 4 illustrates the results for various D2D pairs versus the sum rate, showing that the sum rate increases with an increase in D2D pairs. Specifically, the AOA-based D2D resource allocation scheme achieves an overall sum rate of 12.20 bps/Hz for 100 D2D devices, operating at 30 dB SNR with 10 CUs. In contrast, the PSO-based approach results in a 10.8 bps/Hz sum rate under the same conditions. Increasing the number of D2D pairs enhances spatial resource reuse, effectively utilizing spectrum resources to boost the overall sum rate. Figure 5 illustrates the sum rate performance of the proposed D2D resource allocation method across various SNR levels. The AOA-based D2D resource allocation system achieves the highest sum rate in low SNR regions compared to the PSO algorithm. This outcome highlights the effective balance between exploration and exploitation inherent in the AOA algorithm, which contributes to efficient D2D resource allocation and ultimately yields a larger sum rate.

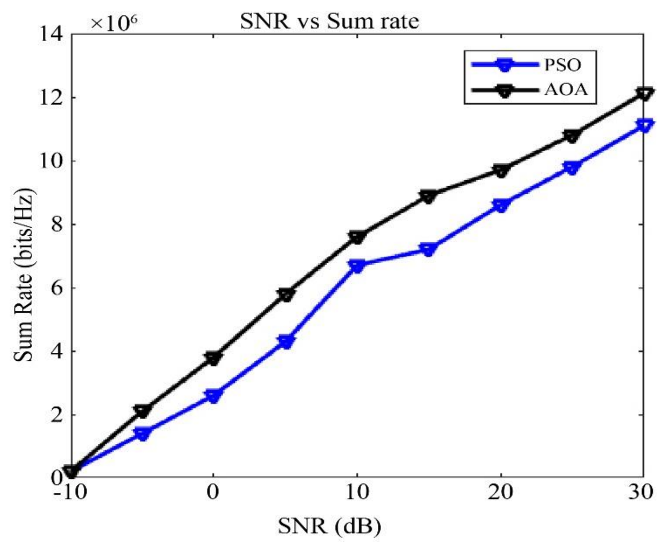

Fig. 5 Performance of SNR vs Sum Rate

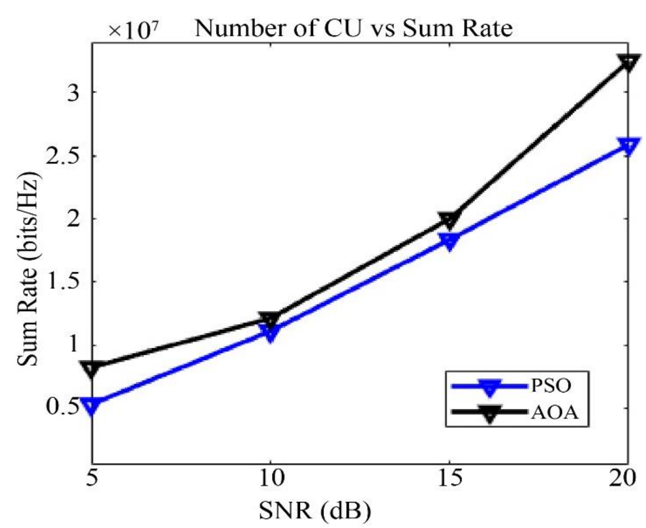

Fig. 6 Performance of Number of CU vs Sum Rate

Table 2. Experimental results and their corresponding analysis of Sum Rate

S. No	Parameter	PSO	Proposed Algorithm AOA	Average% Improvement in AOA over PSO
1	Performance of D2D pairs vs Sum Rate	10.8 bps/Hz	12.20 bps/Hz	12.96%
2	Performance of Number of CU vs Sum Rate	27 bps/Hz	38 bps/Hz	40.74%

Figure 6 depicts the sum rate across varying numbers of CUs. Increasing the number of CUs enhances the opportunity for DUs to multiplex resources, resulting in higher sum rates. A larger number of CUs also improves resource utilization, increasing the sum rate and throughput. Specifically, the AOA and PSO-based D2D resource allocation schemes achieve a sum rate of 12.20 bps/Hz and 10.8 bps/Hz, respectively, when there are 10 CUs. However, with a greater number of CUs, such as 38 CUs, the AOA-based scheme achieves a sum rate of 38 bps/Hz, while the PSO-based scheme achieves 27 bps/Hz. These results show how AOA effectively utilize the increased availability of CUs to optimize resource allocation, thereby enhancing overall sum rate performance. Table 2 presents the experimental results and their corresponding analysis of the performance of D2D pairs and CU vs Sum Rate. The proposed AOA algorithm achieves a 12.96% improvement over PSO in D2D pairs vs. Sum Rate, increasing throughput from 10.8 bps/Hz to 12.2 bps/Hz. The AOA algorithm significantly outperforms PSO in the Number of CU vs. Sum Rate, achieving a 40.74% improvement, with throughput increasing from 27 bps/Hz to 38 bps/Hz. Overall, the AOA algorithm demonstrates superior performance compared to PSO, particularly in scenarios with a higher number of CUs, making it a more efficient resource allocation approach. The throughput results for different D2D pairs, SNR ranges, and number of CUs are depicted in Figures 7, 8, and 9, respectively. The AOA-based D2D resource allocation consistently outperforms the PSO algorithm, delivering superior throughput across all scenarios.

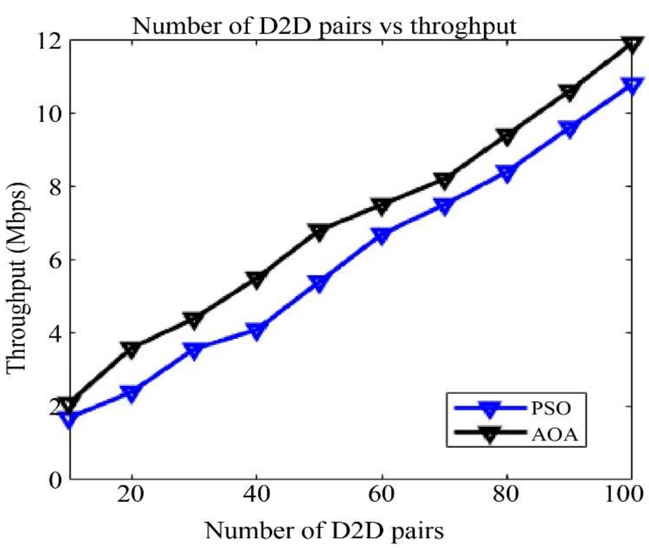

Fig. 7 Performance of number of D2D pairs vs throughput

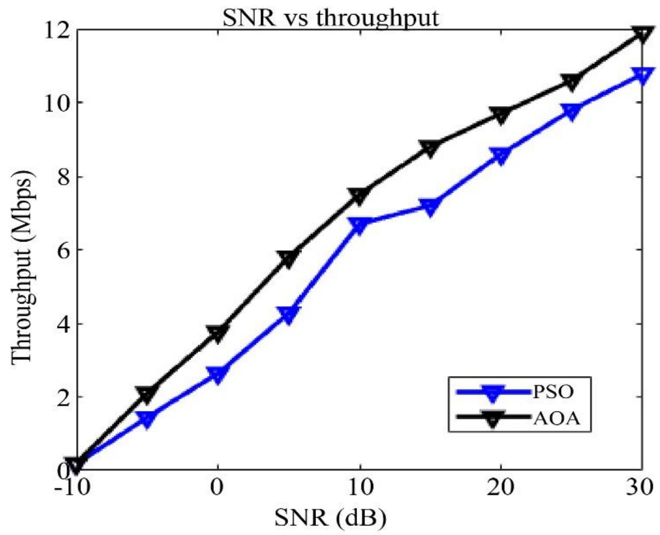

Fig. 8 Performance of SNR vs Throughput

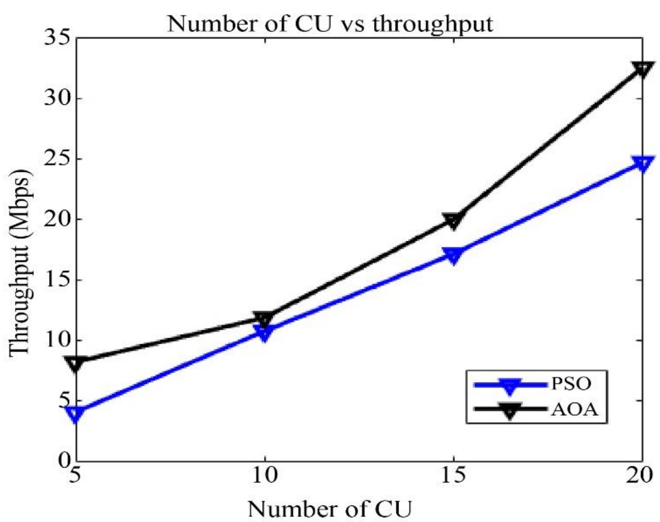

Fig. 9 Performance of Number of CU vs Throughput

Table 3 presents the throughput analysis, where the proposed AOA algorithm achieves a throughput of 7.88 Mbps for the Number of D2D pairs vs throughput, compared to 6.83 Mbps using PSO, resulting in an average improvement of 15.40%. For the Number of CU vs Throughput, the proposed AOA algorithm attains a throughput of 17.38 Mbps, whereas PSO achieves 14.75 Mbps, leading to an average improvement of 17.30%. These results indicate that the AOA algorithm consistently outperforms the PSO method regarding throughput performance.

Table 3. Experimental results and their corresponding analysis of throughput

S. No.	Parameter	PSO	Proposed algorithm AOA	Average % Improvement of AOA over PSO
1	Number of D2D pairs vs Throughput	6.83 Mbps	7.88 Mbps	15.40%
2	Number of CU vs Throughput	14.75 Mbps	17.38 Mbps	17.30%

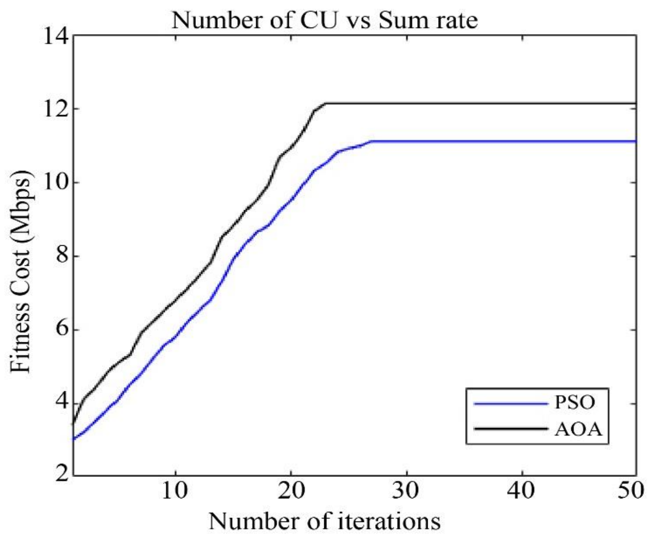

Fig. 10 Fitness cost of AOA and PSO

Figure 10 displays the overall fitness comparison between the AOA and PSO algorithms, revealing higher fitness values for AOA compared to PSO. AOA focuses on balancing exploitation (handling object collisions) and exploration (avoiding collisions) to update its population. This approach efficiently utilizes the existing population while exploring new areas of the search space. The improved balance between exploitation and exploration expands the optimization problem's search space, leading to superior solutions.

6. Conclusion and Future Scope

This paper introduces an AOA algorithm-based approach for D2D resource allocation in multi-cell scenarios. The AOA algorithm uses a multi-objective fitness function to handle multi-cell scenarios involving multiple DUs and CUs. It efficiently allocates spectrum resources from CUs to DUs while considering criteria such as minimum distance, interference, power requirements, and noise robustness.

By striking a balance between exploitation-handling object collisions and exploration-avoiding collisions, the AOA algorithm offers optimal solutions compared to traditional techniques. It significantly enhances the network's sum rate, throughput, and QoS in multi-cell deployments. Compared to PSO, the AOA-based approach demonstrates a notable 12.96% improvement in D2D resource allocation performance, and the average percentage improvement in throughput and fitness cost between the AOA and PSO algorithms is approximately 7.05%.and 7.81%, respectively. Future advancements may include enhancing energy efficiency for both DUs and CUs and extending the application of the AOA-based scheme to real-time resource allocation in IoT systems.

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