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AI and game-based efficient resource allocation and interference mitigation scheme for D2D communication

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ABSTRACT

Device-to-device (D2D) communication essentially means to communicate between two devices without the base station interfering. D2D communication is used in wireless 5G networks, the Internet of Things, Bluetooth and WiFi, and vehicular networks. D2D communication is useful as it increases spectral efficiency, network efficiency, user experience, and throughput, all of which are better than those available in cellular communication. Thus, D2D communication is a preferred mode of communication. However, D2D communication faces issues like mode selection, interference, resource allocation (RA), and security. The need for RA stands because multiple D2D users (DUs) compete for the same resources. Now, the goal should be to optimize RA to enhance the spectrum efficiency and network coverage. Still, the issues here are caused by eavesdroppers (ε), devices that can interfere with communication and encrypt/decrypt the messages. In our proposed scheme, we combined artificial intelligence (AI) and coalition game theory to resolve the issues of optimized RA and security. The coalition game is used for efficient RA, but it will take all the DUs that increase the overhead into the system. To mitigate this issue, we proposed an AI-based solution, which selects the best DUs based on their channel conditions. Our major evaluation parameters were accuracy, sum secrecy capacity and data rate.

1. Introduction

Earlier, mobile communication (MC) was widely used in practice, where it performed communication with the help of a base station (BS). These communications consist of two actors — the sender and the receiver. A sender is an entity offering the data, and a receiver downloads it, and both are connected to the same BS. A situation where multiple numbers of sender and receiver are connected to the same BS is known as BS overload. Overloading of BS will reduce spectral efficiency, data rate, and channel gain. So, this type of communication will only work in low-dense areas; it will cease to work in high-dense areas. This was the problem in prior days, which must be solved with the technological evaluations in wireless communication. The solution to this problem is D2D communication, which enables nearby devices to share and receive data without the BS. It offloads traffic for BS and improves spectral efficiency, system capacity, fairness, and throughput with reduced transmission delay and less congestion in cellular networks.

Although D2D communication has various benefits, it suffers from challenges like interference, resource allocation (RA), device discovery, and security. The effect of interference results in a lesser network efficiency and a reduction in overall performance. Furthermore, D2D communication has loopholes in privacy protection, channel accuracy development, and robustness to attacking behavior. We have focused on identifying secure RA and interference mitigation (IM) in D2D communication. Various researchers have given diverse results for IM by employing different game theory-based solutions such as zero-sum, coalition, and Stackelberg games. In Stackelberg's game theory, one

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leader makes the strategies, and all the other followers will follow him and compete with other followers. Then, the Coalition game theory focuses on various groups, i.e. coalitions, rather than particular agents. Here, individuals will select the best coalitions according to their gain.

There exists various literature where the research community used Stackelberg and coalition game theory for D2D RA. Wang et al. [1] proposed Stackelberg game-based solution for the dynamic D2D RA environment. Their proposed scheme worked for the sub-carrier allocation and power control. Further, they focused on mitigating inter and intra-layer interference in D2D RA. Their proposed scheme focuses on the system throughput of the cellular users (CUs). Although Stackelberg's game theory improves efficiency, one drawback is that one leader and many followers are compulsory. To deter this, the authors utilized a coalition game between CUs and D2D users. Shaoyou et al. [2] proposed a coalition game for power allocation in D2D communication. They convert the concave function into a complex optimization. Through analysis of various aspects, we can identify that coalition game theory gives us the best-required output due to its dynamic nature. Integration of coalition game theory with D2D communication can help to increase performance.

After analyzing the above literature, we found that many existing schemes, like game theory, graph theory, and heuristic, are used for optimizing RA. However, the approaches are computationally expensive, tackle less number of users, and face the issue of computation overhead. Thus, artificial intelligence (AI) is a plausible solution for the aforementioned issues and maximizing the system rate. The authors in [3], presented how machine learning (ML) can be the future of next-gen wireless networks. They explained how reinforcement learning can be efficiently used for relay-aided communication. Then, Xinzhou et al. [4] modified the Stackelberg game by integrating AI that can establish a master–slave relation between CU and D2D users (DUs), optimize the cost parameters and improve transmission power. It performs best when the quality of CUs in the system is guaranteed. Mishra [5] has proposed an AI-based framework to enhance the RA in D2D communication, which overcomes D2D communication challenges and fulfills International mobile telecommunications (IMT)-2020 criteria. From this literature, we identified that these papers faced problems like privacy protection and attacking behavior of DUs, secure transmission, and scheduling manners. Also, RA must be optimized in D2D communication with reduced computation cost.

From the literature, we observed that in the coalition game, all the DUs participate in the RA, which causes interference and increases the computation cost. Motivated by the above facts, this paper proposed an AI and coalition-based secure RA scheme for efficient RA. In the proposed scheme, we used various ML models, which classify the DUs based on their channel quality. The best DUs (selected for the ML model) participate in playing a coalition game for efficient RA in D2D communication. The performance of the proposed scheme was evaluated using accuracy, sum data rate, convergence time, and sum secrecy capacity.

1.1. Motivations and novelty

From the literature [1,2,6,7], we observed that the research community had applied various approaches, such as the Stackelberg and a non-cooperative game for the efficient RA in D2D communication. However, in their proposed approaches, one user is the leader who makes strategies, and the rest must follow that. To overcome this issue, we proposed a coalition game theory-based solution where the various groups participate and are not restricted to the single agent's strategy. Then, there exists literature, such as [8,9], where researchers have used a coalition game-based approach for the RA in D2D communication. However, in their proposed approaches, all the D2D pairs are participating, which causes interference and computation issues. Moreover, an approach that can adapt to a dynamically changing environment is necessary. We also realize that the existing solutions for coalition game-based RA have not considered security aspects, due to which their solutions are not competent to offer a high sum data rate for a longer time. Motivated by the aforementioned facts, we proposed an AI and coalition game theory-enabled RA scheme for the D2D communication environment. In the proposed scheme, we used various AI models, which classify the D2D pairs based on their channel quality. The most suitable DUs (chosen for the AI model) engage in a coalition game to ensure efficient RA in D2D communication. Furthermore, we also included an eavesdropper to analyze the sum secrecy capacity of the D2D systems. The performance of the proposed scheme is evaluated using accuracy, sum data rate, convergence time, and sum secrecy capacity.

1.2. Research contributions

The following are a major research contributions:

- We proposed an AI-based D2D communication scheme to select the best D2D pair for secure D2D communication and IM underlying cellular networks. ML classification algorithm k-nearest neighbors (KNN) is used to select the best D2D pair.
- We then implement the coalition game theory for efficient and secure RA in the proposed D2D communication scheme. In a coalition game, the best D2D pair ended up at the best coalition after applying the transfer utility and preference order.
- The proposed scheme's performance is assessed across multiple parameters, including accuracy, sum secrecy capacity, data rate, average switch operations, and convergence time.

1.3. Organization

The remainder of the sections are distributed as follows: Section 2 presents the existing literature related to the proposed scheme. Section 3 discusses the problem formulation. Section 4 elaborates on the presented scheme. Section 5 shows the results of the proposed scheme. And Section 6 details on the conclusion.

2. Related works

This section contains a state-of-art description of related literature on D2D communication using game theory. The authors in [6] propose a power control approach to attain Nash equilibrium and game theory, which helps to overcome the interference between CU and D2D pairs. They have modeled the power control algorithm as a non-cooperative game. We also see that the algorithm converges rapidly against the Nash equilibrium rate. The pros are that it has reliable connectivity with minimum power consumption, and its applied scheme mitigates the signal-to-interference-plus-noise ratio (SINR). In a Stackelberg game, a player initially precommits, and others have to respond sequentially. It is a strategic game. Using a dynamic 2-stage Stackelberg game theory, authors of [7] have efficiently presented a single leader and multiple followers selection criteria. The power is first calculated using Nash equilibrium and then distributed among CU and DUs. They have taken a leader as a BS and followers as CU and D2D pairs. Furthermore, the paper compares power allocation and sub-carrier adjustment approaches. The results demonstrated that this differential interference pricing enhanced the D2D sum rate compared to other approaches. Ghosh et al. [10] proposed a D2D communication wherein each device is assumed to have its own dew computing capacity (see Table 1).

The authors in [15] targeted to achieve secret key generation in D2D communication. They selected a relay node and then generated a secret key to ensure secrecy from the ϵ. Then, they applied a selection mechanism based on social phenomenon: non-colluding relay nodes for social trust and colluding relay for social reciprocity. Then, they used a coalition game-driven scheme to select the optimal relay node.

Table 1
A comparative analysis of existing D2D RA schemes in D2D communication.

Author	Year	Objective	Type of game used	Evaluation parameter
Proposed approach	2024	Proposed an AI and game-based resource allocation for D2D communication	Coalition	Sum rate, secrecy capacity
Gopal et al [11]	2024	Proposed a hybrid approach for resource allocation for D2D communication to maximize network throughput	Coalition	Spectrum efficiency and network throughput
Gopal et al [12]	2024	Presented a resource allocation algorithm for 5G and B5G D2D communication	Chaos	Network throughput
Saif et al. [6]	2023	Presented a power control algorithm using game theory between CU and D2D pairs	Coalition	Energy efficiency of average power consumption
Najeh et al. [7]	2023	Presented a Stackelberg game theory for distributed CU and DUs	Stackelberg	Due sum rate
Salim et al. [3]	2023	Presented a comparative analysis of one and two-way relay in D2D communication	No	Spectrum access techniques and D2D communication modes
Ao et al. [2]	2023	Proposed RA algorithm using coalition game theory and power allocation algorithm using complex optimization	Coalition	System sum rate
Gupta et al. [8]	2023	Proposed a NOMA-enabled access for cooperative D2D communication	Coalition	Accuracy, overall sum rate, secrecy capacity
Li et al. [4]	2023	Presented an enhanced Stackelberg game theory with deep Q network on CU and D2D pairs	Stackelberg	Price parameters of Stackelberg game theory
Suraci et al. [13]	2021	Presented a SeT- D2D for ensuring trustworthiness and social awareness among network and cellular nodes.	No	–
Gupta et al. [8]	2021	Proposed a blockchain-driven cooperative D2D FC scheme in an eavesdropper's presence.	Coalition	Data rate
Weifeng et al. [14]	2020	Presented a study on trust relationships using a multidimensional trust evaluation mechanism and then using cooperative caching game theory.	Caching game theory	–
Waqas et al. [9]	2018	Proposed an effective way to achieve secret key generation in D2D communication using the fundamentals of coalition game theory and social trust nodes.	Coalition	Secret key generation rate

The highest secret key generation rate was selected based on coalition game theory, relay selection, and social phenomenon. Yan et al. [16] have introduced a trust-oriented partner preference approach that helps choose users with cooperative behavior, thus helping in reducing the chances of selecting users with non-cooperative behavior. Further, they divided the psychological structure of users into three broad categories: cognition, emotion, and behavior. Then, they built a multi-dimensional trust relationship model among sending and cooperative users and classified them into reliable, observed, and unreliable users using naive Bayes. Finally, they chose an optimal partner based on this study.

Suraci et al. [13] presented trustworthiness based on direct interactions and social awareness factors to choose an apt relay node. The authors introduced a model that can access network nodes' trustworthiness and further implemented security approaches to safeguard data transmission between DUs. To achieve this, they have introduced an algorithm to improve the performance and security mechanisms of a multicast conventional multicast scheme. The relay nodes were chosen based on their reputation in the past. For the security of data transmission, they encrypted it using a symmetric encryption approach. The Diffie–Hellman key exchange protocol generated the secret key for the two users. They even secured the user identity using a subscription concealed identifier as per the 3rd generation partnership project TS 33.501. The authors in [9] have researched physical layer security for secret key generation in DUs underlying cooperative relays. They used the coalition game theory to enhance D2D relay selection, and then they developed an algorithm to generate secret keys that protect users from ε and non-trusted relays.

Wang et al. [17] have proposed a game theory-enabled method for D2D RA wherein they have quantified rate influence from power interference by social relations of mobile users. Further, they formulated an optimized solution for the overall transmission rate performance utility function. Then, they reached the Nash equilibrium for an efficient RA scheme. The authors in [8] have proposed a blockchain-driven cooperative D2D FC approach within the presence of an eavesdropper, improving the overall sum rate and system secrecy capacity. The authors used the cooperative game theory to improve the secrecy capacity. They also have used non-orthogonal multiple access schemes to improve certain characteristics of DUs. They used blockchain technology to ensure the data was transmitted securely and with trust.

Farshbafan et al. [18] introduced a bandwidth auction game for spectrum trading in cellular networks. The model involved D2D pairs and service providers bidding on bandwidth. They proposed a learning method based on the best response for efficient decision-making and thus converged to a Nash equilibrium and optimized spectrum utilization. The authors in [19] addressed the challenge of meeting data rate demands beyond 5G networks by proposing a distributed pricing-based resource allocation algorithm for D2D communications. They optimized power allocation to CUs and D2D pairs and ensured minimum quality-of-service requirements. The proposed algorithm was operational in two phases: adjusting power to maximize rate and interference-dependent utility functions and updating link prices based on quality of service requirements.

The authors in [14] have built a multidimensional trust evaluation approach to study trust relationships. They also proposed content cashing to enhance accessibility to efficiency and reduce traffic load in CU. Thus, they introduced a cooperative caching game that motivates users to cache other devices' contents. Yan et al. [20] proposed a trusted framework for multimedia delivery that can select cooperative, trusted D2D users. They classified the trust relationship as capability trust and social trust. They analyze these two types of trust and then decide on cooperative, trustworthy D2D users. Then, they used the Naive Bayes algorithm to find reliable users.

Gopal et al. [11] proposed a hybrid approach for resource allocation in D2D communication, combining both the uplink and downlink techniques. They used random forest and game theory algorithms to address interference problems between CUs and D2D users. However, the critical stages for channel assignment remained complex. The authors in [12] proposed a game theory algorithm to optimize resource sharing in D2D communication in 5G networks in such a manner that network throughput gets maximized and quality of service for both CUs

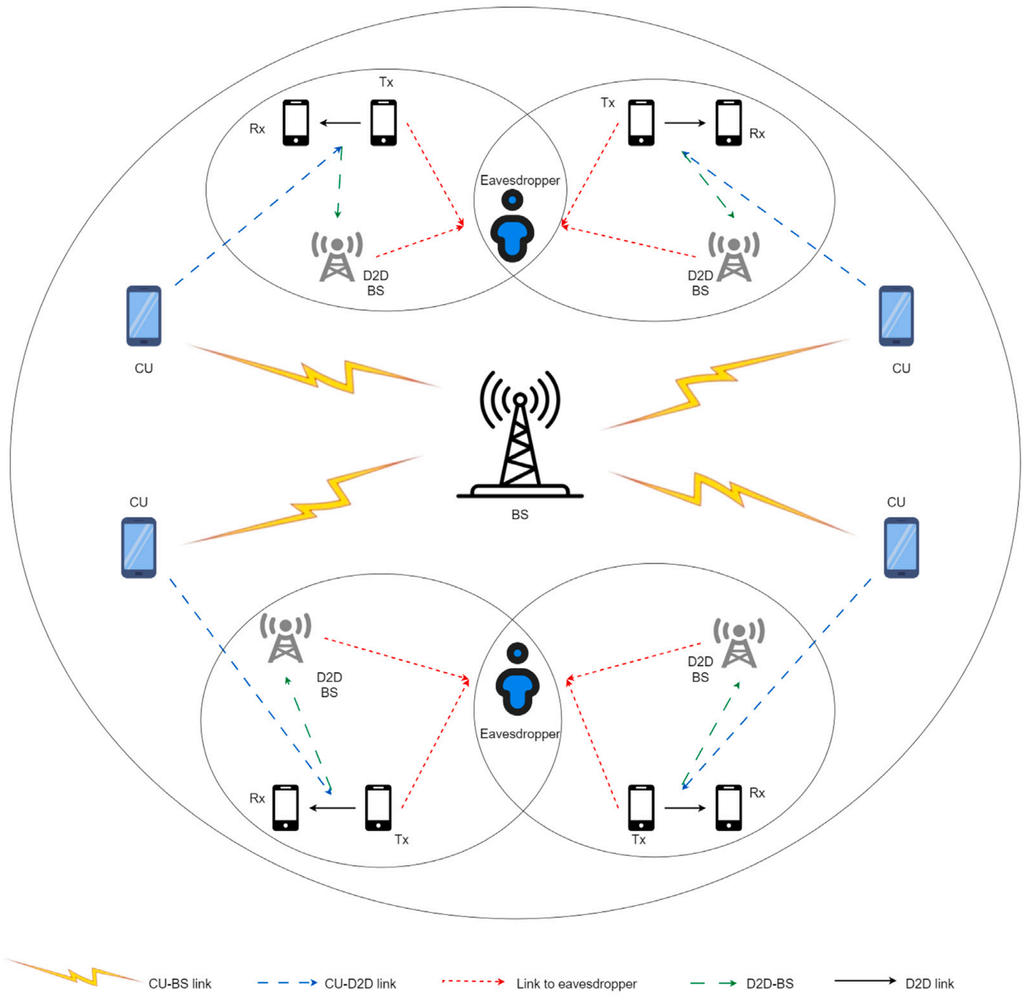


Fig. 1. System model.

and D2D users is maintained. They framed an optimization problem using a chaos game theory algorithm, which addressed subproblems of subchannel assignment and power allocation. However, the proposed approach might face complexity issues due to the NP-hard nature of the subproblems.

In addition, various researchers have used bio-inspired algorithms to solve the resource allocation algorithm, such as swarm-based approach [21] which focused on bee fly patterns to enhance resource allocation and network performance, shuffled frog leaping algorithm [22] for multicast D2D communications to improve spectral efficiency, grey wolf optimization algorithm [23] to perform resource allocation for D2D communication efficiently, particle swarm optimization and genetic algorithm [24] which addressed throughput enhancement and interference management.

From this literature review, we observed that the papers which used the game theory or graph theory only for resource allocation in D2D communication considered all the D2D users, whether trusted or untrusted. The papers which used AI methods were unable to mitigate the interference caused by D2D users and CUs. Thus, we proposed an AI and coalition game theory-based scheme for efficient RA, which overcomes the aforementioned issues in D2D communication.

3. System model and problem formulation

3.1. System model

Fig. 1 depicts the system model, which is considered for our proposed solution. In this paper, CUs are represented as $A = \{1, 2, 3, \dots, a, \dots, A\}$ and D2Ds are represented as $B = \{1, 2, 3, \dots, b, \dots, B\}$. We have considered a single ε. There is a single central macro BS (MBS) represented by s. When two channels communicate through signal transmission among d2D users, the communication channel is influenced by various factors like path loss constant, fading method, and distance.

For a similar case, the channel gain (ζ) among MBS and ath CU is given by:

$$\zeta_{s,a} = \omega f_{s,a} d_{s,a}^{-\nu} \tag{1}$$

where ω is represented as path loss constant, $f_{s,a}$ is a small scale fading value, $d_{s,a}$ is the distance between ath CU and MBS, ν is the pass loss exponent. Similarly, we can get the channel gain among the CU and D2D pair as $\zeta_{a,b}$ and bth D2D pair and b'th D2D pair as $\zeta_{b,b'}$ as shown in Eqs. (2) and (3).

$$\zeta_{a,b} = \omega f_{a,b} d_{a,b}^{-\nu} \tag{2}$$

$$\zeta_{b,b'} = \omega f_{b,b'} d_{b,b'}^{-\nu} \tag{3}$$

where bth D2D pair is transmitter and b'th D2D pair is receiver. Similarly, we can calculate gain between ath CU and ε as $\zeta_{a,\varepsilon}$, bth D2D pair and ε as $\zeta_{b,\varepsilon}$. The received signal $R_{s,a}$ from MBS to ath CU is given by:

$$R_{s,a} = \sqrt{W_s}\zeta_{s,a}T_{s,a} + \sum_{b=1}^{B} \lambda_{a,b}\sqrt{W_b}\zeta_{b,a}T_{b,a} + \mathcal{N}_{s,a} \tag{4}$$

where W_s is MBS's actual transmission power, $\lambda_{a,b}$ is resource reuse indicator, $T_{s,a}$ is the signal transmitted from MBS to ath CU, W_b is D2D pair's transmission power, $N_{s,a}$ is Gaussian noise from MBS to ath CU. Similarly, the Received signal $R_{a,b}$ from ath CU to bth D2D pair is given by:

$$R_{a,b} = \sqrt{W_a}\zeta_{a,b}T_{a,b} + \sum_{b'=1,b'\neq b}^{B} \lambda_{a,b}\sqrt{W_{b'}}\zeta_{b',b}T_{b',b} + \sum_{a'=1,a'\neq a}^{A} \lambda_{a,b}\sqrt{W_{a'}}\zeta_{a',b}T_{a',b} + \mathcal{N}_{a,b} \tag{5}$$

The only difference between Eq. (5) and Eq. (4) is two interferences caused by other CUs and D2D pairs. Likewise, we can get the received signal between bth and b'th D2D pairs as $R_{b,b'}$, ath CU and ε as $R_{a,\varepsilon}$, bth D2D pair and ε as $R_{b,\varepsilon}$. The SINR ratio ψ is based on Eqs. (4) and (5). As per this, $\psi_{s,a}$ for communication from MBS to ath CU is given by:

$$\psi_{s,a} = \frac{W_s|\zeta_{s,a}|^2}{\sum_{b=1}^{B} \lambda_{a,b}W_b|\zeta_{b,a}|^2 + \sigma_{s,a}^2} \tag{6}$$

where $\sigma_{s,a}$ is variance from MBS to ath CU, $|\zeta_{s,a}|$ indicates absolute value. Similarly, $\psi_{a,b}$ for communication between ath CU and bth D2D pair is given by [25]:

$$\psi_{a,b} = \frac{W_s|\zeta_{a,b}|^2}{\sum_{b'=1,b'\neq b}^{B} \lambda_{a,b}W_{b'}|\zeta_{b',b}|^2 + \sum_{a'=1,a'\neq a}^{A} \lambda_{a,b}W_{a'}|\zeta_{a',b}|^2 + \sigma_{s,a}^2} \tag{7}$$

Likewise, we can acquire SINR between bth and b'th D2D pair as $\psi_{b,b'}$, ath CU and ε as $\psi_{a,\varepsilon}$, bth D2D pair and ε as $\psi_{b,\varepsilon}$. The data rate $\eta_{s,a}$ from MBS to ath CU is calculated as:

$$\eta_{s,a} = \log_2\left(1 + \frac{W_s|\zeta_{s,a}|^2}{\sum_{b=1}^{B} \lambda_{a,b}W_b|\zeta_{b,a}|^2 + \sigma_{s,a}^2}\right) \tag{8}$$

Likewise, $\eta_{a,b}$ from ath CU and bth D2D pair is given by:

$$\eta_{a,b} = \log_2(1 + \frac{W_s|\zeta_{a,b}|^2}{\sum_{b'=1,b'\neq b}^{B} \lambda_{a,b}W_{b'}|\zeta_{b',b}|^2 + \sum_{a'=1,a'\neq a}^{A} \lambda_{a,b}W_{a'}|\zeta_{a',b}|^2 + \sigma_{s,a}^2}) \tag{9}$$

Similarly, we can acquire the data rate between bth and b'th D2D pairs as $\eta_{b,b'}$, ath CU and ε as $\eta_{a,\varepsilon}$, bth D2D pair and ε as $\eta_{b,\varepsilon}$. The sum rate of the system is calculated using the data rate of the whole network as given below:

$$\eta_t = \eta_{s,a} + \eta_{a,b} + \eta_{b,b'} \tag{10}$$

The secrecy capacity of ath CU and bth D2D pair against eavesdropper ε is given below:

$$SC_{a,\varepsilon} = [\eta_{a,b} - \eta_{a,\varepsilon}]^+ \tag{11}$$

$$SC_{b,\varepsilon} = [\eta_{b,b'} - \eta_{b,\varepsilon}]^+ \tag{12}$$

Secrecy capacity for the whole channel is given below:

$$SC_{\text{total}} = \left[\sum_{a=1}^{A}\sum_{b=1}^{B} \eta_{a,b} - (\eta_{a,\varepsilon} + \eta_{b,\varepsilon})\right]^+ \tag{13}$$

3.2. Problem formulation

Our proposed scheme focuses on maximizing the overall average sum rate that enhances the average secrecy capacity of the D2D communication system. The constraints for the given problem are mentioned here:

$$P_1 : \max_{\lambda,W_a,W_b} (\eta_t) \tag{14}$$

$s.t.$

$$\begin{aligned}
C_1 &: \lambda_{a,b} \in 0,1\\
C_2 &: 0 \leq W_i \leq W_i^{\max}, \forall i \in a\\
C_3 &: 0 \leq W_j \leq W_j^{\max}, \forall j \in b\\
C_4 &: \psi_i \geq \psi_i^{\min}, \forall i \in a\\
C_5 &: \psi_j \geq \psi_j^{\min}, \forall i \in b\\
C_6 &: SC^{\text{pre}} \geq SC_{a,\varepsilon}\\
C_7 &: SC^{\min} \geq SC_{b,\varepsilon}
\end{aligned}$$

In the above objective function, P_1, W_a and W_b represents transmission powers of ath CU and bth D2D users, respectively, and λ is the resource reuse indicator. Constraint C_1 represents that RA between ath CU and bth D2D are guaranteed. Then, Constraint C_2 states that the transmission power of a CU is always less than or equal to the maximum power of CU as $W^{\max}$. Similarly, C_3 specifies the power constraint for D2D. Constraint C_4 and C_5 show the SINR constraint of a CU and a DU, respectively. Constraint C_2 states that the transmission power of a CU is always less than or equal to the maximum power of CU as $W^{\max}$. Similarly, C_3 specifies the power constraint for D2D. Constraint C_4 shows that the SINR of a CU is greater than or equal to the minimum SINR of CU as $\psi^{\min}$. Similarly, C_5 specifies the SINR constraint for D2D. Furthermore, when the sum rate of the system increases, the average secrecy capacity of the system is also enhanced. Hence, Constraint C_6 and C_7 state that the secrecy capacity of D2D and CU is less than the minimum and predefined secrecy capacity. Table 2 shows the specific notations and their description.

Table 2
Mathematical notations used in the manuscript.

Notations	Description
A	Set of CUs
B	Set of DUs
$\zeta_{s,a}, \zeta_{a,s}$	Channel gain between MBS-CU and CU-MBS
$\zeta_{a,b}, \zeta_{b,a}$	Channel gain between CU-D2D and D2D-CU
$\zeta_{b,b'}, \zeta_{b',b}$	Channel gain between D2D transmitter and D2D receiver and vice versa
$\zeta_{a,\varepsilon}, \zeta_{\varepsilon,a}$	Channel gain between CU-Eavesdropper and vice versa
$\zeta_{b,\varepsilon}, \zeta_{\varepsilon,b}$	Channel gain between D2D-Eavesdropper and vice versa
v	Path loss exponent
ω	Path loss constant
$d_{s,a}$	Distance between MBS-CU
$T_{s,a}$	Signal transmitted from MBS to CU
$T_{a,b}, T_{b,a}$	Signal transmitted between CU-D2D and vice versa
$T_{b,b'}$	Signal transmitted between D2D-D2D
$T_{a,\varepsilon}$	Signal transmitted between CU-Eavesdropper
$T_{b,\varepsilon}$	Signal transmitted between D2D-Eavesdropper
ϑ	Received signal from MBS-CU
$R_{s,a}$	SINR between MBS & CU
$R_{a,b}, R_{b,a}$	SINR between CU-D2D and vice versa
$R_{a,\varepsilon}$	SINR between CU-Eavesdropper
$R_{b,\varepsilon}$	SINR between D2D-Eavesdropper
W_s, W_a, W_b, W_e	Power of MBS, CU, D2D and Eavesdropper
$\lambda_{a,b}$	Binary variable (resource reuse indicate)
σ^2	Variance
$\eta_{a,b}$	Data rate of CU and D2D
$\eta_{a,\varepsilon}, \eta_{b,\varepsilon}$	Data rate of eavesdropper from CU and D2D
$SC_{a,\varepsilon}, SC_{b,\varepsilon}$	Secrecy capacity of CU, D2D
SC_{total}	Secrecy capacity of overall channel

4. The proposed scheme

4.1. AI-based approach optimal D2D selection

4.1.1. Dataset description

The dataset we have used for training and testing consists of five features: reference signal received power, signal-to-noise ratio, continuous quality improvement, reference signal received quality, and received signal strength indicator. All training examples are assigned a class 0 or class 1, indicating 0 for non-trusted and 1 for trusted DUs.

4.1.2. Data preprocessing

Further, the data is preprocessed to make it easier for training. We applied preprocessing techniques such as standardization scaling techniques to remove the mean and scale the features. The operations are independently performed feature-wise. This scaling technique works in the following way: the mean (ϱ) is subtracted from the data, and the obtained result is further divided by the standard deviation(ϖ). The mean is considered to be 0, and the standard deviation is considered to be 1.

$$\kappa = \frac{\chi - \varrho}{\varpi} \tag{15}$$

where χ is the data to be scaled and κ is the scaled data. Applying this to the entire dataset, we obtained the scaled data with a mean of 0 and a variance of 1.

4.1.3. ML models applied

The dataset was passed through an AI model in Python developed using the scikit-learn library. Using different values for hyperparameters, we tried to reduce the loss function and get the optimal results for binary classification. We applied various ML approaches like logistic regression (LR), KNN, gaussian naïve Bayes, support vector machine (SVM), and perceptron learning. The best outcomes were acquired using the KNN algorithm with an accuracy of 98.76%. KNN is a supervised, non-parametric learning classifier that makes use of proximity to make classifications. It is a lazy learning algorithm. All the data points are plotted on a graph, and the distance of the new point is measured from each. Then, the class of the KNN of that point is assigned to the new point. The distances can be measured in different ways: cosine similarity, Euclidean, Manhattan, Minkowski, and Hamming distance. The formula gives Euclidean distance between two points:

$$d_{x,y} = \sqrt{\sum_{i=1}^{n} (y_i - x_i)^2} \tag{16}$$

KNN has very limited hyperparameters, k and the distance matrix. The value of k is decided using the elbow method. In our example, the most optimal value of k turned out to be 3.

4.2. Coalition game based approach

The D2D pair is sharing the resources of the CU for communication purposes. The coalition game refers to the method where players make and change their coalition to achieve common goals. The main approach of coalition game theory is to help D2D pairs make decisions for switching coalitions based on predefined preferences. The process of changing the coalition is done till the Nash equilibrium is achieved. Nash equilibrium needs to provide a saturation state, after which efficiency cannot be increased. In this proposed paper, efficiency is in terms of SC and η.

The proposed scheme has A CUs, B D2Ds, and one MBS. The CU's resources are shared for downlink and uplink communication among DUs to maximize SC and sum rate. B D2D pair makes A disjoint coalitions such that $B > A$. Assume a disjoint coalition $\Upsilon^0 = \{\Upsilon_1, \dots \Upsilon_g \dots \Upsilon_G\}$ $\exists \Upsilon_g \cap \Upsilon_{g'} = \emptyset$. Considering a disjoint coalition $\Upsilon_g \in \Upsilon^0$, which shares the resource of the ath CU, the condition is that both users in D2D pair must be in the same coalition. The preference order through which D2D pair change their coalition is based on the channel gain of CU. The Nash equilibrium is achieved through an iterative process in which all the D2D pairs are checked to find an appropriate channel with maximum gain. After a certain iteration, the sum rate and SC cannot be increased; this stable point is called Nash equilibrium. Any coalition $\Upsilon_{g'}$ can have a maximum of U number of DUs.

$$\Upsilon_{g'} = \sum_{z=1}^{U} b_z, \forall b_z \cup \{b_s, b_w\} \in \Upsilon_{g'} \subset \Upsilon \tag{17}$$

where b_z is the D2D pair from coalition $\Upsilon_{g'}$. b_s and b_w are strong and weak D2D pair, and $\{b_s, b_w\}$ are in a unique coalition $\Upsilon_{g'}$. The D2D pairs are first assigned to different coalitions, then all the D2D pairs are selected one by one, and they choose the best CU based on the channel gain. The SC of the D2D pair is then compared with the minimum SC of CU. If the SC of D2D is greater than the minimum SC of CU, then the coalition of the D2D pair is switched to the new coalition. If the condition of the SC is not satisfied, the CU with the next maximum channel gain is selected, and all the steps are done repeatedly. This switching is done in a loop till all the D2D pair gets into the best possible coalition; that is how Nash equilibrium is achieved.

In the coalition game approach, the D2D pair changes their coalition related to the preference order. A preference order $\Upsilon_{g'} \succ_i \Upsilon_g$ indicates that pair b_i prefers $\Upsilon_{g'}$ over Υ_g, where $\Upsilon_{g'}, \Upsilon_g \subseteq \Upsilon^0$. The equations of preference order for D2D pairs are provided as follows:

$$\Upsilon_{g'} \succ_k \Upsilon_g \qquad SC(b_i) \geq SC_{(\min)}(b_i). \tag{18}$$

where $SC(b_i)$ indicates secrecy capacity of D2D pair and $SC_{(min)}(b_i)$ indicates minimum secrecy capacity by any D2D pair present in $\Upsilon_{g'}$. Algorithm 1 describes the coalition game formulation for D2D communication with AI for IM and sum-rate maximization. This algorithm stops when the game reaches a Nash partition. The Nash partition indicates a stable coalition where no D2D pair is incentivized to move to another coalition. This is directly derived after Nash equilibrium, a state where no player can benefit by changing their strategy. In this context, every D2D pair is in a coalition where its current position offers the highest possible channel gain.

Algorithm 1 Coalition game formulation using AI for IM and secure D2D communication

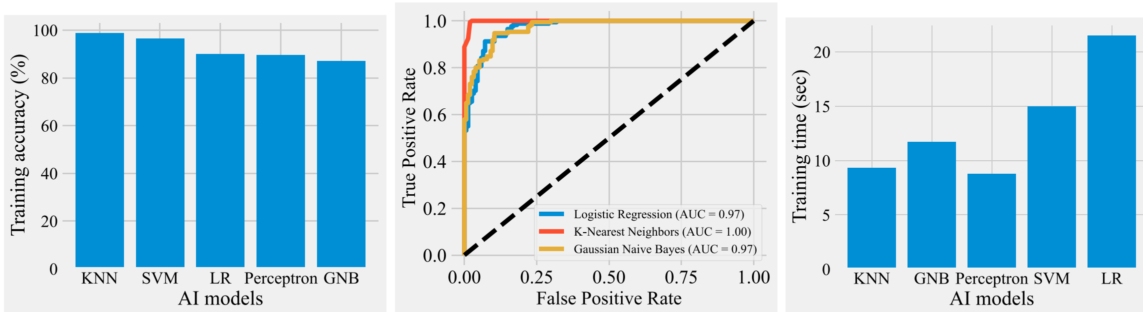
1: Initialization by random partitioned coalition $\Upsilon^0 = \Upsilon_1, \dots \Upsilon_g, \dots, \Upsilon_G$
2: Υ^0 is chosen as current coalition Υ_{cur}
3: **repeat**
4: Choose D2D pair randomly $b_i \in B$, which belongs to $\Upsilon_g \in \Upsilon_{cur}$
5: Choose another coalition based on the best channel gain $\Upsilon_{g'} \in \Upsilon_{cur}$ and $\Upsilon_g \neq \Upsilon_{g'}$
6: Perform switch operation from Υ_g to $\Upsilon_{g'}$ after checking via preference order in equation (18)
7: **if** equation (18) satisfies **then** goto line 10
8: **else**goto line 5
9: **end if**
10: D2D pair splits from its present coalition Υ_g, and merges with $\Upsilon_{g'}$ as a new current coalition
11: $(\Upsilon_{cur} \backslash \{\Upsilon_{g'}, \Upsilon_g\}) \cup \{\Upsilon_g \backslash \{i\}, \Upsilon_{g'} \cup \{i\}\} \rightarrow \Upsilon_{cur}$
12: **until** Nash partition

5. Results and discussion

This section discusses the proposed scheme's performance analysis. We have considered different evaluation metrics, such as accuracy, precision, recall, F1-score, sum data rate, secrecy capacity, and convergence time. Furthermore, we summarized the experimental setup and tools used for the AI and coalition game-based scheme.

5.1. Experimental setup and tools

In the proposed scheme, the D2D communication environment was setup using Matlab R2022a. Then, we used Google Colab Notebook, which uses Python 3.6 to implement diverse AI models. For that, we have considered different Python libraries like Numpy, Pandas, Matplotlib, and Scikit-learn(sklearn). From sklearn library, modules such as model_selection, preprocessing, ensemble, SVM, linear_model, neighbors, metrics, naive_bayes were used to import functions like train_test_split, StandardScaler, RandomForestClassifier, GradientBoostingClassifier, support vector classifier (SVC), LogisticRegression, KNeighborsClassifier, accuracy_score, GuassianNB and Perceptron. The Tables 3 and 4 highlight the hyper-parameters and simulation parameters used for the D2D environment setup and AI model, respectively [26]:



(a) (b) (c)

Fig. 2. (a) Comparison of training accuracy among AI models, (b) ROC curve comparison, and (c) training time comparison of different AI models.

Table 3
Simulation parameters.

Parameter	Value
Cell structure	Circular
Cell radius	500 m
D2D pairs radius	25 m
Bandwidth	10 MHz
Number of CU	5–15
Number of D2D pairs	5–150
Transmit power of CU	25 dBm
Transmit power of D2D pairs	23 dBm
Path loss model	128.1 + 37.6log 10 km
Path loss exponent	3
Path loss constant	10^{-2}

Table 4
Hyperparameters used in AI models.

AI model	Parameter with values
KNN	neighbors: 5, weights: ‘uniform’, leaf size: 35, metric: ‘callable’
GNB	var_smoothing: float, default: 1e−9
Perceptron	alphafloat: [0.0001], max_iter: [1000]
LR	penalty: l2, intercept_scaling: 1, solver: lbfgs
SVM	gamma = ‘scale’, probability = True, kernel: [‘poly’]

5.2. Performance analysis of the AI algorithms

Fig. 2(a) depicts the accuracy comparisons of different AI algorithms used in classifying D2D pairs based on their channel indicator values, i.e., RSSI, SINR, RSRP, and RSRQ. From the graph, it is evident that KNN outperforms other AI models in terms of accuracy, i.e., 98.76%. The rationale behind the high accuracy of KNN is that the dataset has a few dimensions (only channel indicator values), which makes it easy for KNN to get trained. It is highly efficient in training datasets with a few dimensions and non-linear decision boundaries; therefore, KNN has higher training accuracy. However, we did not rely solely on accuracy parameters; we used other statistical measures, such as precision, recall, and F1 score, to justify the higher training accuracy of the KNN model. From Table 5, we can infer that KNN again shows outperformance in all the statistical measures compared to other AI models. Further, the receiver operating characteristic (ROC) curve offers the performance of binary classifiers at all thresholds (0–1). The false positive rate is designed on the X-axis against the true positive rate on the Y-axis. The area under the curve (AUC) of the ROC curve should ideally be as near to 1 as possible. From Fig. 2(b), the AUC for LR and GNB is 0.97, whereas KNN has AUC = 1. Thus, by comparing the trade-offs between sensitivity (true positive rate) and specificity (false positive rate) of the ROC curve, we can find the most suitable model (i.e., KNN model) to solve the binary classification problem.

Fig. 2(c) shows the training time of all the AI classifiers used in the proposed scheme. Training time depends on various factors, such as the size of the dataset, dimensionality, and the underlying functions used in the implementation. Since KNN is highly efficient for non-linear decision problems and for smaller datasets, it has lower training time compared to SVM, NB, and LR. Furthermore, it has lower computational complexity than other classifiers, i.e., $\mathcal{O}(ND)$, where N and D indicate the number of training samples and dataset size. Since the dataset has only channel indicator values, it signifies the dataset's dimensionality (D) is smaller. If the dimensionality is smaller, KNN can efficiently classify the D2D pairs based on their channel indicator values. Consequently, it has a lower training time, i.e., 9.32 s However, we can observe from Fig. 2(c) that perceptron is outperforming in terms of training time (8.79 s) but on the cost of lower training accuracy 89.53%. Also, other statistical measures shown in Table 5 reveal that perceptron has a lower precision, recall, and F1 score. So, even though perceptron has a lower training time, it is not efficient in solving the binary classification problem — classifying D2D pairs on the basis of channel indicator values. This is essential to efficiently solve binary classification problems because we want to allow only optimal D2D pairs to be part of the coalition game. So, if D2D pairs are not classified properly, the coalition game becomes computationally expensive, consequently reducing the sum rate of the overall D2D communication.

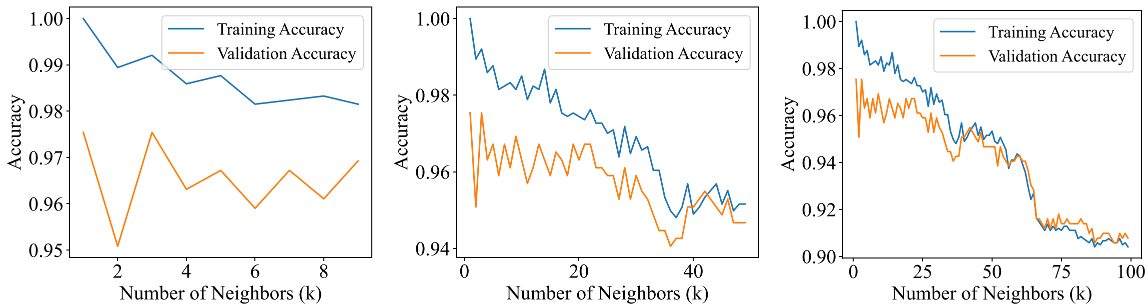
Table 5
Statistical measures of AI algorithms.

AI models	Accuracy	Precision	Recall	F1 score
LR	90.15	87.98	94.15	90.96
SVM	96.61	94.94	98.83	96.85
KNN	98.76	98.27	99.42	98.84
GNB	87.07	82.74	95.32	88.59
Perceptron	89.53	85.13	97.08	90.71

We also evaluate the KNN algorithm using the validation curve as shown in Fig. 3 by changing the number of neighbors (k). From Fig. 3, we can observe that with a small number of neighbors (k = 10), the training and validation accuracy has a gap of 2% — not converged well. However, as we increase the number of ‘k’ (i.e., k = 50 and 100), we can see a steep decrease in the training and validation accuracy whilst converging smoothly on the cost of lower accuracy. Therefore, we used k = 3 as the final number of neighbors to get an improved training accuracy, i.e., 98.76% by the KNN model. Increasing the number of ‘k’ reduces the chances of overfitting, but it also reduces the accuracy and increases the computational complexity of the proposed scheme.

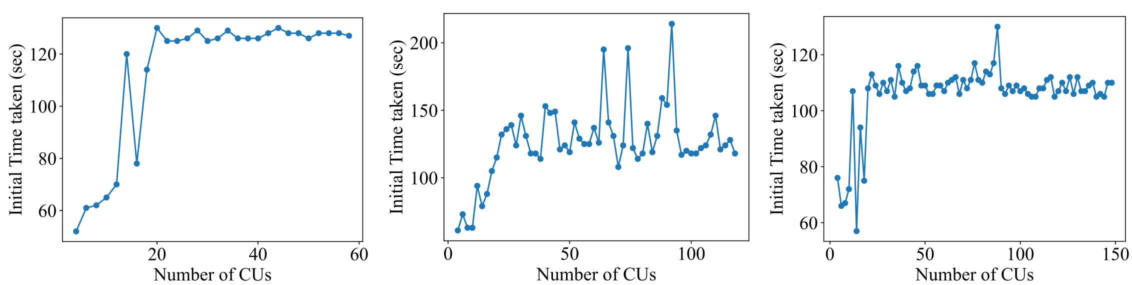
5.3. Performance analysis of the coalition game

Fig. 4 shows the initial time taken to form a CUs coalition in the proposed coalition game. We compare the coalition formation time by varying the number of CUs, i.e., 20, 60, and 120. Initially, with fewer CUs = 60, the coalitions get readily formed in 125.43 s. However, as we increase the number of CUs = 120 and 150, coalition formation time also increases. It is important to note that at every iteration, the



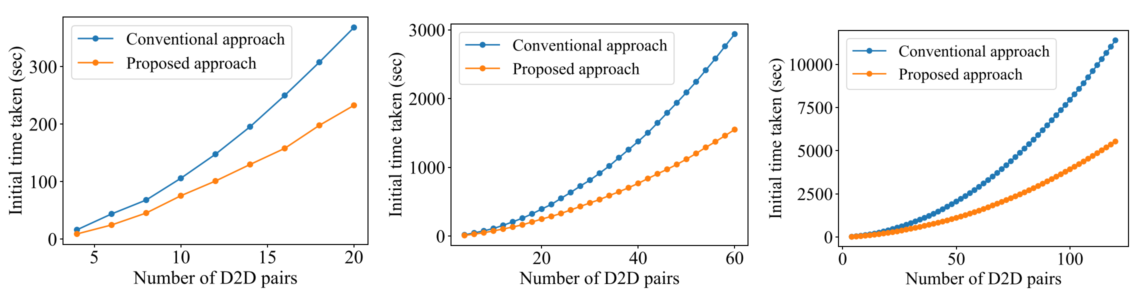
(a) (b) (c)

Fig. 3. Validation curve for the different number of 'k' values (a) k =10, (b) k = 50, and (c) k = 100.



(a) (b) (c)

Fig. 4. Initial time taken versus the number of CUs = (a) 20, (b) 60, and (c) 120.



(a) (b) (c)

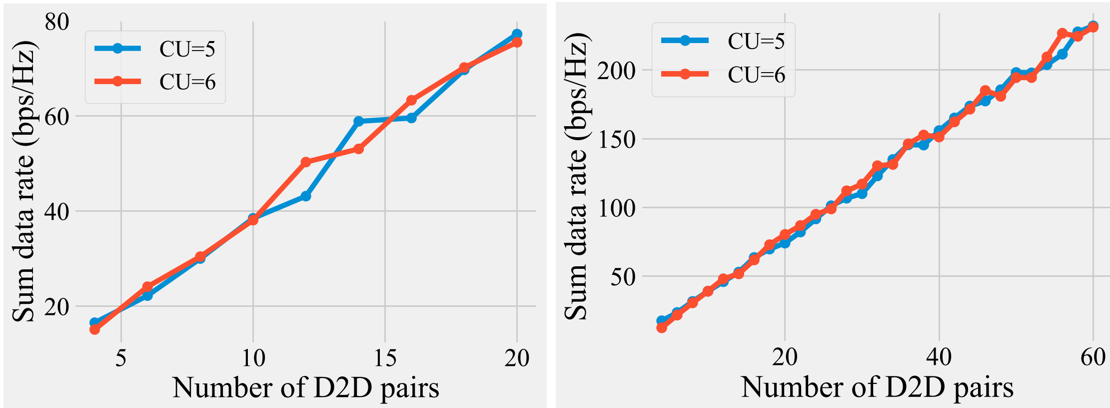
Fig. 5. Comparison of initial time taken to form a coalition between conventional and the proposed scheme at D2D pairs = (a) 20, (b) 60, and (c) 120.

coalition formation time changes because it depends on the quality of CUs and the optimal D2D users from the AI algorithm. That is, if the CUs and D2D users have better channel conditions (optimal resources), it can take minimum time to form coalitions for RA tasks. Therefore, in Fig. 4, the initial time taken (blue line) has higher and lower spikes representing the quality of CUs and, based on that, the coalition formation time taken.

Similarly, in Fig. 5, we compared the coalition formation time for the proposed scheme and the conventional scheme (RA without employing AI). It is evident from Fig. 5 that as the number of optimal D2D pairs increases in the coalition game, the time taken to form a coalition also increases; however, it will always be less than the conventional scheme. As a result, we can conclude that the proposed coalition game (blending with AI) has higher competency in terms of convergence, computational complexity, and offering sum rate than the conventional scheme. This can be seen in Fig. 5, where at D2D pairs = 20, the proposed scheme takes 223.62 s to form coalitions. Similarly, at D2D pairs = 60 and 120, the proposed scheme takes 1392.16 s and 5298.80 s, respectively, less time taken than the conventional scheme.

Next, we evaluate the proposed scheme on the basis of the sum data rate. In that view, Fig. 6 shows the changes in CUs sum data rate when D2D pairs are varied. The X-axis depicts the increasing number of D2D pairs, and the Y-axis represents the sum data rate in bits/s/Hz. The blue line shows the sum data rate of 5 CUs, and the orange line shows the sum data rate for 6 CUs with varying D2D pairs. From Fig. 6(a) shows the fluctuating sum data rate of CUs when varying D2D pairs from 4–20. They are not converging well since the game has not yet attained the Nash equilibrium. However, as we increase the number of optimal D2D pairs from 20 to 60, we can sum data rate increases and converge well for both the CUs in Fig. 6(b). At D2D pairs = 60, the maximum attained CUs sum data rate = 251 bps/Hz. This high sum data rate comes due to the presence of optimal D2D users from the AI algorithm, where we efficiently found optimal D2D pairs based on their channel indicator values. We created a dataset comprised of those optimal D2D pairs to be the players for the coalition game-based RA.

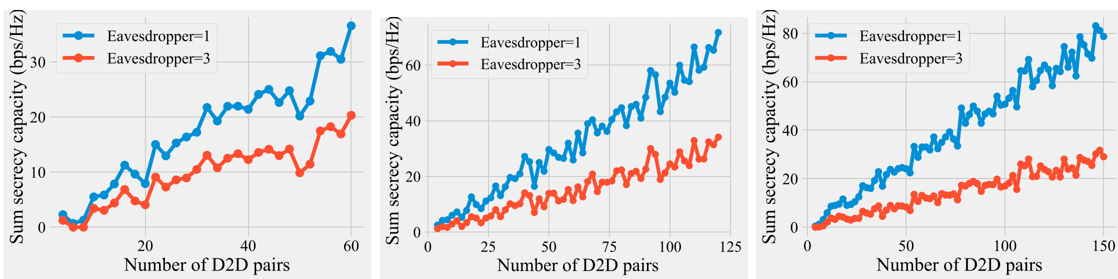
In this proposed scheme, we calculated the sum SC by varying D2D pairs and eavesdroppers. In Fig. 7, we have taken the number of D2D pairs on the X-axis and the sum SC on the Y-axis. The blue indicates a single eavesdropper is considered, and the orange line for multiple eavesdroppers is considered. The sum SC is calculated by evaluating the D2D data rate against the data rate of the eavesdroppers. The data rate is calculated with the help of SINR as discussed in Eq. (13). From



(a)

(b)

Fig. 6. Sum data rate versus the number of D2D pair, when CU = 5 and CU = 6 at (a) D2D pairs = 20 and (b) D2D pairs = 60.

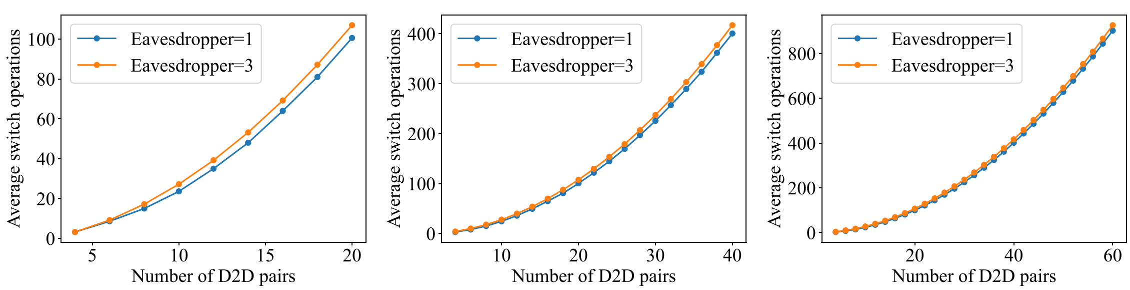


(a)

(b)

(c)

Fig. 7. Sum secrecy capacity versus the number of D2D pairs, when Eave = 1 and Eave = 3. (a) D2D pairs = 60, (b) D2D pairs = 120, and (c) D2D pairs = 150.



(a)

(b)

(c)

Fig. 8. Average number of switch operations versus the number of D2D pairs, when Eave = 1 and Eave = 3. (a) D2D pairs = 20, (b) D2D pairs = 40, and (c) D2D pairs = 60.

Fig. 7, we can depict that when the number of D2D increases, the sum SC will also increase. Consequently, when the number of eavesdroppers exceeds, the sum SC will decrease. The eradication of eavesdroppers is due to the optimal RA by employing AI and a coalition game in the D2D environment.

Further, the coalition game is assessed on the basis of D2D's switch transfer between different coalitions. The D2D pair changes its coalition when the alternate coalition has more channel gain and relatively lower interference than the other coalition. In Fig. 8, we take the number of D2D pairs on the X-axis and the number of average switch operations on the Y-axis. The blue line is for a single eavesdropper, and the orange line is for multiple eavesdroppers. Fig. 8, shows the overall number of switch operations in the coalition game; it increases with the number of D2D pairs. Switch operations slightly increase when the number of eavesdroppers increases from single to multiple with varying D2D pairs. The higher switch operation at D2D pairs = 40 and 60 indicates that the coalition game is attempting to find better coalitions to optimize the RA task.

In the proposed scheme, time is considered whenever there is a need to find a new D2D pair or compare coalitions. As shown in Fig. 4, the time to achieve initial partitions increases when the number of CUs increases. The same resemblance can be observed in Fig. 9, the X-axis represents the number of D2D pairs, and the Y-axis represents the convergence time taken. When eavesdropper = 1, the blue line is taken into consideration, and when there are three eavesdroppers, the orange line is taken into consideration. The graph clearly shows that as the D2D pairs increase, they tend to converge in terms of time taken.

6. Conclusion

This paper proposed an AI and coalition game-based efficient RA scheme for D2D communication. In the proposed scheme, AI plays a

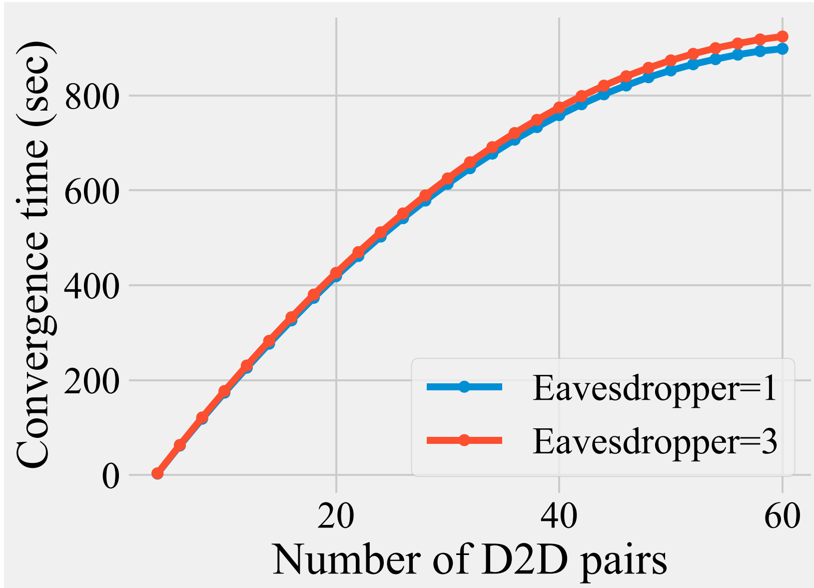


Fig. 9. Time to converge vs. the number of D2D pairs, when Eave = 1 and Eave = 3.

vital role in selecting the most compatible D2D pairs for CUs, which reduces the interference effect of other D2D pairs with less computational complexity. For the same, we applied different AI models, such as LR, SVM, KNN, GNB, and perceptron, to select the best D2D users. Out of these, the KNN algorithm performs well and selects the best D2D user with an accuracy of 98.76%. We then used a coalition game theory for optimal RA in the presence of varying numbers of eavesdroppers. It also reduces the co-channel interference and improves the overall sum data rate and secrecy capacity of D2D users in the proposed scheme. We achieved the sum data rate of 78 bps/Hz and 251 bps/Hz with 20 D2D pairs and 60 D2D pairs, respectively. The maximum sum secrecy capacity of the proposed scheme with 150 D2D pairs in the presence of 01 and 03 eavesdroppers are approx. 80 bps/Hz and 31 bps/Hz, respectively.

In the future, we aim to consider non-orthogonal multiple access (NOMA) for simultaneous resource allocation to multiple users in a heterogeneous network scenario.

CRediT authorship contribution statement

Jenil Akhyani: Writing – review & editing, Writing – original draft, Validation, Data curation, Conceptualization. **Vartika Desai:** Writing – original draft, Software, Formal analysis, Data curation, Conceptualization. **Rajesh Gupta:** Writing – review & editing, Supervision, Software, Resources, Methodology, Investigation. **Nilesh Kumar Jadav:** Writing – review & editing, Visualization, Validation, Supervision, Software, Resources, Data curation. **Tejal Rathod:** Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Resources. **Sudeep Tanwar:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Methodology. **Sandeep Malhotra:** Writing – review & editing, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

There is no Conflict of Interest

Data availability

No data was used for the research described in the article.

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