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Resource allocation optimization of device-to-device communication using machine learning algorithms

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Abstract

Device-to-device communication is envisioning next-generation wireless communication. The utility of the device-to-device communication model encourages emerging communication systems such as 5G and the Internet of Things. The allocation of resources and channel interference are major challenges in device-to-device communication. This paper proposes machine-learning-based algorithms for resource allocation and optimization of device-to-device communication. The proposed machine learning algorithm is a cascaded support vector machine. The cascaded support vector machine mapped the parameters of CUEs and DUEs. We create an iterative algorithm to achieve low-power, energy-efficient resource allocation with mode selection by formulating a novel optimization problem to maximize energy efficiency using the subtractive form method to solve a fractional objective function. We obtain data samples from a suboptimal algorithm to train the cascaded algorithm and verify the trained algorithm. Our numerical results show that the proposed cascaded machine learning-based transmission algorithm's accuracy reaches about 88%–95% despite its simple structure due to the limitation in computing power. The analysis of results suggests that the proposed algorithm is more efficient than SVM, DSVM, and the reinforcement learning (RL) algorithm.

Keywords: D2D Communication; Cellular Communication; Machine Learning; Optimization

1. Introduction

Coverage and reliability of next-generation wireless communications are major issues. The increase in emerging wireless network traffic demand, such as high-speed data rates and new support for various communication modes, necessitates a significant increase in bandwidth and resources to cover the wireless communication system. Device-to-device communication models reduce the impact of wireless traffic and improve the performance of cellular networks as well as local, dependent communication systems. D2D communication doesn't require any infrastructure, such as base stations and access points, so operators are considering new communication models for D2D communication without investing in additional spectrum [1]. D2D communication offers proximity, commercial, and emergency services. Devices cannot speak to one another directly in a traditional wireless cellular system because base stations must be used for all communications [2]. More than 10 exabytes of traffic growth per month will be moving across cellular networks by 2019 thanks to the evolution of 4G and 5G and the predicted almost 30-fold increase in traffic. The switching system offered by the dynamic cooperative transmission policy allows users to alternate between various D2D nodes and conventional cellular communication as needed [3]. Early in the 1990s, wireless communications evolved, bringing with it digital cellular technology. The implementation of 3G as a strategy to achieve high-speed data networks began in 1997 [3, 4]. One of the most difficult problems, radio resource management for D2D networks, is also examined in this paper. We take into account a cellular overlay D2D network where cellular and D2D links don't interfere with one another. All D2D devices are permitted to share predetermined radio spectra to increase spectral efficiency. As a result, we must select the best possible set of D2D links to transmit data while taking D2D device

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interference into account. The majority of earlier studies used heuristic or mathematical methods to suggest resource management algorithms for D2D networks. These methods continuously introduce complexity into each scheduling decision, and the total complexity will be extremely high if it is accumulated. According to the report survey, machine learning algorithms can be used as resource management tools in the D2D communication model. Machine learning algorithms reduced local interference and increased radio frequency coverage for cellular and local users. Machine learning provides various categories of algorithms, such as supervised, unsupervised, and reinforced learning. Authors [14, 15] apply RLA (reinforced learning) for parameter estimation. To provide the best D2D communication link, the reinforcement-learning-based latency-controlled D2D connectivity algorithm learns the D2D network parameters, such as communication range, latency, or the packets in the buffer queue and their neighbors. Additionally, the RL-LCDC algorithm gauges communication latency by counting the number of packets in the buffer queue. More packets in the buffer indicate a communication link with higher communication latency. For the sake of clarity, this paper refers to communication latency as "latency." Despite its dynamic behavior, the algorithm attempts to maintain connectivity between devices in an indoor network. To achieve maximum connectivity, this paper evaluates the algorithm over energy. This paper proposes cascaded machine learning algorithms for resource allocation and optimization for the proposed system of D2D communication. The proposed cascaded machine learning algorithms learn the channel parameters of CUEs and DUEs. The single cell unit of frequency reuse and pair device sharing the main objective of this paper is to enhance the throughput of communication models and reduce inter-channel interference. The remainder of the article is organized as follows: related work in Section II; proposed methodology in Section III; experimental analysis in Section IV; and conclusion and future work in Section V.

2. Related Work

The continuous effort of several authors and the advancement of machine learning algorithms enhance the efficacy of the D2D communication system underpinning cellular networks. Recently proposed algorithms for resource allocation and optimization in D2D communication, some of which are important, are described here. The author [1] proposes security and privacy issues in DD, which are highlighted in DD. To broaden the scope of the study, network- and system-level S&P issues in distributed and centralized systems environments with and without central management are investigated. Along with an extensive survey concerning the most recent work on DD concerning security and privacy issues, a comparison between in-band and out-band DD is made. The author [2] introduces and compares contemporary spectrum efficiency strategies in 5G through D2D communication. The use of various strategies to increase spectrum efficiency is the main focus. Additionally, the proposed work's issues in interference management, resource usage, power control, and mode selection are contrasted. The author [3] proposes the RF-EH method be used to model a sum throughput maximization problem for a CR-assisted D2D network. The problem is decomposed into several sub-problems using the duality theory, and the Karush-Kuhn-Tucker conditions are employed to solve the sub-problems. The simulation results are offered to support our recommended strategies. The author [4] presents a D2D-assisted heterogeneous collaborative edge caching system by concurrently optimizing node selection and cache replacement in mobile networks, based on flexible trilateral cooperation among user equipment, edge base stations, and a cloud server. We demonstrate the usefulness of the proposed AWFDRL framework in reducing average content access delay, enhancing hit rate, and unloading traffic by proving the convergence of the corresponding algorithm and presenting simulation data. The author [5] proposes an authentication and key agreement mechanism for secure and anonymous D2D group communications in 5G cellular networks that combines the benefits of certificates public key cryptography (CL-PKC) and elliptic curve cryptography (ECC). We analyze the suggested solution's performance in terms of computing, communication, and energy expenses. The findings show that the idea is both light and efficient. The author [6] proposes SCMA technology be implemented in a D2D cellular network to exploit the SCMA scheme's overloading feature to accommodate more device connectivity while improving overall network performance. Simulations that illustrate the benefits of the suggested solutions under different situations are used to evaluate the performance of the proposed schemes. The author [7] proposes speed-IoT as a multi-hop, multi-channel routing strategy for D2D communication in an IoT mesh network that is spectrum-conscious and energy-efficient. We assume that we have access to a radio environment map (REM) generated by dedicated spectrum sensors that record spatiotemporal spectrum usage. The author [8] proposes Existing work on resource allocation for in-band underlay D2D communication mode is reviewed, with several scenarios for sharing common resources across cellular and D2D users considered. A summary of existing research approaches such as energy harvesting with SWIPT and base station sleep mode (BS) is offered. In addition, this research provides insight into green communication from the perspective of D2D. The author [9] Using an adaptive genetic algorithm, a novel energy consumption optimization (ECO) approach for green D2D multimedia communications has been developed. When compared to other methods, the experimental results showed that our proposed ECO approach could save up to 64% on average energy consumption while maintaining good video quality and meeting constrained bandwidth constraints. The author [10] provides a cellular network relaying service, which is capable of expanding network coverage and reducing traffic over cellular networks through D2D communication. According to the experiments, the proposed technique with 5-surely maintains D2D communication for a longer time than standard strategies. As a result, users that are outside of network coverage are supplied for longer periods by expanding the ENB's network coverage and relaying data using D2D offloading. The author [11] discussed a user association scheme based on game theory to determine optimal associations in D2D wireless networks. In addition, we created an evolutionary game-theoretic model for D2D link generation in the network when nodes are dynamically added, which may be used to find an evolutionarily stable strategy, or ESS, when simulated. The author [12] proposes a double auction approach to resource distribution with social ties and sentiment categorization that merges the social and physical worlds for D2D communications. Finally, simulation findings show that not only can the suggested double auction technique attain an optimal solution with less complexity, but also that social links have an impact on D2D communications. The author [13] looked into resource allocation approaches, mode selection for underlay communications in terms of device-to-device communication, and cooperative communication mechanisms. in terms of long-term evolution and long-term evolution-advanced platforms. Better spectrum use is also depicted, which is done on the basis of analysis to determine whether proper resource allocation, whether it is power, frequency, or time, and mode selection are done in a planned manner, which will result in less interference and a secure system. The author [14] presents DM-COM as a viable approach for allowing D2D and MU-MIMO subsystems to coexist in cellular networks. The DM-COM enabler is a new solution for managing mutual interference between the two subsystems that does not require channel state information and is thus practical to deploy. D2D users obtain 1.9 bit/s/Hz spectral efficiency utilizing DM-COM in a small cellular network, whereas MU-MIMO users see less than 8% throughput degradation when compared to the case without D2D users. The author [15] proposed a novel problem that integrates the three major modules of D2D communication—resource management, mode selection, and power management—into one. A novel joint low-power and energy-efficient resource allocation with mode selection for the D2D communication underlay in-band with transmit power, interference, and data rate constraints is investigated. Numerical analysis demonstrates and validates the novel proposed algorithm's optimal low-power and energy-efficient characteristics with all constraints to ensure communication quality for D2D communication, 5G, and IoT applications with the industrial need for low-power and energy-efficient devices to promote energy conservation and green communication. The author [16] proposes the reinforcement-learning-based latency-controlled D2D connectivity (RL-LCDC) method and its Q-learning technique for strong 5G connectivity with minimal latency. in an indoor D2D communication network. When compared to other traditional methods, the results reveal that RL-LCDC optimizes connectivity with a shorter end-to-end delay, higher energy efficiency, and faster convergence time. The author [17] proposes that direct mode, two-hop mode, and cooperative mode are all supported in this collaborative resource management method. The proposed schemes' practicality is confirmed by simulation results, which indicate the effects of system characteristics such as QoS, distance between D2D source and destination, relay position, and the number of D2D pairs on the EE of D2D systems. The author [18] proposes a fast algorithm based on the particle swarm optimization concept. The fundamental idea is to enhance energy efficiency by constructing a spectrum and power allocation matrix based on the overall link optimization of D2D user pairs. When compared to other competing options, simulation results show that the suggested approach effectively enhanced energy efficiency and spectrum utilization. The author [19] investigates a cellular overlay D2D network in which a dedicated radio resource is allocated for D2D communications to eliminate cross-interference with cellular communications, and all D2D devices share the dedicated radio resource to increase spectral efficiency. To eliminate cross-interference with cellular communications, study a cellular overlay D2D network in which a dedicated radio resource is allocated for D2D communications, and all D2D devices share the dedicated radio resource to improve spectral efficiency. The author [20] proposes a novel cellular communication architecture that combines energy-conscious cloud computing with socially conscious device-to-device connectivity. Because it moves the calculation of social ties to the cloud, which has a limitless capacity of resources and memory, the suggested architecture promises to be energy efficient in terms of energy consumption. The author [21] proposes the MMSE, MRT, and ZF precoding approaches be studied for the MMIMO technique. from an EE standpoint. The findings indicate the optimization of EE in relation to the number of customers, allocated base stations, and launch input power in the system. The author [22] proposes the resource allocation for RIS-enabled device-to-device (D2D) communication beneath a cellular network, in which an RIS is used to enhance desirable signals and minimize interference between paired D2D and cellular links. The proposed design outperforms the typical D2D network without RIS, according to numerical data. The author [23] gives a brief introduction to D2D communication and a discussion of various D2D applications. It proposes a network services abstraction and advises mapping existing research to the abstraction, which may be used to accelerate the development and implementation of D2D communication applications in 5G networks. The report also discusses future research opportunities for D2D communication in 5G networks. The author [24] Using the inherent unpredictability of wireless transmissions, an application layer solution technique is used to bootstrap secure communications. The suggested approach is simple to implement, lightweight, and compatible with a wide range of physical-layer wireless technologies. This study examines the scheme's security and conducts tests to establish its viability. The author [25] gives a comprehensive assessment of various strategies for improving D2D communication security. The research's major purpose is to provide a comprehensive overview of recent developments in several D2D sectors, such as the discovery process, mode selection schemes, interference management, power control strategies, and finally mode selection for D2D applications for 5G technologies. The author [26] proposes to use spectrum sharing to optimise power for NGNS in order to achieve excellent spectrum and energy efficiency for both the primary and secondary systems without the use of a secondary transmitter. The proposed model's performance was compared to that of the opportunistic spectrum-sharing model and other widely used resource allocation techniques. The collected findings support the efficacy of the proposed approach for improved system performance.

3. Proposed Methodology

The proposed resource optimization and allocation are employed in the downlink transmission of a D2D communication underlying a cellular network in a single cell. There are N subchannels several active cellular users and D2D pairs. The proposed approach applies to the pairing of D2D communication reuse frequency resource of CUE. The system model of D2D communication has three pairs of D2D. the resouce allocated to CUE-1 can be shared with pair1 and pair2 or paor2 and pair3. Pair2 sharing the same frequency resources with pair1 is better than sharing with pair3

Consider it a set of C={C1,…………., Cj} for the CUEs and a set of D={D1,…………, Dk} of the pairs. However, the set I={ C1,……, Cj, D1,……….., Dk} is a set of all the CUEs and D2D pairs. Now Xi,n is the resource allocation process, here I is the index of all the mobile devices including CUEs and D2D pairs, and N is the index of the frequency resource of the OFDMA system. Here, Xi,n is a binary variable. When Xi,n equals 1 that means frequency resouce n is allocated to user I and when Xi,n equal 0, the frequency resource is not allocated. Now Xi,n as the matrix of resource allocation.

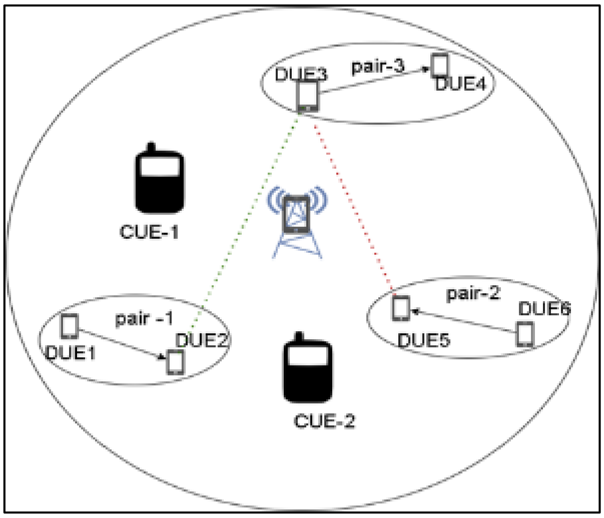

Figure 1 System model of D2D communication

The proposed algorithm of resource optimization and resource allocation in the D2D communication model. The cascaded machine learning algorithm is cascading of support vector machine. The machine learning algorithms implied the role of interference re-education and proper allocation of resource for cellular communication. The machine learning set the rate of training for the purpose of minimization of training errors during the process of transmission. The machine learning algorithm is derived from SVM. The SVM processes the signal value without interfering with other layers of signals.

- Input: set frequency vector $Sv = \{f_1, \dots \dots, fn\}$
- Output: set of $gain(ML) = \{ML(fn), \dots \dots \dots, DT(f_n)\}$
- Transpose code matric in vector space Sv*ML
- $[decode]$ ← 0; {null vector space}
- for all $SV \in ML$ do
- $ML(fn) \leftarrow$ SV (V)
- if the set of vectors of the resource
- $(M1) \leftarrow m - S(fn)$
- for all $singal \in\ ML$ do
- end for return

Consider the base class classifier signal is S. The S signal set is an optimized vector subset of the invariant. The ML classifier is C1, C2,……….Cn. Each ML classifier is categorized by the non-separable plan of SVM. These categorizations are non-overlapping, that is $C_d \cap C_e = \emptyset \forall_{d \neq e}$.

- Consider base class vector signal SV = $\{s_1, s_2, \dots \dots \dots sn\}$, where each $s_j = \{o_{j1}, o_{j2}, \dots \dots . o_{js}\}$is a set of vectors and the ML classes $\{C_1, C_2, \dots \dots \dots C_k\}$, determine the non-overlapping categorization ofsv, a ML set ET of class C_k, ET(C_k), is the mapping of vectors of the ML class. That is,$ET(C_K)$ should predict the vector of C_k.

$$ET(C_k) = \left\{\{o_j, o_k, \dots \dots . o_m\} \subseteq \{o_1, ao_2, \dots \dots . o_s\}\right\} \dots \dots \dots . . (1)$$

- Let L_i be the line of separation of base class and ML class the condition of a hyper plan of ML class is

$$L_{i+1}\left[ET\left(C_g\right) = ET\left(C_g\right) \cup o_r\right] > P_i[ET(C_K)] \dots \dots \dots \dots \dots \dots \dots (2)$$

$$L_{i+1}[ET(C_k) \cup ao_r] > L_{i+1}[ET(C_K) \cup o_t], \forall t \neq r \dots \dots \dots \dots \dots \dots \dots (3)$$

- Prediction class process of mapped vector of ML class of vectors is$ET(C_k)$.

$$VOT_{ES(C_K)} = Vot\left(ES(C_K)\right) \leq M \dots \dots \dots \dots \dots . (4)$$

Process of algorithm

Input: training signal SV = $\{s1, s2, \dots \dots \dots sn\}$,

where each $si = \left\{o_{j1}, o_{j2}, \dots \dots . o_{js}\right\}$ is a set of vectors of ML classes $\{C_1, C_2, \dots \dots \dots . C_k\}$

Output: outage probability ET(Ck)

for each $C_i, i: 1\ to\ k$

$ET\_vector[] = 0$

$ET(C_i) = \emptyset$

$pS = 0$

$\boldsymbol{repeat}$

$space = 0$

$vector = 0$

$f = o_j$

$\boldsymbol{for}\ each\ vector\ o_{jh} \in f_j, where\ h: 1\ to\ f$

$ET(C_i)' = ET(C_i)' \cup o_{jh}$

$f = f - o_{jh}$

$train\ classifier\ with\ ML$

$test\ classifier\ with\ ET)$

$Compute\ MATRIX\ m$

$\boldsymbol{if} pS > S * M$

$$ps = Ooutage$$

$$ps = ps + 1$$

$\boldsymbol{Until}\ \{EST_{outage[ps]} \leq ET\}$

$ET[i] = ET(C_i)$

4. Experimental Analysis

To validate the proposed algorithm for the D2D communication model, use MATLAB software. MATLAB has well-known computational and communication software for the analysis of the algorithm. The system's hardware configuration is an I7 process 16GB RAM and 1TB HDD with the Windows operating system. The simulation process is carried out on randomly distributed D2D users in network environments—the location of the base station is situated in the center of D2D users and cellular users at a certain distance—the rest of the simulation parameters are mentioned in the table[1].

Table 1 Simulation parameters of proposed D2D communication systems

Parameter	Value
Number of devices	30-100
Max. communication range (Rmax)	5m
Transmission power	10dbm
BW(bandwidth)	20 MHz
Number of rounds	40
ND2DU	4
UmaxP	250 mW
Cpc	100 mW
Simulation iteration	1000

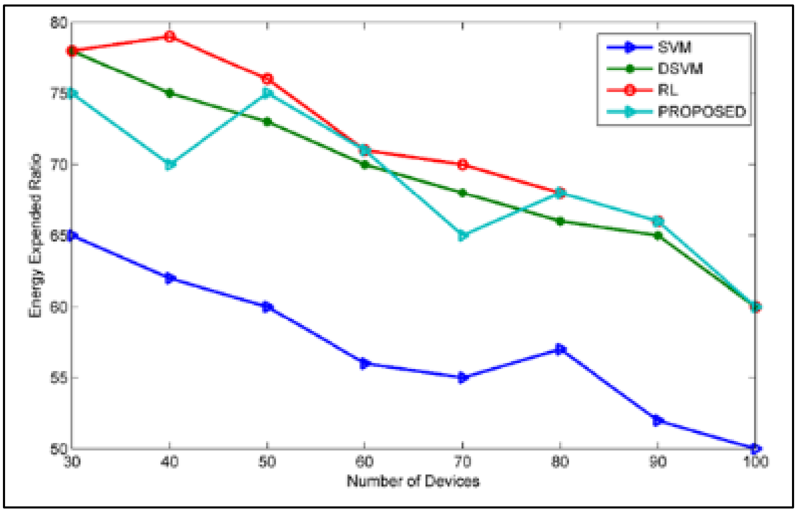

Figure 2 Performance analysis of expected energy utilization using SVM, RL and proposed algorithm

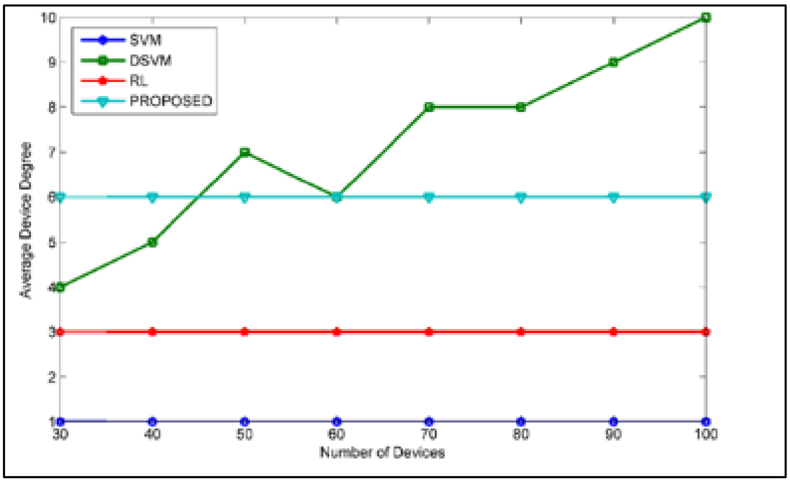

Figure 3 Performance analysis of degree of device in D2D selection mode using SVM, RL and proposed algorithm.

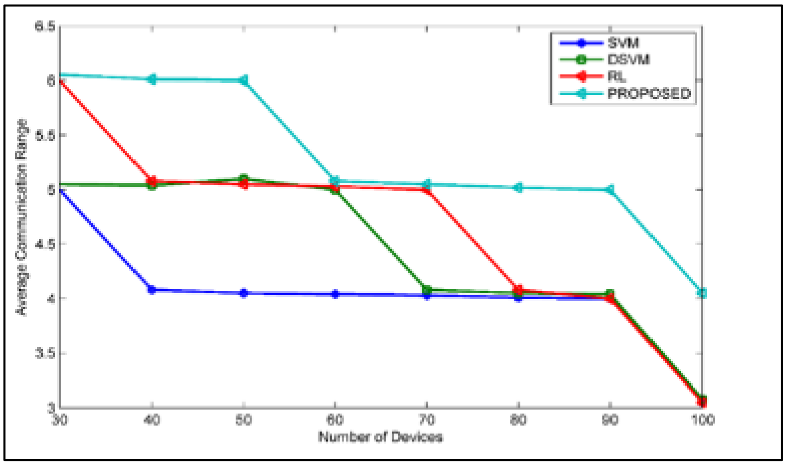

Figure 4 Performance analysis of coverage range of communication using SVM, RL and proposed algorithm

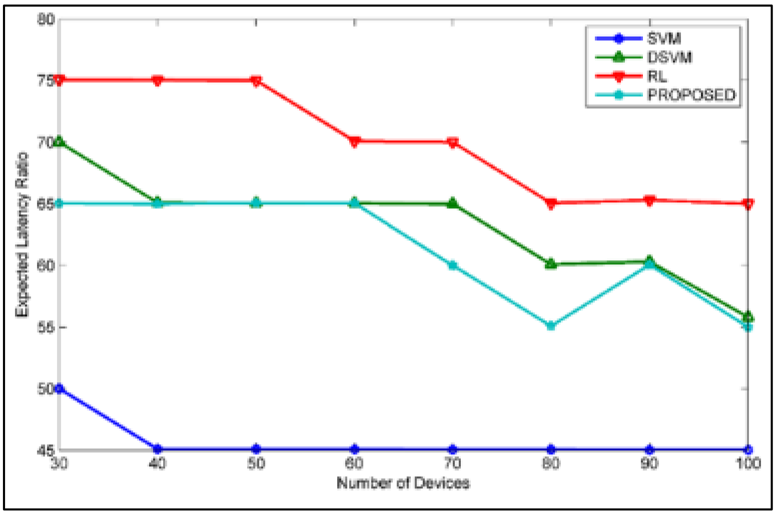

Figure 5 Performance analysis of latency of communication using SVM, RL and proposed algorithm

5. Conclusion and Future Work

This paper proposes an efficient resource optimization algorithm for device-to-device communication. The proposed algorithm is an approach called cascading support vector machines. The cascading of support vectors reduces cellular and device user equipment training error. To reduce complexity, a sub-optimal algorithm based on the optimal algorithm has been suggested. To demonstrate the improvement, we have specifically provided the proposed algorithms' steps and their average time complexity. It has been demonstrated through simulation results that several variables, including D2D distance, relay location, power, and network data rate, have an impact on the outcome of mode selection. This paper enhances the particle swarm algorithm to maximize energy efficiency while ensuring user QoS and proposes a joint power control and resource allocation algorithm to improve energy efficiency and resource utilization. Through simulation verification, the algorithm suggested in this paper has significantly improved the system's energy efficiency and resource utilization compared to the case where a D2D user can only reuse at most one CU resource, offering a swarm intelligence optimization solution for system energy efficiency optimization. It is necessary to conduct more research on how to simplify the algorithms used in intelligent optimization and multi-cell resource allocation scenarios.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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