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# Genetic Algorithm-Based Energy Efficiency Maximization for Social-Aware Device-to-Device Communications

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**ABSTRACT** In this paper, we propose a novel energy efficiency maximization scheme for social-aware device-to-device (D2D) communications based on a genetic algorithm (GA). The proposed scheme incorporates both social and physical parameters of users to model the energy efficiency maximization problem. The formulated problem considers the spectral reuse, spectral efficiency, and the transmit power constraints of both cellular and D2D users to satisfy their quality of service requirements. Moreover, an algorithm based on the self-adaptive penalty function is applied to convert the constrained problem into an unconstrained problem. Next, GA is utilized to maximize the unconstrained problem. The feasibility of the proposed scheme is shown by computing its time complexity in terms of big-$O$ notation. Moreover, the convergence of the proposed scheme is analyzed by comparing the maximum and average values of the overall energy efficiencies for different iterations. Likewise, the performance is evaluated in terms of overall energy efficiency and system throughput for various D2D communications scenarios. To demonstrate the efficiency of the proposed scheme, the results are compared with those for a static penalty-based GA algorithm. Furthermore, to demonstrate the significance of combining the two types of parameters (i.e., social and physical), the performance of the proposed scheme is compared with schemes based on only social or physical parameters.

**INDEX TERMS** Social-aware, energy efficiency, genetic algorithm, self-adaptive penalty function.

## I. INTRODUCTION

The enormous growth in demand for multimedia and other social networking services and applications has significantly increased the network load on the current cellular communication system [1], [2]. Since the number of interconnected devices is expected to exceed three times the global population by the year 2023, this trend will continue [3]. Despite advancements in networking and radio access technologies, the current cellular communications system is struggling to fulfill its rapidly increasing requirements [4]. This has motivated the need to offload cellular traffic in the 5G system. Device-to-device (D2D) communications have emerged as a promising offloading solution as it enables the direct sharing of data between neighboring cellular devices with little assistance from the base station (BS) [5], [6]. This significantly alleviates the burden on the BS by offloading the traffic from proximity applications to direct communications.

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The social network assisted D2D communications have gained a significant research attention in the recent times [7]. Because the profiles of humans on social networking applications reflect their real-life behavior, this information may be exploited for the improvement of D2D communications [8]. Therefore, most recent studies have exploited the social network information of users along with their physical parameters to enable D2D communications between users who have social friendships or similar interests [9]. This significantly improves the willingness of users to share data of common interest within their social circle.

A major concern that arises in social-aware D2D communications is the increasing energy consumption of devices [10]. As the cellular devices used for D2D communications have limited battery power, D2D communications may drain the battery rather quickly [11]. Moreover, advancements in the battery technology have not kept pace with the high power requirements of such devices [12]. Hence, D2D communications require energy efficient schemes for peer discovery, relay selection, cluster formation, medium access control, and transmission power allocation to realize the future 5G communication systems [13]. This can be achieved by designing protocols that incorporate the energy efficiency optimization at the mentioned dimensions while ensuring the quality of service (QoS) requirements [1]. Therefore, studying the energy efficiency optimization problem in social-aware D2D networks and addressing the aforementioned challenges and issues are vital.

### A. RELATED WORKS

The studies on the energy efficiency of social-aware D2D communications can be divided into different categories based on their goals, including peer discovery, relay selection, cluster formation, medium access control, and transmit power allocation. Prasad *et al.* presented a social-application based peer discovery method to improve the energy efficiency of social-aware D2D communications [14]. Their method introduced a cloud-based region that enabled users of the same interest to probe peer discovery when they are in proximity. This cloud-based approach enabled the offloading of the discovery process from D2D networks as well as LTE core networks. Moreover, their method reduced the frequency of peer discovery, which significantly improved energy efficiency. Similarly, Zhang *et al.* proposed a neighbor discovery algorithm for social-aware D2D communications by dividing neighboring users into groups based on their community and centrality attributes [15]. Their method improved the performance in terms of peer discovery, energy efficiency, and data transmission by selecting the optimal beacon probe rate. In addition, Wang *et al.* proposed a social-aware D2D neighbor discovery method based on the overlapping communities in social networks [16]. The proposed method exploited the connection status between D2D users to determine the overlapping communities. The overlapping nodes played the role of communication bridges to enhance data sharing between different communities. Moreover, the dynamic selection of beacon detection rates improved the neighbor discovery, power consumption, and energy efficiency. Although these methods significantly improved the energy efficiency of social-aware D2D communications, obtaining optimal beacon probe and detection rates in these methods remains a challenging task.

Social-aware relay selection is another domain for improving the energy efficiency of D2D communications. Addressing this issue, Li *et al.* proposed a social-aware relay selection scheme based on the social and physical parameters of D2D users in [17]. They aimed to select trustworthy D2D users to act as relays and forward data to their friends in a social circle. Moreover, they proposed a dynamic transmit power adjustment algorithm to improve the energy efficiency of the system. A similar D2D relay selection algorithm based on distance between source and destination and social trust was also proposed in [18], wherein the QoS and the power consumption parameters of D2D users were considered when performing relay selection. These relay selection based studies demonstrated a significant improvement in the energy efficiency of social-aware D2D communications, but they may not be suitable for scenarios with less number of friend users in proximity.

The energy efficiency of social-aware D2D communications can be significantly improved by clustering D2D users and assigning resources to the cluster head supervising the D2D transmissions of its cluster members. In this regard, Wang *et al.* proposed a cluster formation algorithm for social-aware D2D communications in [19]. The problem was formulated as a multi-objective problem based on the Chinese restaurant process (CRP) and enhanced CRP. The method allowed new nodes to join a cluster to improve its link data-rate. The results revealed an improvement of the proposed algorithm in terms of energy efficiency in comparison to existing algorithms. A similar social-aware D2D clustering and resource algorithm was proposed in [1]. The algorithm divided the D2D users into various multicast groups and selected a cluster head to assist the multicast group. Moreover, the study proposed an energy-efficient power control and resource allocation scheme by considering the QoS requirements. However, the cluster head selection in a distributed manner based on social and physical parameters can lead to a privacy concern in social-aware D2D communications. Zhang *et al.* proposed a clustering and resource allocation scheme for social-aware D2D communications to improve the energy and spectral efficiencies in [20]. They exploited the redundancy in user demand to form D2D clusters and perform multicast transmission inside the clusters. They also proposed half- and full-duplex transmission strategies to manage channel sharing between cellular devices and D2D links. However, the performance of the proposed scheme degraded in dense D2D scenarios.

In contrast to the work proposed in [19], [1] and [20], the work in [11] and [21] addressed the social-aware D2D energy efficiency in terms of the medium access control (MAC) protocol. In particular, the work in [11] focused on designing a socially cooperative D2D (SCD2D) MAC protocol to improve the D2D energy efficiency. This method reduced power consumption by enabling cooperation among sociable D2D nodes without hampering the completion time of content exchange. However, interference mitigation was not considered in the design of the SCD2D MAC protocol. In [21], virtualization was introduced with social-awareness for designing an energy efficient virtual MAC protocol for D2D communications. The protocol allowed multiple network operators to share resources by performing resource optimization for both cellular and D2D users. Moreover, the network energy efficiency was formulated as a multi-objective problem, which was solved to improve the energy efficiency. Although these previous studies provide adequate guidelines toward designing an energy efficient cooperative MAC protocol for social-aware D2D communications, the domain requires further research to resolve practical concerns related to the exploitation of virtualization and social-awareness while designing a MAC protocol for D2D communications.

An efficient way to improve the energy efficiency of social-aware D2D communications is to optimize the transmit power allocation of D2D nodes [22], [8]. For this purpose, in [22], the authors focused on maximizing the energy efficiency of D2D users by optimizing the transmit power and sub-channel allocation. The method jointly allocated the transmit powers and sub-channels to the D2D users using penalty function and dual-decomposition methods, respectively, while guaranteeing the QoS for cellular users. The results demonstrated performance improvement in terms of energy efficiency. However, this method did not incorporate the social parameters of users. The authors in [8] aimed to solve the problem of energy efficiency maximization by considering both social and physical parameters of users. They used a genetic algorithm (GA) with a static penalty-based constraint handling method to maximize the energy efficiency of cellular and D2D users. The algorithm improved the overall energy efficiency and system throughput while fulfilling the QoS of both types of users. However, the static penalty function method involved careful tuning of the penalty coefficients, which either requires the prior knowledge of the problem or a large number of iterations to obtain the optimal results.

### B. CONTRIBUTIONS

In this study, we aim to maximize the energy efficiency of cellular and D2D users using a self-adaptive penalty-based GA. Differing from the studies discussed in the previous subsection, we propose a social-aware energy efficiency scheme based on GA with a self-adaptive penalty function algorithm for constraint handling. The proposed algorithm is easy to implement and does not require prior knowledge of the problem or tuning of the penalty coefficients (as needed in the static penalty function method). Moreover, it efficiently adapts the penalty values according to the number of feasible and infeasible individuals in the population. To the best of our knowledge, no similar work has been presented in literature. The major contributions of this paper are as follows.

1) In our previous study related to social-aware D2D peer selection, we computed the "cumulative closeness coefficient" (i.e., $\Delta$), which combines the social and physical parameters of D2D users [4]. Herein, we use the computed $\Delta$ to derive the signal-to-noise plus interference ratio (SINR) and data rate for D2D users [23]. Moreover, we utilize the "social closeness coefficient" (i.e., $\delta_{soc}$) proposed in [4] to calculate the power consumption coefficient of cellular (i.e., $\rho_{C_m}$) and D2D (i.e., $\rho_{DD_p}$) users [24]. We use these parameters to derive the energy efficiencies for cellular and D2D users. We compute the overall energy efficiency of the system by adding the energy efficiency of cellular and D2D users.
2) We formulate the objective function (function to be maximized) as a constrained maximization problem of the overall energy efficiency with constraints for the spectral reuse, spectral efficiency, and transmit powers for cellular and D2D users.
3) To solve the problem using GA, we convert the constrained problem to an unconstrained problem using a self-adaptive penalty function algorithm. We derive a final objective function for the overall energy efficiency. Then, we utilize the GA to maximize the overall energy efficiency.
4) We perform extensive simulations of the proposed scheme. The feasibility of the proposed scheme is shown in terms of convergence between the maximum and average values of the objective function. Moreover, the performance is compared with the static penalty-based GA in terms of overall energy efficiency and system throughput for various scenarios [8]. Finally, the importance of combining social and physical parameters is shown in terms of overall energy efficiency and system throughput with respect to the distance between D2D users.

### C. PAPER ORGANIZATION

The remainder of the paper is organized as follows: the system model is described in Section II, the algorithm description and formulation is presented in Section III, and the numerical results followed by the conclusions and future work are given in Sections IV and V, respectively.

## II. SYSTEM MODEL

In this section, we describe the system model for the proposed scheme, which consists of the system architecture, and the network model.

### A. SYSTEM ARCHITECTURE

We consider two types of parameters, i.e., social parameters and physical parameters in our proposed scheme. Accordingly, we divide the system model into two layers, i.e., a social proximity layer (SPL) and a physical proximity layer (PPL) (Fig. 1). The SPL describes the social parameters of the users based on their profile on the social network database. The human users have different levels of interaction with each other via social networks. These social network interactions significantly affect the willingness of the users to perform D2D communications. The social parameters utilized in our proposed scheme include *Social Friendship Index, Social Closeness Index,* and *Interest Similarity Index.* We follow the definitions of these parameters done in [4].

Likewise, the PPL characterizes the physical and network parameters of the users, ensuring physical proximity of users, which is a basic requirement for D2D communications. We exploit the physical parameters defined in [4], which include *Encounter Duration, Distance between D2D Users,* and *Number of D2D Users*. We assume that the BS can obtain the social parameters of users from the social network database while it can estimate their physical parameters [4].

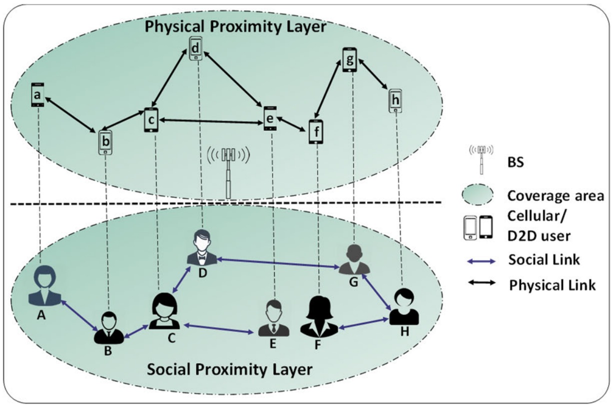


**FIGURE 1. Proposed two-layer D2D architecture with social proximity layer and physical proximity layer.**

### B. NETWORK MODEL

We consider a single-cell network composed of cellular and D2D users. The system works in a centralized manner, wherein the proposed algorithm runs at the BS. We assume a set of cellular users as $\Omega_C = \{C_1, C_{2,\ldots}, C_M\}$, such that an arbitrary cellular user is denoted by $C_m \epsilon \Omega_C$ (where $m = 1, 2, \ldots M$). Likewise, the set of D2D users is defined as $\Omega_D = \{D_1, D_2 \ldots, D_N\}$, such that an arbitrary D2D user is denoted by $D_n \epsilon \Omega_D$ (where $n = 1, 2, \ldots, N$). Because D2D communications occur between pairs of D2D users, we assume a set of D2D pairs as $\Omega_{DD} = \{DD_1, DD_{2,\ldots}, DD_P\}$, where $P = \binom{N}{2}$. Hence, $DD_p$ is an arbitrary D2D pair with $D_i$ as the D2D transmitter and $D_j$ as the D2D receiver, such that $1 \leq i,j \leq N$ (where $i \neq j$). The cellular users perform communications using the BS, whereas D2D users are capable of performing communications with or without the assistance of the BS. Both the cellular and D2D users use LTE-A air interface for their communications. We model the channels in our proposed system using the Rayleigh fading model.

The cellular users communicate using orthogonal sub-channels, whereas the D2D pairs reuse the same sub-channels allocated to the cellular users. Therefore, the cellular users do not interfere with each other. Furthermore, the BS mitigates interference among D2D users by ensuring the reuse of the cellular resource by only one D2D pair in a slot. Nevertheless, there is a potential for interference among cellular and D2D users as they share the same spectrum resource. Hence, we consider the interference between cellular users and D2D pairs.

When a D2D user wants to perform D2D communications, it sends a request to the BS. The BS selects a D2D peer among the available D2D users based on both social and physical parameters using the method proposed in [4]. It assigns the uplink spectrum channel to the D2D pair ($DD_p$) and computes the allowable transmit power and other QoS parameters according to the constraints of the D2D transmitter (i.e., $D_i$).

## III. ALGORITHM DESCRIPTION AND FORMULATION

This section first presents the motivation and overview of the GA used for the energy efficiency maximization in our proposed scheme. Moreover, we define various GA-related terms used in the upcoming sections. We then briefly describe the self-adaptive penalty function algorithm used for handling the constraints in our proposed scheme. Furthermore, we define a few terms related to the self-adaptive penalty algorithm and describe the problem formulation for the proposed scheme.

### A. GA MOTIVATION AND OVERVIEW

GA is a widely used nature-inspired algorithm based on biological evolutionary steps, such as natural selection, crossover, and mutation. It is a powerful but easy tool for solving various continuous, discrete, and nonlinear optimization and search problems [25]. It provides an implicit parallelism that enables it to efficiently solve problems with a wide range of search space and obtain optimal solutions [26]. Although the proposed energy efficiency maximization problem for social-aware D2D communications can be solved using the traditional Lagrangian method, it may lead to high computational complexity [27]. Hence, we used GA to solve the proposed problem. The algorithm starts by generating a set of initial solutions, which is termed the population. Each solution in the population is called an individual. These individuals undergo the process of selection, crossover, and mutation to generate a new set of individuals. The individuals are compared based on their fitness values. The individuals with better (maximum or minimum) fitness are selected to produce subsequent generations of the population while those with lower fitness values are discarded from the population.

### B. SELF-ADAPTIVE PENALTY FUNCTION ALGORITHM

Since our proposed model comprises inequality constraints related to the spectral reuse, spectral efficiency, and transmit power of cellular and D2D users, we cannot directly use GA as it will lead to infeasible solutions. Therefore, we use a self-adaptive penalty function algorithm to convert the constrained problem into an unconstrained problem. This method overcomes the problem of tuning the penalty coefficients, which is found with the static penalty function method. Moreover, it utilizes the information from infeasible individuals (i.e., the individuals that fail to satisfy one or more constraints) to obtain the optimal solution.

As the proposed method is based on the principle of the penalty algorithm, it penalizes the infeasible individuals according to their violation of constraints (i.e., not satisfying the constraints). For this purpose, it computes the penalty factor (i.e., $P_\varepsilon$) as a part of the final objective function. Furthermore, the algorithm computes the distance parameter (i.e., $d_\varepsilon$) for each individual in the population to achieve two goals. First, it guides the algorithm to find feasible individuals when all the individuals in the current population are infeasible. Second, if the current population has feasible individuals, it directs the algorithm to search for the optimal individuals. The distance parameter and penalty factor are added to obtain the final (unconstrained) objective function. Then, GA is applied to the computed final objective function to maximize the energy efficiency of cellular and D2D users.

### C. PROBLEM FORMULATION

We divide the formulation of the proposed algorithm into the following steps.

#### 1) OVERALL ENERGY EFFICIENCY AND SYSTEM THROUGHPUT DERIVATION

Energy efficiency is defined as the number of bits transmitted per unit power [28]. The underlying goal of our study is to improve the overall energy efficiency of cellular and D2D communications while satisfying their transmission power and spectral efficiency constraints. For this purpose, we first compute the data rates for cellular and D2D users using Shannon's theorem. The data rate between $C_m$ and BS (i.e., $R_{C_m-BS}$) is given by

$$R_{C_m-BS} = W_{C_m-BS} log_2(1 + \gamma_{C_m-BS}), \quad (1)$$

where $W_{C_m-BS}$ is the cellular bandwidth and $\gamma_{C_m-BS}$ is the SINR between $C_m$ and BS, which is computed as

$$\gamma_{C_m-BS} = \frac{P_{C_m} \left|h_{C_m-BS}\right|^2 D_{C_m-BS}^{-\beta}}{I_{C_m} + \sigma^2}. \quad (2)$$

Here, $P_{C_m}$ is the transmit power of $C_m$, $\left|h_{C_m-BS}\right|^2$ is the Rayleigh fading coefficient for cellular channel, $D_{C_m-BS}$ is the distance between $C_m$ and BS, $\beta$ is the path loss coefficient, $\sigma^2$ is additive white Gaussian noise power, and $I_{C_m}$ is the interference at $C_m$ calculated as

$$I_{C_m} = \sum\nolimits_{p=1}^{P} \phi_{C_m-DD_p} P_{DD_p} \left|h_{DD_p}\right|^2 D_{DD_p}^{-\beta}. \quad (3)$$

Here, $\phi_{C_m-DD_p}$ is the spectrum reuse coefficient between $C_m$ and the D2D pair $DD_p$ [29]. It reflects the reuse of the cellular spectrum by the D2D pair and satisfies $\phi_{C_m-DD_p} \epsilon \{0,1\}$. We assume that $\phi_{C_m-DD_p} = 1$ when $DD_p$ reuses the spectrum resource of $C_m$, otherwise $\phi_{C_m-DD_p} = 0$. Hence, interference occurs between $C_m$ and $DD_p$ when $\phi_{C_m-DD_p} = 1$. Moreover, $P_{DD_p}$ is the transmit power of $DD_p$ (i.e., $D_i$), $\left|h_{DD_p}\right|^2$ is the Rayleigh fading coefficient for the D2D channel, and $D_{DD_p}$ is the distance between $D_i$ and $D_j$.

Likewise, the data rate for $DD_p$ is computed as

$$R_{DD_p} = W_{DD_p} log_2(1 + \gamma_{DD_p}), \quad (4)$$

where $W_{DD_p}$ is the D2D bandwidth and $\gamma_{DD_p}$ is the SINR received at $D_j$ from $D_i$, which is computed as

$$\gamma_{DD_p} = \frac{P_{DD_p} \left|h_{DD_p}\right|^2 D_{DD_p}^{-\beta} \Delta_{DD_p}}{I_{DD_p} + \sigma^2}, \quad (5)$$

It has been reported that combining the social parameters of D2D users with the physical parameters significantly improves the performance of D2D communications [7], [9]. There are various methods to integrate the social and physical parameters of D2D users [4], [8], [23]. One method to do this is to compute a joint social-physical metric and utilize it to determine the SINR for D2D communications [4], [23]. We follow the mentioned method in our scheme and compute a joint social-physical metric called "Cumulative closeness coefficient" (denoted by $\Delta_{DD_p}$) for each D2D pair $DD_p$ [4]. The $\Delta_{DD_p}$ is utilized in (5) to compute the SINR for $DD_p$ [23]. The computed SINR is utilized to calculate the data rate for D2D communications in (4). The calculated data rate is used in (8) when computing the energy efficiency of $DD_p$ and in (11) when calculating the throughput.

The parameter $I_{DD_p}$ in (5) is the interference at the D2D receiver $D_j$ due to $C_m$ and is calculated as

$$I_{DD_p} = \sum\nolimits_{m=1}^{M} \phi_{C_m-DD_p} P_{C_m} \left|h_{C_m-DD_p}\right|^2 D_{C_m-D_j}^{-\beta}. \quad (6)$$

We use the $\Delta_{DD_p}$ parameter while computing $\gamma_{DD_p}$ [23] in (5), which is the "cumulative closeness coefficient" between two D2D users (i.e., $D_i$ and $D_j$) of pair $DD_p$. It is obtained by adding the social closeness coefficient $\delta_{soc}$ and the physical closeness coefficient $\delta_{phy}$, as proposed in [4]. The parameter $\delta_{soc}$ between the two users reflects their closeness based on the social parameters obtained from the social network database. Likewise, the parameter $\delta_{phy}$ shows their closeness based on the physical parameters. Both $\delta_{soc}$ and $\delta_{phy}$ are computed using the "technique for order preference by similarity to ideal solution" (TOPSIS) [30]. The social and physical parameters used to compute the social and physical closeness coefficients, respectively, are defined in [4].

We derive the energy efficiency expression for $C_m$ (i.e., $\varepsilon_{Cm}$) and $DD_p$ (i.e., $\varepsilon_{DD_p}$) as

$$\varepsilon_{Cm} = \frac{R_{C_m-BS}}{P_{C_m} + P_{C_m}^{Ckt}} - \rho_{C_m} \varepsilon_{C_m}^{init}, \quad (7)$$

$$\varepsilon_{DD_p} = \frac{R_{DD_p}}{P_{DD_p} + P_{DD_p}^{Ckt}} - \rho_{DD_p} \varepsilon_{DD_p}^{init}, \quad (8)$$

where $P_{C_m}^{Ckt}$ and $P_{DD_p}^{Ckt}$ are the powers dissipated in cellular and D2D circuits, respectively. Because energy efficiency is based on the power consumption of the device, which comprises the transmit power as well as the power dissipated in the circuit of the device, we incorporate $P_{C_m}^{Ckt}$ and $P_{DD_p}^{Ckt}$ when computing $\varepsilon_{Cm}$ and $\varepsilon_{DD_p}$, respectively. Moreover, $\varepsilon_{C_m}^{init}$ and $\varepsilon_{DD_p}^{init}$ are the initial energy efficiencies of $C_m$ and $DD_p$, respectively, as introduced in [8]; their values are given in Table 2. The parameters $\rho_{C_m}$ and $\rho_{DD_p}$ are the power consumption coefficients for $C_m$ and $DD_p$, respectively, and are modeled as an exponential decay function [23]:

$$\rho_{C_m} = \rho_{DD_p} = \delta e^{-\eta \delta_{soc C_m-DD_p}}, \quad (9)$$

where $\eta$ is the influence factor of the social closeness coefficient, which influences the exponential decay function, as defined in [23]; its value is given in Table 2. Moreover, $\delta_{soc C_m-DD_p}$ is the social closeness coefficient between $C_m$ and $DD_p$, as defined in [4]. The stronger the social friendship between the two users is (i.e., the higher the value of $\delta_{soc C_m-DD_p}$), the lower are the values of $\rho_{C_m}$ and $\rho_{DD_p}$.

Hence, their multiplication with $\varepsilon_{C_m}^{init}$ and $\varepsilon_{DD_p}^{init}$ in (7) and (8), respectively, will further decrease the subtraction terms, resulting in higher values of $\varepsilon_{Cm}$ and $\varepsilon_{DD_p}$. The overall energy efficiency denoted by $\varepsilon$ incorporates the energy efficiencies of all the cellular users in $\Omega_C$ and D2D pairs in $\Omega_{DD}$, and it is computed as given in [8]:

$$\varepsilon = \sum\nolimits_{m=1}^{M} \left( \varepsilon_{C_m} + \sum\nolimits_{p=1}^{P} \phi_{C_m-DD_p} \varepsilon_{DD_p} \right). \tag{10}$$

Next, we calculate the system throughput for the cellular users in both $\Omega_C$ and D2D pairs in $\Omega_{DD}$, as given by [8]:

$$\tau = \sum\nolimits_{m=1}^{M} \left( R_{C_m-BS} + \sum\nolimits_{p=1}^{P} \phi_{C_m-DD_p} R_{DD_p} \right). \tag{11}$$

### 2) INITIAL MAXIMIZATION PROBLEM FORMULATION

We assume the $\varepsilon$ problem in (10) as the initial objective function, which can be formulated as a maximization problem given by

$$\max_{\{\phi_{C_m-DD_p}, P_{C_m}, P_{DD_p}\}} \varepsilon, \tag{12}$$

$$\begin{cases} C1: \sum_{m=1}^{M} \phi_{C_m-DD_p} \epsilon \{0, 1\}, \\ C2: SE_{C_m} \geq \mu_{C_m}, \\ C3: SE_{DD_p} \geq \mu_{DD_p}, \\ C4: 0 \leq P_{C_m} \leq P_{C_m}^{max}, \\ C5: 0 \leq P_{DD_p} \leq P_{DD_p}^{max}. \end{cases} \tag{13}$$

Here, $SE_{C_m}$ and $SE_{DD_p}$ are the spectral efficiencies of $C_m$ and $DD_p$, respectively, defined as the number of bits transmitted successfully per unit time per Hz [31]. In addition, $\mu_{C_m}$ and $\mu_{DD_p}$ denote the minimum data rates for cellular and D2D communications, respectively, while $P_{C_m}^{max}$ and $P_{DD_p}^{max}$ denote the maximum allowed transmit powers of $C_m$ and $DD_p$, respectively. The constraint $C1$ ensures that at most one D2D pair must reuse the spectrum of a cellular user to avoid interference between D2D pairs. Because the energy and spectral efficiencies conflict with each other [32], we take the spectral efficiency constraints in $C2$ and $C3$ to guarantee the spectral efficiency of $C_m$ and $DD_p$, respectively, while fulfilling their QoS requirements. Moreover, $C4$ and $C5$ regulate the transmit powers of $C_m$ and $DD_p$ to satisfy their communication requirements and control interference between cellular users and D2D pairs.

### 3) FORMULATION OF CONSTRAINT-FREE OBJECTIVE FUNCTION

The problem formulated in (12) has constraints, as given in (13). Therefore, it cannot be directly solved using GA as GA cannot handle the constraints [8]. Therefore, we employ the self-adaptive penalty function method for constraint handling in the formulated problem [33], [34]. For this, we first need to compute $\varepsilon_{min}$ and $\varepsilon_{max}$ from (10):

$$\varepsilon_{min} = min\left(\varepsilon\right), \tag{14}$$

$$\varepsilon_{max} = max\left(\varepsilon\right). \tag{15}$$

**Algorithm 1** Pseudocode to compute $\boldsymbol{d_{\varepsilon_j}}$

**Input:** Population size $N$, $\varepsilon_j$, $\varepsilon_{min}$, $\varepsilon_{max}$, $\frac{1}{K}\sum_{k=1}^{K}\frac{V_k}{V_{max}}$, $r_f \forall j, j = 1, 2, \ldots, N$
**Output**: $d_{\varepsilon_j} \forall j, j = 1, 2, \ldots, N$
**Begin**
**If** $r_f = 0$ **then**
  **For** $j = 1$ to $N$
  $d_{\varepsilon_j} \leftarrow \frac{1}{K}\sum_{k=1}^{K}\frac{V_k}{V_{max}}$
  **End For**
**Else**
  **For** $j = 1$ to $N$
  $\|\varepsilon_j\| \leftarrow \frac{\varepsilon_j - \varepsilon_{min}}{\varepsilon_{max} - \varepsilon_{min}}$
  $d_{\varepsilon_j} \leftarrow Sqrt((\|\varepsilon_j\|)^2 + (\frac{1}{K}\sum_{k=1}^{K}\frac{V_k}{V_{max}})^2$
  **End For**
**End If**
**End**

Using $\varepsilon_{min}$ and $\varepsilon_{max}$ from (14) and (15), respectively, we normalize the $\varepsilon$ problem in (10) to scale its values between 0 and 1:

$$\|\varepsilon\| = \frac{\varepsilon - \varepsilon_{min}}{\varepsilon_{max} - \varepsilon_{min}}. \tag{16}$$

Following the approach of the self-adaptive penalty function method in [34], we calculate the distance parameter (i.e., $d_\varepsilon$) for each individual in the population from the optimal point based on their normalized values and constraint violation. The calculation method of $d_\varepsilon$ differs based on the number of feasible individuals (population members that satisfy all the constraints) in the population, as given by (17), as shown at the bottom of the next page, where $k = 1, 2, \ldots, K$ represents the number of constraints. In our formulated problem, $K = 5$, as given in (13). The parameter $v_{max}$ is the maximum value among all the constraint violations and $v_k$ represents the violation of the $k_{\text{th}}$ constraint, which is given by

$$v_k = max(0, g_k), \tag{18}$$

where $g_k$ is the $k_{\text{th}}$ inequality constraint. The expression $\frac{1}{K}\sum_{k=1}^{K}\frac{v_k}{v_{max}}$ in (17) represents the sum of normalized constraint violations divided by the number of constraints. (17) clearly denotes that the distance parameter will be equal to the sum of normalized constraint violations divided by the number of constraints when there are no feasible individuals in the current population. Hence, individuals with a smaller constraint violation are better than those with a larger violation. This guides the algorithm to quickly approach feasible solutions. In the case where some feasible individuals are present in the population, the distance parameter is equal to the squared root of the normalized objective function and the sum of normalized constraint violations divided by the number of constraints. This guides the algorithm to approach the optimal solution. The mechanism to compute $d_{\varepsilon_j}$ is summarized in Algorithm 1.

**Algorithm 2** Pseudocode to compute $P_{\boldsymbol{\varepsilon}_j}$

**Input:** Population size $N$, $\varepsilon_j$, $\varepsilon_{min}$, $\varepsilon_{max}$, $\frac{1}{K}\sum_{k=1}^{K}\frac{V_k}{V_{max}}$, $r_f \forall j, j = 1, 2, \ldots, N$
**Output**: $P_{\varepsilon_j} \forall j, j = 1, 2, \ldots, N$
**Begin**
  **For** $j = 1$ to $N$
    **If** $r_f = 0$ **then**
      $\lambda_{1_j} \leftarrow 0$
      $\lambda_{2_j} \leftarrow \|\varepsilon_j\|$
    **Else**
      $\lambda_{1_j} \leftarrow \frac{1}{K}\sum_{k=1}^{K}\frac{V_k}{V_{max}}$
      $\lambda_{2_j} \leftarrow 0$
    **End If**
      $P_{\boldsymbol{\varepsilon}_j} \leftarrow \left(1 - r_f\right)\lambda_{1_j} + r_f\lambda_{2_j}$
  **End For**
**End**

Next, we compute the self-adaptive penalty factor $P_\varepsilon$, which is determined by the number of feasible individuals in the population:

$$P_\varepsilon = (1 - r_f)\lambda_1 + r_f\lambda_2, \tag{19}$$

where $r_f$ is the ratio of the number of feasible individuals in the population to the size of the population, whereas $\lambda_1$ and $\lambda_2$ are the self-adaptive penalty coefficients computed as

$$\lambda_1 = \begin{cases} 0, & \text{if } r_f = 0 \\ \frac{1}{K}\sum_{k=1}^{K}\frac{v_k}{v_{max}}, & \text{otherwise} \end{cases}, \tag{20}$$

$$\lambda_2 = \begin{cases} 0, & \text{if } r_f \neq 0 \\ \|\varepsilon\|, & \text{otherwise} \end{cases}. \tag{21}$$

Equation (19) shows that coefficient $\lambda_1$ has a greater impact than coefficient $\lambda_2$ when few feasible individuals are present in the population. In contrast, the impact of $\lambda_2$ is dominant when the number of feasible individuals in the population is greater than that of infeasible individuals. The mechanism to compute $P_{\boldsymbol{\varepsilon}_j}$ is summarized in Algorithm 2.

The self-adaptive penalty function algorithm utilizes the information from the infeasible solution to guide the algorithm toward the optimal solution. This is done by computing the distance parameter (i.e., $d_\varepsilon$) and self-adaptive penalty factor (i.e., $P_\varepsilon$). Hence, the final constraint-free objective function (i.e., $\varepsilon'$) is computed by adding (17) and (19):

$$\varepsilon' = d_\varepsilon + P_\varepsilon. \tag{22}$$

Finally, we obtain the problem without constraints.

**TABLE 1. List of symbols.**

| Symbol | Description |
|---|---|
| $\Omega_C / \Omega_D / \Omega_{DD}$ | Set of cellular users/D2D users/D2D pairs |
| $C_m/D_n/DD_p$ | Arbitrary cellular user/D2D user/D2D pair |
| $D_i / D_j$ | D2D transmitter/receiver |
| SPL/PPL | Social/Physical proximity layer |
| $R_{C_m-BS}/R_{DD_p}$ | Data rate for cellular user/D2D pair |
| $W_{C_m-BS}/W_{DD_p}$ | Bandwidth of cellular user/D2D pair |
| $\gamma_{C_m-BS}/\gamma_{DD_p}$ | SINR of cellular user/D2D pair |
| $D_{C_m-BS}/D_{DD_p}$ | Distance between $C_m$ and BS/D2D pair users |
| $\lvert h_{C_m-BS}\rvert^2/\lvert h_{DD_p}\rvert^2$ | Rayleigh fading coefficient for cellular/D2D channel |
| $I_{C_m}/I_{DD_p}$ | Interference to cellular user/D2D pair |
| $\phi_{C_m-DD_p}$ | Spectrum reuse coefficient between $C_m$ and D2D pair $DD_p$ |
| $\sigma^2$ | Additive White Gaussian Noise |
| $P_{C_m}/P_{DD_p}$ | Transmit power of $C_m$ and $DD_p$ (i.e., $D_i$) |
| $\Delta_{DD_p}$ | Cumulative closeness coefficient between $D_i$ and $D_j$ |
| $\varepsilon_{C_m}/\varepsilon_{DD_p}/\varepsilon$ | Energy efficiency of $C_m/DD_p$ /overall |
| $\beta$ | Path loss coefficient |
| $P_{C_m}^{Ckt}/P_{DD_p}^{Ckt}$ | Circuit dissipated power for $C_m/DD_p$ |
| $\rho_{C_m}/\rho_{DD_p}$ | Power consumption coefficient for $C_m/DD_p$ |
| $\varepsilon_{C_m}^{init}/\varepsilon_{DD_p}^{init}$ | Initial energy efficiency for $C_m/DD_p$ |
| $\delta_{soc_{C_m-DD_p}}$ | Social closeness coefficient between $C_m$ and $DD_p$ |
| $\eta$ | Influence factor of social closeness coefficient |
| $\tau$ | System throughput |
| $SE_{C_m}/SE_{DD_p}$ | Spectral efficiency of $C_m/DD_p$ |
| $\mu_{C_m}/\mu_{DD_p}$ | Minimum required data rate for $C_m$ /$DD_p$ |
| *C1–C5* | Constraints for the objective function |
| $P_{C_m}^{max}/P_{DD_p}^{max}$ | Maximum transmit power of $C_m$ /$DD_p$ |
| $\varepsilon / \| \varepsilon \| / \varepsilon'$ | Initial/Normalized/Final objective function |
| $d_\varepsilon$ | Distance parameter |
| $r_f$ | Ratio of the number of feasible solutions to the population size |
| $\lambda_1/\lambda_2$ | Self-adaptive penalty coefficients |
| $v_k/v_{max}$ | $k_{\text{th}}$/Maximum constraint violation |
| $P_\varepsilon$ | Self-adaptive penalty factor |

#### 4) APPLYING GA TO THE CONSTRAINT-FREE PROBLEM

To maximize the overall energy efficiency, we apply GA to the final objective function computed in (22), which can be expressed as

$$\max_{\{\phi_{C_m-DD_p}, P_{C_m}, P_{DD_p}\}} \varepsilon'. \tag{23}$$

Algorithm 3 summarizes the steps of the proposed scheme. Its working mechanism is described using a flowchart in Fig. 2. Table 1 lists the symbols used in the paper.

The proposed algorithm starts by randomly initializing the population of a solution set $S_s = \left\{\phi_{C_m-DD_p}, P_{C_m}, P_{DD_p}\right\}$.

$$d_\varepsilon = \begin{cases} \dfrac{1}{K}\sum_{k=1}^{K}\dfrac{v_k}{v_{max}}, & \text{if all population is infeasible} \\ \sqrt{(\|\varepsilon\|)^2 + \left(\dfrac{1}{K}\sum_{k=1}^{K}\dfrac{v_k}{v_{max}}\right)^2}, & \text{otherwise} \end{cases} \tag{17}$$

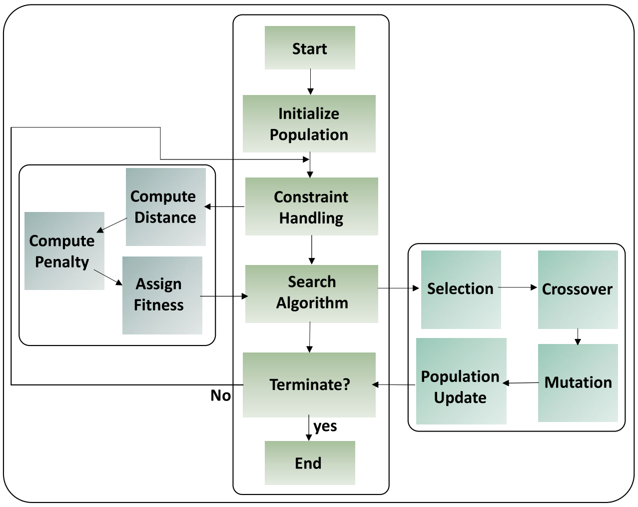


**FIGURE 2.** Flowchart diagram to illustrate the mechanism of proposed scheme.

For all the population members, it computes $d_\varepsilon$ and $P_\varepsilon$ using the methods given in Algorithms 1 and 2, respectively. The $\varepsilon'$ value is calculated using the computed $d_\varepsilon$ and $P_\varepsilon$. GA operators, such as selection, crossover, and mutation, are then used to generate a new population. The current population is updated by comparing the new population with the older one until the algorithm reaches the final iteration.

## IV. NUMERICAL RESULTS

In this section, we present and discuss the numerical results obtained from the simulations of the proposed scheme to validate its performance. We assume a hexagonal single-cell environment of a radius 500 m with cellular and D2D users for our simulations, as shown in Fig. 3. The social and physical parameters described in Section II are assigned numerical values according to their definitions in [4]. Then, the algorithm proposed in same paper is used to compute $\Delta_{DD_p}$. On the basis of $\Delta_{DD_p}$ and other parameters listed in Table 2, the proposed algorithm computes the SINR, data rate, energy efficiency, and throughput. Finally, the self-adaptive penalty based GA is applied to maximize the overall energy efficiency.

The feasibility of the proposed scheme is analyzed in terms of time complexity and the convergence between the maximum and average values of the energy efficiencies regarding the number of iterations. The performance is also shown in terms of overall energy efficiency and system throughput for various scenarios. The comparisons with the state-of-the-art algorithm are performed in two ways. First, the proposed algorithm is compared with the static penalty-based GA algorithm [8] in terms of overall energy efficiency and system throughput for different numbers of cellular and D2D users. Second, the impact of combining the social and physical parameters is investigated by comparing the proposed scheme with schemes based only on the social or physical parameters.

The time complexity of our proposed scheme depends on the TOPSIS algorithm (from [4]), self-adaptive penalty algorithm, and GA. The maximum time complexity of TOPSIS algorithm is O(n$^2$), which results from the normalization and weight assignment [35]. Moreover, we divide the self-adaptive penalty algorithm in two sub-algorithms (Algorithm 1 and 2). The time complexity of each of these sub-algorithms is O(n). Finally, the time complexity of GA (i.e., Algorithm 3) is O(n$^2$). Hence, the maximum time complexity of our proposed scheme is O(n$^2$), which is considered feasible for less number of inputs [36].

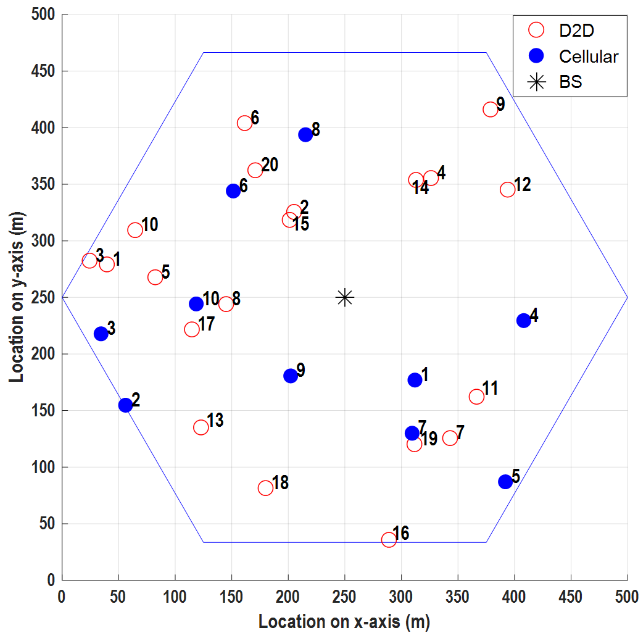


**FIGURE 3.** Simulation model for the proposed scheme.

**TABLE 2.** Simulation parameters.

| Parameter | Value |
|---|---|
| Network | Single Cell |
| Cell radius | 500 m |
| User distribution | Uniform |
| Number of cellular users | 2–20 |
| Number of D2D pairs | 1–5 |
| $\beta$ | 3 |
| $Q$ | 3 |
| $\varepsilon_{C_m}^{init}/\varepsilon_{DD_p}^{init}$ | 1 Kbps/W |
| $P_{C_m}^{Ckt}/P_{DD_p}^{Ckt}$ | 0.01 W |
| $\eta$ | 10 |
| $\sigma^2$ | −101 dBm |
| D2D channel Bandwidth | 15 KHz |
| Cellular channel Bandwidth | 180 KHz |
| $\mu_{C_m}$ | 50 Kbps |
| $\mu_{DD_p}$ | 5 Kbps |
| $P_{C_m}/P_{DD_p}$ | 30 dBm |
| BS Transmit power | 46 dBm |
| Population size | 100 |
| Maximum number of iterations | 100 |
| Crossover probability | 0.7 |
| Mutation probability | 0.1 |

**Algorithm 3** Pseudocode for the proposed scheme

**Input:** Population size $N$, Number of Iterations $T$, Mutation Probability $P_{mu}$, Crossover Probability $P_{cr}$, $S_s = \left\{ \phi_{C_{mj}-DD_{pj}}, P_{C_{mj}}, P_{DD_{pj}} \right\}, \forall j, j = 1, 2, \ldots, N$

**Output**: $S_s$ with maximum value for $\varepsilon'_j$

**Begin**

1. **Generate** an initial population ($S_s$) randomly
   *//Constraint Handling based on Self-Adaptive Penalty Function Algorithm*
2. **For** $j = 1$ to $N$
3.    **Evaluate** $d_{\varepsilon_j}$ and $P_{\varepsilon_j}$ for current Population and compute $\varepsilon'_j$
4. **End For**
5. **Compute** $r_f$
   *//Genetic Algorithm*
6. **For** $j = 1$ to $N$
7.    $num\_iter \leftarrow 0$
8.    **While** ($num\_iter < T$)
9.       **Select** parents for generating offspring from $S_s$
10.       **Generate** offspring through mutation and crossover
11.       **Evaluate** $d_{\varepsilon_j}$ and $P_{\varepsilon_j}$ for generated offspring solution and compute $\varepsilon'_j$
12.       **Update** population in $S_s$
13.       $num\_iter \leftarrow num\_iter+1$
14.    **End While**
15. **End For**
16. **End**

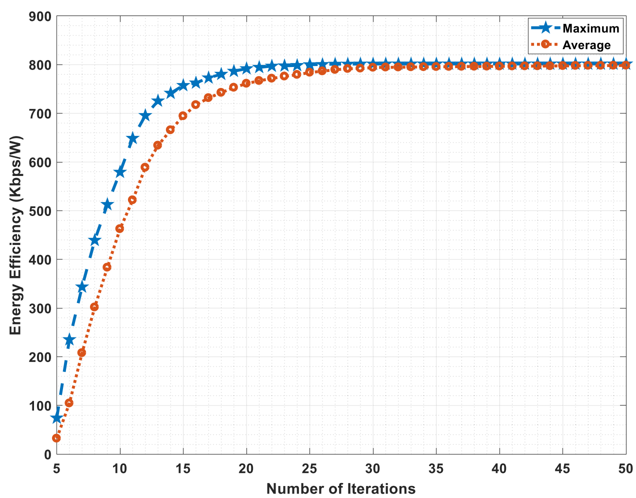


**FIGURE 4.** Convergence analysis of the proposed scheme.

To demonstrate the feasibility of our proposed scheme, we perform simulations for 50 iterations. The average of the energy efficiency values is taken after every five iterations and compared with the maximum overall energy efficiency value achieved during those iterations. Fig. 4 shows that the maximum value of the overall energy efficiency converges at ∼25 iterations. Moreover, the average value approaches the maximum value at ∼30 iterations, which shows the feasibility of the proposed algorithm for solving the energy efficiency maximization problem.

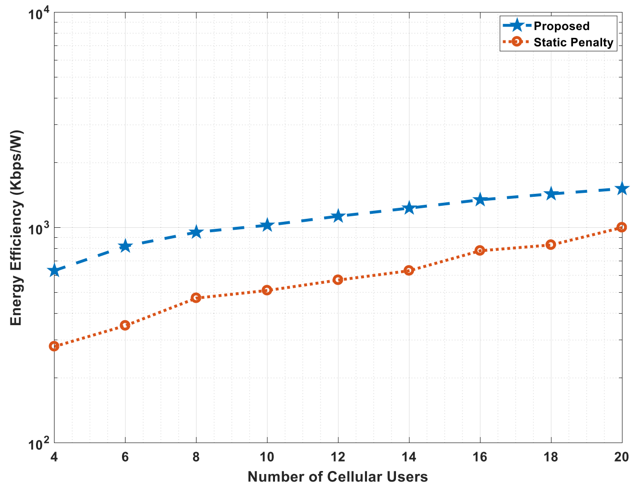


**FIGURE 5.** Impact of increasing the number of cellular users on the overall energy efficiency.

Figure 5 shows the impact of increasing the number of cellular users on the overall energy efficiency of the proposed scheme. The number of D2D pairs is kept constant at five. The overall energy efficiency with the number of cellular users is increased. This is because more cellular users contribute to improve the overall energy efficiency. Moreover, the number of channels available for reuse by the D2D pairs is increased. Hence, a D2D pair obtains a better reuse channel in cases where there are more cellular users. This increases the energy efficiency of the cellular and D2D users and ultimately the overall energy efficiency. The initial rate of increase in the overall energy efficiency for the proposed scheme is faster than that of the static penalty-based GA algorithm as the chances for a D2D pair to avail a better reuse channel are increased. However, with further increases in the number of cellular users, the growth rate in the overall energy efficiency slows down as the number of available channels for reuse by the D2D pairs exceeds the number of required channels. Therefore, some of the channels remain unused. In the case of the static penalty-based GA algorithm, the energy efficiency also increases but the rate of increase is uneven because it requires tuning of the penalty coefficients to obtain the optimal solution. Furthermore, the overall energy efficiency of the proposed scheme is much better than that of the static penalty-based GA scheme. The reason for this is that the proposed algorithm efficiently uses the information available from the infeasible solutions to guide the algorithm toward feasible solutions and ultimately the optimal solution. Furthermore, it limits the transmit power of the cellular and D2D users while fulfilling the QoS requirements. In addition, the proposed scheme uses the TOPSIS algorithm to combine the social and physical parameters of the D2D users and utilize it to compute the SINR as described in Section III.C.1. Then, it utilizes the SINR to calculate data rate and ultimately

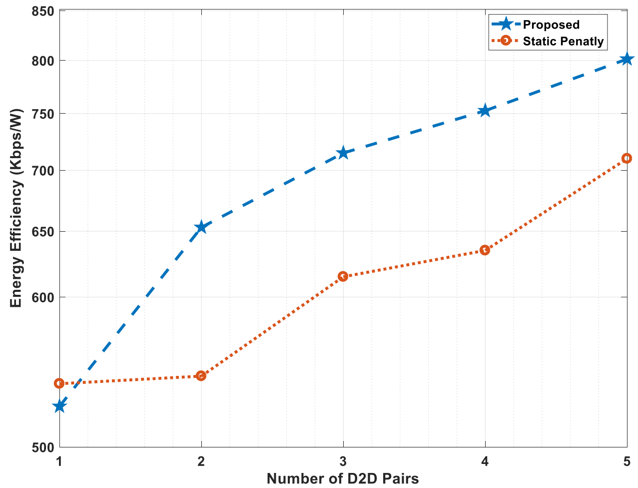


**FIGURE 6. Impact of increasing the number D2D pairs on the overall energy efficiency.**

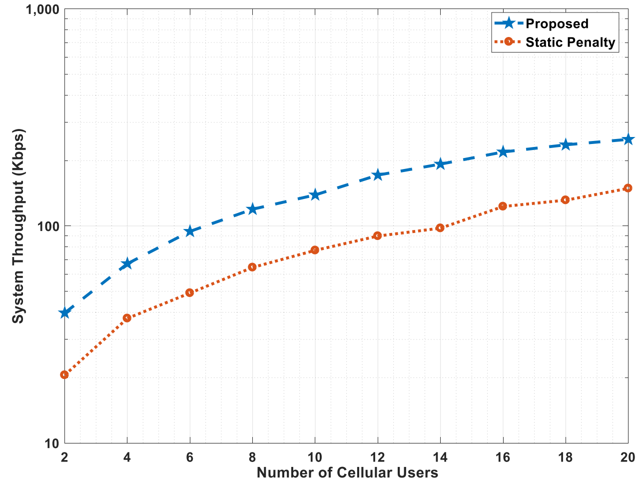


**FIGURE 7. Impact of increasing the number of cellular users on the system throughput.**

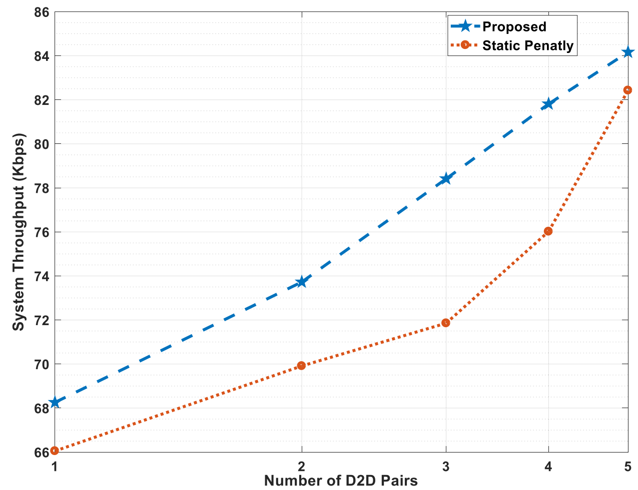


**FIGURE 8. Impact of increasing the number of D2D pairs on the system throughput.**

the overall energy efficiency, which further improves its performance.

Figure 6 shows the impact of increasing the number of D2D pairs on the overall energy efficiency of the proposed scheme and the static penalty-based GA scheme. The number of cellular users is kept constant at five. The figure clearly shows that the overall energy efficiency increases for both schemes because the number of cellular channels reused by the D2D pairs also increases. Moreover, no interference occurs between the D2D pairs as both schemes ensure the allocation of a cellular channel to (at most) one D2D pair. In the beginning, the static penalty-based GA algorithm scheme has slightly better energy efficiency as it may rarely obtain the optimal penalty coefficients in few computations. However, the energy efficiency of the proposed scheme rapidly increases with the number of D2D pairs as more D2D pairs contribute to the overall energy efficiency improvement. Furthermore, as stated earlier, the proposed scheme utilizes the TOPSIS algorithm to incorporate the social and physical parameters of the D2D users and exploit it to compute the SINR, data rate, and the overall energy efficiency, which adds to the improvement in overall energy efficiency.

Figure 7 depicts the impact of increasing the number of cellular users on the system throughput of the proposed and static penalty-based GA schemes. The number of D2D pairs is kept constant at five. The graph demonstrates that the system throughput increases with the number of cellular users because a greater number of reuse cellular channels is available for the D2D pairs. The initial rate of increase in the system throughput is higher for the proposed scheme as the D2D pairs tend to obtain better reuse channels for their communications. Moreover, the proposed scheme utilizes the information from infeasible solutions to direct the algorithm toward the optimal solution. In contrast, the static penalty-based GA algorithm scheme requires tuning of the penalty coefficients, leading to suboptimal results. Likewise, the integration of social and physical parameters of D2D users using the TOPSIS algorithm by the proposed scheme improves the SINR, data rate, and system throughput.

Figure 8 illustrates the impact of increasing the number of D2D pairs on the system throughput for the proposed and static penalty-based GA schemes. The number of cellular users is kept constant at five. The figure shows that the system throughput increases with the number of D2D pairs because the number of cellular channels reused by the D2D pairs is increased. The proposed scheme shows a monotonic increase as it achieves the optimal result using information from the infeasible solutions without the need to adjust the penalty coefficients (as required in the static penalty-based GA scheme). The system throughput of the static penalty-based GA algorithm scheme also rapidly increases when the number of D2D pairs is three, becoming closer to the proposed scheme at five D2D pairs, which is the maximum. However, the overall performance trend shows that at best it can get closer to the proposed scheme when both schemes achieve the optimal solutions.

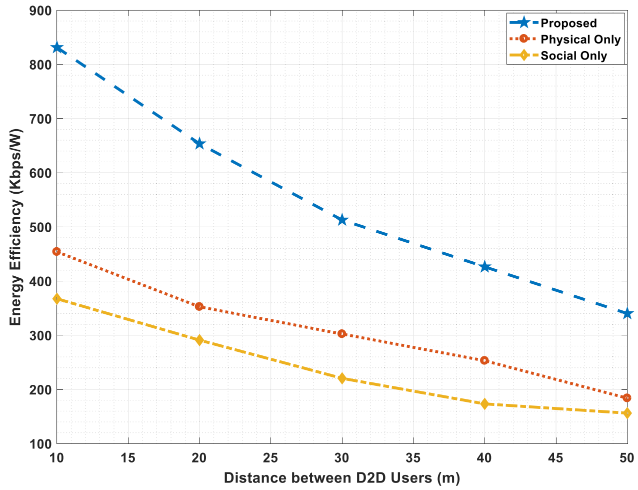


**FIGURE 9.** **Impact of increasing the D2D distance on the overall energy efficiency.**

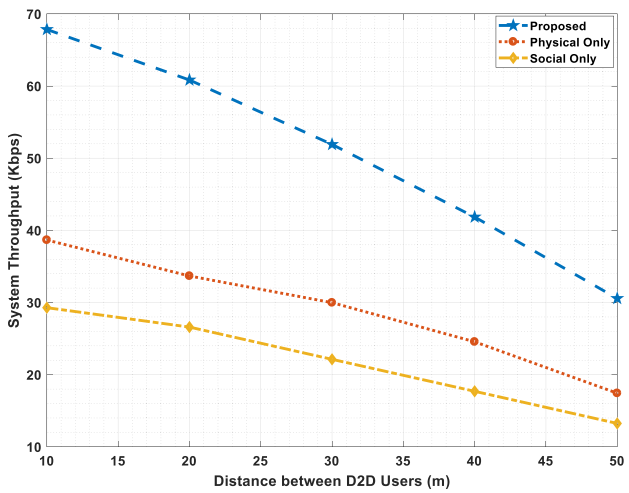


**FIGURE 10.** **Impact of increasing the D2D distance on the system throughput.**

Figure 9 demonstrates the impact of increasing the distance between D2D users on the overall energy efficiency of the proposed scheme. Moreover, the influence of combining the social and physical parameters of the users is shown by comparing the performance of the proposed social-aware scheme with two schemes based on only one type of parameter: physical or social. The distance between D2D users is changed within the range of 10–50 m while the number of cellular users and D2D pairs are each maintained as five. The figure shows that the overall energy efficiency decreases with increasing distance between D2D users. This is because when the distance increases, the path losses increase and higher transmission power is required, consequently decreasing the overall energy efficiency. Because the proposed scheme efficiently integrates both the physical and social parameters of users, its performance is significantly better than the schemes based on one type of parameter only. Furthermore, it is clear that physical parameters have greater impact on the performance of D2D communications than social parameters. However, the incorporation of social parameters definitely improves the performance.

Figure 10 depicts the impact of increasing the distance between D2D users on the system throughput of the proposed scheme. Similar to the results in Fig. 9, the proposed algorithm is compared with two algorithms, each based on one type of parameter (i.e., social or physical). The numbers of cellular users and D2D pairs are each kept at five. The figure shows that the throughput graph declines with increasing D2D distance for both the proposed and comparing schemes. This is because the increase in the distance negatively affects the SINR, data rate, and ultimately the system throughput. However, the throughput of the proposed social-aware scheme is much better than that for single-parameter schemes as it efficiently exploits both types of parameter.

## V. CONCLUSION AND FUTURE WORK

Herein, we propose a novel algorithm for energy efficiency maximization in social-aware D2D communications. We exploit both social and physical parameters of D2D users to formulate their energy efficiencies and compute the overall energy efficiency of the system by adding the energy efficiency of cellular and D2D users. Furthermore, we derive an objective function with constraints for the spectral reuse, spectral efficiency, and transmit power of cellular and D2D users. A self-adaptive penalty function method is used to handle the constraints in the problem. Moreover, we use GA to maximize the overall energy efficiency. The results are obtained in terms of algorithm convergence, time complexity, overall energy efficiency, and throughput for different scenarios to demonstrate the feasibility of the proposed scheme and its efficiency over the static penalty-based GA algorithm. Furthermore, the importance of combining the social and physical parameters of users is demonstrated in terms of the overall energy efficiency and system throughput. The proposed method is easy to implement and does not require the tuning of the penalty coefficients. In the future, we aim to extend this study to unmanned aerial vehicle-assisted social-aware D2D communications.

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