Exploiting Collaborative Behavior for User QoE Enhancement in Device-to-Device Networks

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This work was supported in part by the National Natural Science Foundation of China under Grant 61231008, in part by the 863 Project under Grant 2017ZX03001010, and in part by the 111 Project under Grant B08038.

Abstract: - The emergence of device-to-device (D2D) communication has become crucial in the evolution of 5G systems, enabling efficient distributed communication. D2D communication optimizes spectrum and energy utilization, reduces transmission latency, and alleviates base station traffic by establishing direct connections between nearby devices. However, in large and intricate D2D networks, optimizing the number of reliable links poses a significant challenge given the impact on communication quality. This paper introduces the computation-enhanced fireworks algorithm (CEFA) as a means to enable collaborative communication among devices, facilitating informed decision-making for communication paths to benefit network users. Our approach takes into account the communication behavior of nodes to assess link quality and its direct influence on user's quality of experience (QoE). A graph-based communication system is utilized, where devices act as nodes and the graph edges indicate the connection between them. Additionally, we employ a weighted graph to gauge connection reliability, with edge weights representing the mean opinion score (MOS) value. Optimizing the number of reliable links enhances connection quality and ensures QoE. Through CEFA, nodes can effectively and collaboratively reorganize the graph to facilitate communication. The scheme utilizes an elite selection strategy and mutation for communication diversity coordination, along with a mapping operator for media content sharing among devices. A fitness function is designed to evaluate the effectiveness of the proposed scheme, and extensive simulations demonstrate its efficiency even with increased nodes and communication complexity.

Keywords*:* Computation enhanced fireworks algorithm, D2D, MOS, QoE.

1. Introduction

The ongoing transition towards 5th and 6th generation networking standards signifies the convergence of Internet services, often termed as "mobile internet," across heterogeneous networks [1]. As next-generation networks evolve, the pursuit of technological trends focused on cost-efficient data transmission, service omnipresence, and high-speed connectivity is gaining prominence [2]. The concept of device-to-device (D2D) communication, enabling direct connections between client devices in close proximity, is increasingly popular and attracting significant interest from mobile industry stakeholders [3]. D2D communication offers the flexibility for operators to offload traffic from core networks, thereby reducing costs per bit and energy consumption. Leveraging proximity-based communication services holds promise for enriching social networks through equitable broadcasting within network coverage. Additionally, D2D communication has the potential to extend cellular coverage and introduce novel wireless peer-to-peer services through user cooperation [4], [5]. Consequently, evaluating the efficacy of D2D communication remains imperative, as it leverages existing cellular infrastructure to enhance network service support and introduce novel schemes for improved user cooperation.

In practical scenarios within densely populated environments like open-air festivals or sports arenas, smartphone users often encounter challenges relying on centralized infrastructure for media services. Proximity-based technologies empower mobile devices to obtain media services directly from neighboring users through cooperative communication, inspiring ongoing research endeavors. Traditional algorithms in engineering and science may not always offer optimal solutions for optimization challenges in dynamic and intricate search spaces. Hence, the introduction of new swarm intelligence (SI) algorithms, harnessing colony social behavior for problem optimization in complex distributions, is gaining traction. Modern intelligent algorithms, such as differential evolution (DE) [6], genetic algorithms (GA) [7], particle swarm optimization (PSO) [8], and evolution strategy (ES) [9], capitalize on social integration for search optimization in wireless networks. Facilitating communication through user-defined paths based on interests helps users select quality links, thereby enhancing network Quality of Experience (QoE). Adopting new SI algorithms for communication strategies promises to uncover and disseminate information efficiently in networks, bolstering QoE through user collaboration.

The mean opinion score (MOS) serves as a prevalent method for analyzing connection quality, acting as a benchmark derived from subjective tests and serving as a reference point for objective quality modeling [10]. The network devices are further collaborated using the multiple broadcasts information generated by the newly selected intelligent algorithm to decide the path of communication to share the media services. While sharing the media services, the link quality between nodes is assigned the MOS values to communicate based on graphs reconstruction to achieve the possible optimal user’s satisfaction that can grantee QoE. Moreover, MOS value of the link in the communication is assigned with a single rational number, which is commonly expressed from the range 1 to 5, where 1 is set for the lowest perceived quality, as well as the link weight 5 is the highest perceived quality. The sore opinion value is computed by average score obtained by all observers for a given stimulus in a subjective quality evaluation test during content communication among nodes [11]. Thus, the sore weight values reflect the degree of users’ satisfaction in the network with n-factor graph for n number of incoming and outgoing weighted connection links allowed to communicate with neighboring devices.

Furthermore, in various facets of D2D communication, the optimization of users' QoE remains a challenge due to the following factors.

1) User satisfaction: Users may exhibit diverse content preferences, even when accessing the same media service. Additionally, individual users may experience varying levels of link quality associated with priority levels during content transmission.

2) Cooperative communication: Addressing the challenge of transmitting and receiving content among users, as some may be reluctant to collaborate in sharing content with others without adequate motivation.

Therefore, users aim to access as much content as possible, striving to send more to maintain fairness in multimedia content sharing across devices within the network. Achieving fair distribution of information fosters collaboration among users for effective communication. Thus, proposing an innovative intelligent scheme for collaborative communication in D2D networks becomes crucial, ensuring optimal user satisfaction within a vast and intricate search space while safeguarding users' QoE.

In this study, we are inspired by the discussions outlined above, focusing on a content communication scheme that leverages computation enhancement through the Fireworks Algorithm, abbreviated as CEFA. This approach incorporates graph reconstruction to facilitate collaboration among users through effective information propagation within the network. Our scheme, a multi-agent swarm intelligence algorithm, serves as a significant optimization tool. Specifically, the Fireworks Algorithm (FA) is enhanced by improving the explosion operator through propagation, enhancing the mutation operator, and introducing elite selection strategies.

To achieve optimal solutions for the objective functions, we compare our CEFA scheme with other swarm intelligence algorithms such as Particle Swarm Optimization (PSO), Genetic Algorithms (GAs), and Differential

Evolution (DE), which are commonly employed in various practical problems. Previous research in [12] and [13] highlighted the utility of swarm intelligence algorithms in self-organized systems, social behavior prediction, network communication enhancement, and resource sharing cooperation.

In our proposal, CEFA encourages individual User Equipments (UEs) to collaborate with neighboring UEs by generating sparks through propagation, facilitating D2D communication to explore the search space for media services. The primary focus of this work is on optimizing the number of poor connection links between nodes. In D2D communication, connection links with a score value below two are considered poor connections. All UEs in the network are assumed to have cache capabilities, and communication is driven by mutual interest in cooperation within specified intervals, allowing the scheme to select links via weighted directed graph reconstruction. In summary, the key contributions of our work include:

1) Facilitate extensive communication among users within the communication range by utilizing mutation operators to trigger a potential spark explosion through the propagation of network information. This scheme equips each User Equipment (UE) with the necessary information to determine their communication path and location effectively.

2) Implement an elite selection strategy that carefully chooses a designated set of connection links according to user collaboration patterns. This strategy identifies the optimal communication path among users, prioritizing those with a higher probability of selection.

3) Develop and refine the objective function in accordance with predefined standards utilizing the CEFA scheme, particularly in a scenario where nodes possess caching capabilities. This scheme enables proportional computation for content communication across all nodes, offering ample data to reduce the occurrence of poor communication links while fostering collaboration within the network. By involving a substantial number of nodes in collaboration with acceptable link qualities, both local and global optimal characteristics are attained effectively.

4) The fitness functions within the scheme are tailored to evaluate potential solutions in alignment with the predefined objective function. By leveraging the selection path, the function guides the identification of candidate solutions for subsequent evaluations.

The subsequent sections of this paper are structured as follows: Section II presents the system model and communication matrices, Section III delves into media content computation preliminaries, Section IV describes the proposed methodology with its associated operators and strategies, Section V provides insights into simulation setup, numerical results, and comparative discussions, and, finally, Section VI concludes our work.

2. System Model and Content Communication Matrices

This section introduces the fundamental assumptions of the network system and outlines the various content communication scenarios considered in this study.

A. System Model

In this system, we consider large storage modern smartphones are cache enabled with D2D network among n devices. Let $U = \{u_1, u_2, \dots, u_n\}$ denote the set of UEs and $M = \{m_1, m_2, \dots m_n\}$ denote distinct media content, where m_k is specific media content. The system is in underlay mode where the D2D users and cellular users are allocated orthogonal resources. In the network, the macro base station (MBS) is located at the center of the cell to serve all UEs to download contents during off-peak times. In our system, the MBS is responsible for resource allocation for D2D users. For simplicity, the D2D users with a distance smaller than given threshold Th_0 will be allocated with orthogonal resources by MBS otherwise they can reuse the same resources. To show the network connectivity among devices, we represent the network with a graph $G = (V, E)$,where V denotes set of UEs as vertices and E denote the set of weighted links as an edge. A link among two nodes, node $i \in V$ to node $j \in V$ is represented as $(i, j) \in E$. The adjacency matrix $A(G)$ of graph G is the symmetric $n \times n$ matrix (a_{ij}) such that G is directed as

$$a_{ij} = \begin{cases} 1 \; if \; there \; is \; some \; edge(v_i, v_j) \in E \\ 0 \; otherwise \end{cases}$$

In D2D network there are at least two UEs to send and receive content within communication distance range R apart each other. In the network, each user u_j makes individualistic decisions when it demands media contents among other neighboring devices N_i in the network communication range R.

$$N_i = \{u_j \in U : \|u_i - u_j\| < R\} \tag{1}$$

Every UE in the sets is allowed to select the communication link based on its interest in the neighboring set of UEs directly. Since modern UEs are equipped with large storage size of l, the number of media content M is tremendously much greater than number of UEs U in the network communication range R. let vector variable $X^i = [x_1{}^i, x_2{}^i, \dots, x_n{}^i]$ shows the possible

communication status of media content of the user i as

$$x_k{}^i = \begin{cases} 1, \quad if \; user \; i \; communicate \; media \; content \; m_k \\ 0, if \; not \end{cases}$$

The media content $m_k (m_k \in M)$ allocation of the vector X should meet the possible restraint of unique cache size for a user $i (i \in U)$ denoted as

$$\sum_{u_i=1}^{U} \sum_{m_k=1}^{M} X_{m_k}{}^i \leq 1 \qquad \forall_i \in U \tag{2}$$

We considered that whenever the user is interested in parts or all the media content but may have only parts of them accessed it generates demand broadcast. The vector $X_j{}^i \triangleq X^i - X^j = [x_1, x_2, \dots, x_n]$, as $x_k \in [0,1]$, which shows the possible content communication status between two nodes i and j. As a result, when x_k , the nodes have the same content communication status for content m_k, i.e., they both possess or both lack content m_k. When $x_k = 1$, this assures node i possesses m_k while node j does not possess. In the communication, we consider if node i sends media content m_k to node j, then the link of connection is denoted as $\varrho_{ij}{}^k$. The opinion scores of transmitters i and receiver j are influenced by classification of demanded content m_k. The estimated MOS value of node j as receiver (Rx) node is denoted by

$$R_{X_i}{}^j(m_k) = \emptyset^j(m_k) \tag{3}$$

Simultaneously, when node i is the transmitter (Tx) that establishes content communication connection as

$$T_{X_i}{}^j(m_k) = \varphi^i(m_k) \tag{4}$$

Where φ^j and $\varphi^i$are assigned connection mapping function in Eq. (3) and Eq. (4) for weighted metrics to MOS values assigned to j acting as a receiver and i as a transmitter in the communication scenario.

In the system, the UEs can be connected directly to each other within a geographically allowed communication range R by setting up a direct transmission link for local data exchange without the assistance of infrastructures and then improve the utilization of network resources [14], [15]. Here, we only focus on D2D transmissions proposed to assure appropriate users' communication through proportional broadcasting to guarantee the link quality which lends to optimal QoE. In network there are studies showed resource sharing can benefit the overall efficiency of D2D and can provide relatively higher data rate, as D2D connections are much closer to each other than to the base stations [16]. Even though simultaneous links in a single device have a possible communication, conflict while connecting each other as researched in [17] and also have confirmed that directional antenna in wireless communication can enable consistent full-duplex communication efficiently. It is mandatory to consider the Signal-to-Interference-Ratio (SIR) as an essential parameter of communication that shows the quality of a link between a transmitter and a receiver in a multi transmitter-receiver environment. For network of N number of transmitters and receivers using the same channel. Then the received SIR at UE i is denoted as:

$$SIR_i(k) = \gamma_i(k) = \frac{g_{ij} p_i(k)}{v_i + \sum_{j=1, j \neq i}^{N} g_{ij} p_j(k)}, \forall_{i,j} \in N \tag{5}$$

where $p_i(k)$ is the transmission power of transmitter i further at time step k, g_{ij}stands for the link gain from transmitter i to receiver j and v_i represents the receiver noise at i. Generally, in cellular radio systems, every transmitter attempts to optimize its power $p_i(\kappa)$ such that the received $SIR_i(k) = \gamma_i(k)$in Eq. (5) is kept at a target SIR value for, γ_i threshold th_0.

The study by authors in [18], computed the dynamic system-version of the SIR, referred by $\omega_i(k)$, by rewriting the Eq. (5) with propagation of network terminology as $\omega_i(k)$ is represented as:

$$\omega_i(k) = \frac{a_{ii}x_i(k)}{b_i+\sum_{j=1,j\neq i}^{N} a_{ij}x_j(k)}, \forall_{i,j} \in N \tag{6}$$

where $\omega_i(k)$ is the fixed assumed as SIR at time step κ, $x_i(\kappa)$ is the state of the i^{th} the transmitter device, $a_{ii}$is the feedback coefficient from its state to its input layer of the adjacency matrix, a_{ij} is the weight from the state of the j^{th}recover from set of UEs and b_i is constant.

This paper allows a CEFA scheme to generate explosion sparks by broadcasting to all UEs in the network via network propagation, aimed to get local and global optimal search outputs.

The fitness of existing links is determined by selection status of connection links resulted in their MOS values. The redundant explosion sparks generated to address the UEs to check the communication with number of lousy links of MOS values less than the threshold in the competition. This drives the network to generate strong amplitude in the search space with mutual collaboration.

The main point is that the schemes with better objective optimization are smaller fitness values for minimization problems of fireworks which can generate a more significant population search explosion sparks within a smaller redundancy of amplitudes. Therefore, a small amplitude results in better fitness where a local search in a few redundancy sparks and global search considers adequate optimal within the generated explosion in the network coverage.

B. Content Communication Matrices

Content communication considers various media content stored and demanded among UEs in the network.

The UEs in the network communicate based on principle graph theory focusing network reconstruction as a key step to discover users inter communication by broadcasting demands during content communication. The UEs are represented as a set of vertices V and the link between vertices is represented as an edge E.

In the network there are n vertices are connected $V.V$ in a closer range of D2D communication to effectively share demanded content M via E as connection edges, i.e. ($E \subseteq V.V$). The explosion of amplitude sparks broadcast the demand media content to vertices $V = \{v_1, v_2, \dots v_n\}$ and edge $e \in E$ as $E = \{\{v_1, v_2\}, \{v_2, v_3\}, \dots, \{v_{n-1}, v_n\}, \{v_n, v_1\}\}$ connect the vertices [19], [20].

The communication path is denoted as P for connection of v_1 to v_n. The connection among set nodes as the edges $E \triangleq \{(i,j)^k | \varrho_{ij}{}^k = 1, \forall_{i,j} \in N, m_k \in M\}$ as connection edge set where$\varrho_{ij}{}^k = 1$ when possible, connection formulated among UEs of node j and i. The communication sub-path P from vertices v_i to v_j is denoted as $v_i P v_j$and the sub-path from v_{i+1} to v_j is assigned as $v_i{}^0 P v_j$.

Where the graph G is mapped in each vertices V connected to each other through connection edges E as $V = \{v_1, v_2, v_3, v_4, v_5, v_6, v_7\}$and $E = \begin{Bmatrix} \{v_1,v_2\},\{v_1,v_3\},\{v_2,v_3\},\{v_2,v_4\},\{v_3,v_1\},\{v_3,v_2\},\{v_3,v_4\}, \\ \{v_3,v_5\},\{v_3,v_6\},\{v_4,v_2\},\{v_4,v_3\},\{v_4,v_7\},\{v_5,v_1\},\{v_5,v_6\}, \\ \{v_5,v_7\},\{v_6,v_3\},\{v_6,v_4\},\{v_6,v_5\},\{v_6,v_7\},\{v_7,v_4\},\{v_7,v_6\} \end{Bmatrix}$.

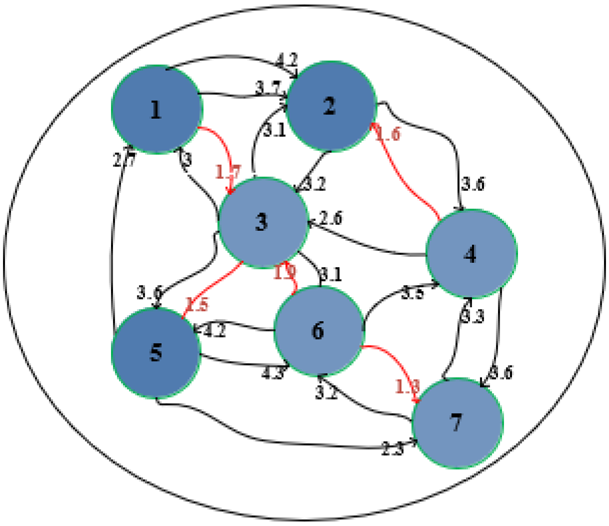

FIGURE 1. Architectural diagram of weighted directed graph model showing k number of incoming and outgoing edges with n number of missing links in the communication system

Table I Adjacency list of communication and its adjacency matrix for Figure 1.

Node	1	2	3	4	5	6	7
1	0	1	0	0	0	0	0
2	0	0	1	1	0	0	0
3	1	1	0	0	1	1	0
4	0	0	1	0	0	0	1
5	1	0	0	0	0	1	1
6	0	0	0	1	1	0	0
7	0	0	0	1	0	1	0

Node	Connection of vertices of communication
1	3,5
2	1,3,4←
3	→1,2,4,6←
4	2,6,7
5	→3,6
6	3,5,7
7	4,5,6←

vertex $A_{n\times n}$ of a graph G is $P(A) = \{a_{1j1}, a_{2j2}, \dots a_{njn}\}$ for all mutation" (*j*) = {*j*1, *j*2, ..., *j*n}. Here we use the adjacency matrix to manage the storage memory complexity. If the graph is sparse, then most of the entries are 0, which would be inefficient which results in connection link of vertices. As such, another method used to represent graphs is the adjacency list to confirm the possible communication vertices. Indeed, the graph consists of a list of all communication vertices, and each vertex connected other vertices. The main advantage here is using less memory when the graph is sparse with better communication, but it takes more time to uncover whether an edge exists or not (e.g. if we want to check for edge (i, j). We have to traverse the list of adjacent vertices of *i* until we find *j*, or reach the end). The adjacency list and adjacency matrix are the most common methods to encode graphs as a good indication to show the connection of UEs.

The study by authors in [21], confirmed usefulness of the method in certain situations as the Laplacian matrix, where the diagonal entries of the matrix correspond to the degree of each node (the number of edges connected to a node). The of matrix of the entries are 0 if there is no edge, and 1 if there is an edge. A weighted graph is a pair of $G = (V,W)$, as $V = \{v_1, v_2, \dots, v_n\}$is denoted for a set of vertices or nodes W is a symmetric matrix named the weight matrix , such$w_{ij} > 0$ for all $i, j \in \{1,2,,...,m\}$ and when $w_{ij} = 0$ towards $i = \{1,2,...,m\}$. Here we consider that a set $\{v_i, v_j\}$ is an edge if and only if $w_{i,j} > 0$.

To establish effective media communication, the devices can send and receive content; the mapping function is used to connect the vertices. In the network service, the user's opinion score measurements which results in users QoE for content communication over wireless network studied in [22]– [24] and assigned with a given vector x in the QoE results in a value of *y* [25]. In communication network from receiver *j* is assigned,$\emptyset^j$ and mapped as

$$\emptyset^j : x \mapsto y = \emptyset^j(m_k) \in [L; H] \quad (7)$$

as well the connection from the transmitter i is which φ^i is mapped as

$$\varphi^i : x \mapsto y = \varphi^i(m_k) \in [L; H] \quad (8)$$

In mapping the communication, user i corresponding with MOS value parameters are $x_{i,}$ for the QoE value v_i as to get media content m_k. Where L is denotes, the lower limit which corresponds to the lousy connection quality of communication and H is assigned to the possible upper limit which is mapped with excellent opinion score connection quality. Indeed the

MOS value assigned for L = 1 and H = 5 is used as QoE evaluation parameter according [22], [23]. Here the mapping function is used to connect the MOS parameters into the QoE domain for values of [L; H] in the communication network. The connection quality rendered based on the objective values of user studies as MOS scores are mostly used in QoE evaluation parameters.

3. Preliminaries Of Content Computation

The design of the computation enhanced fireworks algorithm is inspired by the explosions of search sparks in a communication network to provide necessary information to all UEs. The UEs are represented in a weighted directed graph G (V, E, A), as $V = \{v_1, v_2, ..., v_n\}$ denoted as nodes, $E \subseteq V \times V$ represents set of edge, $A = [a_{ij}]$ is the weighted adjacency matrix as $a_{ij} > 0$ if ($i, j \in E$) and $a_{ij} = 0$ otherwise. Our scheme works by exploring a set of solutions, and then simulating an explosion around each solution which generates a set of broadcasts. The broadcast that are generated for corresponding solutions which is in vicinity of the originally generated the explosion. Finally, the best solutions are taken, and new sparks are generated until a termination condition is met. To prevent the algorithm from converging prematurely, the distance at which a spark can be generated is based on the performance and current convergence. The explosion sparks in the communication network are minimal in a good communication network with designing appropriate fitness function. Assume that the CEFA is designed for the general optimization problem as:

$$minimize\ (f(x_i) \in R,\ x_{i\text{–}}min \leq x_i \leq x_{i\text{–}}max). \quad (9)$$

The Eq. (9) is used to calculate the number of lousy links in the network. Where i^{th} (i.e., $x_i, \forall_i = 1, 2, ... , n$) that shows the redundancy of generated sparks within communication range. The UEs are can be coordinated within the cluster search space to achieve optimal communication quality. Here $f(x_i)$ is used to represent an objective function used to evaluate the sparks, and $x_{i\text{–}}min$ and $x_{i\text{–}}max$ indicate the links communication in the bounds of search space. The computation of UEs in the network is mandatory and acknowledged for the UEs with higher MOS value communication links. Meanwhile, UEs communicating with minimal MOS values (i.e., MOS value less than the threshold) is considered as lousy links where our scheme explores the diversity by generating sparks to provide information and exploitation of x_i as follows

$$s_i = v \frac{y_{max-f(x_i)+\omega}}{\sum_{i=1}^{n}(y_{max}-f(x_i))+\omega} \quad (10)$$

As shown in Eq. (10), v is a constant controlling parameter. It is used to measure the explosion of sparks which is generated by N fireworks. Moreover, $y_{max} = max(f(x_i))$ as (i = 1, 2, ..., n) shows that the max is the (worst) value when a lot of users have connection with the lousy links according to the objective function. ω shows the smallest value in communication value.

To avoid the enormous consequence of magnificent fireworks, the bounce is established for s_i, which is denoted in Eq. (11)

$$\widehat{s_i} = \begin{cases} round(l, v) & if\ s_i < lv \\ round(\mu, v) & if\ s_i > \mu v, v < \mu < 1 \\ round(s_i) & if\ not \end{cases} \quad (11)$$

As shown in Eq. (11), $\hat{s}$ stands for a number of explosion sparks and the parameters ι and μ are used as constant parameters between 0 and 1 but $\iota < \mu < 1$.

In general, to analyze the explosion amplitude in the communication environment, it is specified follows;

$$A_i = \hat{A}\frac{f(x_i)-y_{min}+\omega}{\sum_{i=1}^{N}(f(x_i)-y_{min})+\omega} \tag{12}$$

As shown in Eq.(12), A_i stands for the amplitude of each user, $\hat{A}$ denotes the coefficient the amplitudes, whereas y_{min} stands for the fitness values of the best individual in the communication link among the N fireworks. The fireworks with bigger amplitude of fitness value is worse, and it generates less communication sparks than other fireworks. Where $f(x_i)$ denotes the function and ω stands for the smallest communication value.

4. Proposed Methodology

In the D2D content communication, we have to choose the best scheme used to construct the maximum 1 and 2factor graph to show the complexity level. In this work, first, we describe a mutation operator to keep the diversity of link quality at each generation in the scheme. The mapping operator which is used to represent the mapping of a specific vertices of the computational domain of communication. Then communication link selection strategy is used among the users the communication range r between each pair of users during D2D communication by explosion of the sparks. Finally, we designed the CEFA to get the optimal output of our evaluation. The fitness function is also designed to check the evaluation output through reconstruction of 1 and 2-factor graphs with their optimal solutions for each graph at different evaluations.

A. Computation Enhanced Fireworks Algorithm

The users in the network environment are cache enabled, where the CEFA focuses on improvement of computation among devices based on collaboration. The communication of links with higher MOS values assures the existence of sufficient communication information, while those with minimal MOS values allowed to compute at every broadcast generated during the communication.

Here the scheme sets firework signals of sparks to locate possible paths in the local space of communication generated in the explosion. Since all UEs in the network are well informed on their computation, selection to find out links of x_i satisfying $f(x_i) = y$, the scheme can consequently set off fireworks in possible communication range till one 'spark' marks or is fairly nearby the link x_i.

A structural representation for the procedural setting off CEFA is shown in Fig. 2. In the CEFA, for each generation of explosion, the scheme firstly select n edges in the communication range, where n fireworks are set off. Next explosion in the communication range sparks and obtains the possible communication links generated. Then evaluate the path of the graphical communication by MOS value obtained by the sparks.

Finally, when the optimal communication links of targeted MOS found the algorithm stops. If not, n other scheme reselects the links by regenerating the sparks and fireworks also start the other explosion as network propagation.

From the structural Fig. 2, it can be seen that the success of the CEFA lies in a good design of the explosion process and a proper method for selecting possible optimal links. In this scheme all UEs are highly interested to communicate with the best path of MOS values and the minimal links are discouraged for media communication, results in achieving optimal QoE based on users' information access broadcasted in D2D communication.

B. Communication Link Selection Strategy

Appropriate selection strategy is mandatory to maintain the achieve the target of the objective function. In a swarm the opinion score information is obtained through iteration as a subset of the entire population has to be selected in the network. It is confirmed that link selection strategy is used cellular

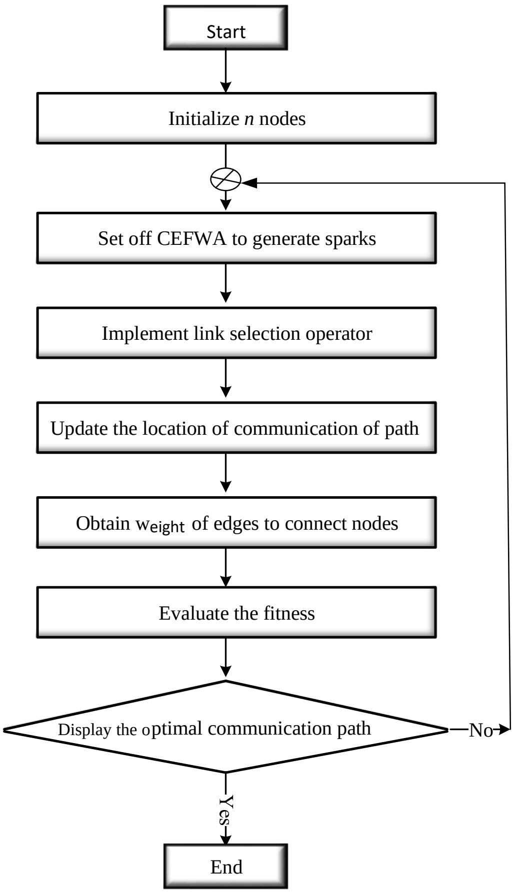

Figure 2. Structure of computation enhanced fireworks algorithm

network and short-range communication system to optimize the communication [26]. The CEFA works with independent selection strategy which chooses *N* vertices independently of the next generation which is computationally efficient. When *N* fireworks produced the possible best small elite group is set being selected links of communication. Even though the location of the node is strategically mandatory, the selection process is highly randomized; only the best individual is kept, and all other individuals are chosen randomly. The bounce off strategy filters the vertices and edges of the selected sparks than the vertices with lousy connection links are well informed to get ready for next sparks.

In the selection strategy, the communication distance between devices is measured, where r (x_i, x_j) refers the Euclidean distance among two UEs x_i and x_j.

$$R(x_i) = \sum_{j=1}^{N} r(x_i, x_j) = \sum_{j=1}^{N} \|x_i - x_j\| \quad (13)$$

where $R(x_i)$ denotes the sum of connection distances among individual x_i and all the other UEs in the network. $j \in N$ means the position of node j is domain of set N, where N is the set that includes both the explosion sparks generated and mutation operator in the communication scenario.

Algorithm 1 Computation Enhanced Fireworks Algorithm

1. Initialize: N computational fireworks, R communication range, X population, and M media content in l shortage size.
2. Evaluate the fitness form n to n-1 computation according to the objective function
3. While terminate the computational condition is not converged do

4. Compute the explosion sparks s_i
5. Compute the amplitude A_i of the computation
6. Regenerate the explosion sparks with in R communication distance with the amplitude
7. Broadcast the network information to all users to get ready for content communication
8. Check the weight of communication link for specific media content m_k
9. Generate the function of mutation operator
10. Compute the covariance Cov among UEs i and j in the communication range
11. Propose connection path P of media access with feasible fitness
12. Compute the mean m of each function
13. Communicate based on mapping operator
14. Find the candidate selection of communication links to content m_k within generated operators
15. Select N-1 explosion sparks of computational fireworks
16. End while
17. Return x with the value of f(x) for $x \in X$

The communication path is used to select vertices for next generation, as the chance for selecting device x_i should be denoted as $p(x_i)$, where the communication is assigned as;

$$p(x_i) = \frac{R(x_i)}{\sum_{j \in N} R(x_j)} \quad (14)$$

As shown in Eq. (14), the UEs located at larger distance from other are advised to get all possible information by redundantly generating explosion sparks to be selected may all interested UEs in the communication rage. In the network, the A_i and S_i, of the explosion operator is computed. For generation each of S_i sparks to each bounce of firework X_i, Algorithm 2 is implemented once. In the Algorithm 2, the operator of the modulo operation, and X_{min}^k and X_{max}^k denotes the bounds of the lower and the upper search space for of k in R communication dimension. The pseudopod of generating the broadcast of the sparks in the communication environment shown in Algorithm 2.

C. Connection Mutation Operator

we use a mutation operator to show the diversity the network population, since it has much more sophisticated than conventional evolutionary strategies.

In conventional strategies, the mutation rate is applied until a success rate of 1/5 is shown in Algorithm 2 and obtained (the 1⁄5 success rule), as this maximizes convergence speed. However, the solutions it obtains are generally spaced in a similar distance to the solution undergoing mutation as used in [27] and [28]. Whereas in CEFA the covariance mutation exploits information from the sparks produced by the explosion of the firework, instead of exclusively converging on the single most magnificent spark. Unlike previous mutation operators, covariance mutation uses both the sparks produced by the fireworks with best fitness values from the current generation and from the single most recent generation to calculate an optimal solution. On the other hand, the CEFA scheme provides necessary information to all nodes to compute for possible optimal output. By using sparks from the previous generation, the co-variant mutation selects better sparks with proper fitness values than conventional schemes.

The covariance mutation selects the sparks as network propagation with better fitness evaluation produced by a firework, calculates the mean value of the selected sparks and the covariance matrix of all the sparks. With the mean value and covariance matrix, covariance mutation estimates the local distribution of a function and produces sparks according to a standard distribution, aiming to find potential sparks with better fitness values. To confirm the acceptable convergence of mutation operator the scheme focuses on; primarily the explosion sparks produced by a firework and mean value is calculated. Hence the notation f denotes the sum of generated sparks and β represents the number of selected exploited sparks and z which denotes the mean value chosen sparks form N fireworks.

$$z = \sum_{i=1}^{\beta} x_i \quad (15)$$

Algorithm 2 Generating the Explosion of broadcast sparks

1. Initialize: indicate the communication in location through broadcasting as explosion sparks: $x_i = x_j$
2. Compute the number of explosion sparks s_i
3. Compute the explosion amplitude A_i
4. Set $z = rand(1, r)$
5. For $k = 1{:}r$ do
6. If $k \in z$ then
7. ${x_i}^k = {x_i}^k + rand(0, A_i)$
8. $if\ {x_i}^k$ out of bounds then
9. ${x_i}^k = {x_{max}}^k + |{x_i}^k| \% ({x_{max}}^k - {x_{min}}^k)$ with in r communication distance
10. End if
11. End if
12. End for

where x_i is used to represent the selected exposition sparks and z is the mean value as well β is number of selected exploited sparks in the environment.

The covariance adjacency matrix A among the given f sparks is calculated based on i^{th} row and j^{th} column, the matrix A denoted as A_{ij} is shown as:

$$A_{ij} = cov(r_i, r_j)(i, j = 1, 2, \dots, R) \quad (16)$$

In Eq. (16), the possible D2D constant communication range R is specifically allowed to be connected with dimensional standard function and section r_i is the explosion sparks in their i^{th} coverage distance. Here the $cov(r_i, r_j)$ which stands to show the covariance of the explosion sparks in i^{th} and j^{th} dimensional distance and is shown in Eq. (17).

$$cov(r_i, r_j) = \frac{\sum_{e=1}^{\beta} (g_e - \bar{G})(h_e - \bar{H})}{\beta} \quad (17)$$

where the variables g_e and h_e shows the e^{th} explosion spark in its i^{th} and j^{th} distance, $\bar{G}$ and $\bar{H}$ are the average value of all the τ explosion sparks in the distance of i and j. Conventionally the covariance is calculated differently whereas here the denominator is not $\beta - 1$ as usual in calculating the covariance.

Algorithm 3 Covariance of Mutation

1. Initialize: N computational fireworks, m mean, Cov covariance
2. Compile sub graphs of communication
3. Compute m of the good explosion broadcast
4. Get the Cov

5. Generate mutation of explosion broadcast with $N(m, Cov)$

D. Connection Mapping Operator

For the network connection the mapping operator is used for computation of the instantaneous, that allows both the transmitter and receiver users to be interconnected based on the direction of proposed communication strategy. To provide network information, the users in communication range generates communication demands, and users are allowed to be linked within their possible communication boundaries. When a firework is close to the boundary, the generated sparks can easily stray out of the boundary when distributed by a relatively large explosion amplitude. The mapping rules basically rely on social behavior using graphs, or mapping links between users. According to [29] in a scale-free graph, the degree between nodes is not uniform: when generating a scale-free graph, nodes with a larger degree have a larger chance to get new connections than nodes with few edges. The scale-free graphs were generated to handle error and attack tolerance according to study in [28]. In this work, the connection mapping operator is almost related to the conventional fireworks scheme, where the distant sparks are produced randomly to all the individuals in the feasible communication coverage.

$$X = X_{min} + rand(0,1) * (X_{max} - X_{min}) \tag{18}$$

where X is the explosion of the spark in the feasible communication space, X_{max} and X_{min} represent the maximum and minimum communication boundaries. The function $rand(0,1)$ generates a random number outputs of values from 0 to 1 range as uniform distribution to show the existence of communication link.

E. Fitness Function

The proposed the algorithms need to design appropriate fitness functions that confirm the achievements of the objective functions to summarize the effectiveness of the solution. Indeed, the fitness function is one of the best methods used to evaluate the achievements of an objective function in the optimization of various telecommunication matrices and updated its candidate solutions [30], [31]. It ideally considers the global optimal of the fitness should be the solution, and the number of local optima is to be minimized, and an adjustment in the value of an edge $e \in [0,1]$ to show the existence of the connection link that should yield different fitness value. It is important to design a fitness function that is guaranteed to have these properties of the objective function. Moreover, 1 and 2-factor functions are designed to address the complexity, with different design elements and values. Then, the function computed to compared and examine the evaluation results, by taking the mean value of the maximum factor gain of each algorithm.

In the function, the *n*-factor of communication uses the function $\overline{f(x)}$as the links of connection. The factor of α is used in the experiment, we set as α=0.5 for possible reconstruction of candidate link. Besides, we consider the value *m*, the mean value of the reconstructed path links. By using this variable, we favor more certain solutions based on the factors. To evaluate the fitness we employed $\overline{g_1(x)}$and $\overline{g_2(x)}$where $\overline{g(x)}$yields a matrix the same size as *x* with the original likelihood values of the extracted *n* factor edges and all other edges are set to weighted values of adjacency does the same, without taking into account the edges selected by $\overline{g(x)}$.Next, we took the corresponding likelihood of each edge, and using them as a 'punishment factor', we took the sum of the edges selected by solutions multiplied by the weights of the weight graph. The functions are formulated as $f(x) = P(\overline{g(x)}w)$ for 1-factor and $f(x) = P\left(\overline{g(x)}w\right) + 0.5\left(\overline{g(x)}w\right)$ for 2-factor reconstruction graph during content communication.

5. Numerical Results

In this section, we provide the performance of our proposed CEFA scheme using MATLAB R2015a as a simulation tool. To reveal improvements, an extensive simulation is done to compare our scheme with other latest standard algorithms. Hence, the algorithms used for comparison are described as follows;

1. DE: is one of direct search technique for problem optimization that iteratively trying to improve a candidate solution to a given measure of quality in a vast network. DE can minimize the aggregate cost involved

in the wireless network, as it optimizes proposed strategies for combinatorial optimization problem to solve the location management issue in the cellular network [32].

In DE generates a mutation operator as new parameter vectors by adding the weighted difference between two population vectors to a third vector and further used in mixing parameters like a crossover to relay on selection strategy [33]. This idea motivated us to use ED as one of comparison scheme.

2. GA: It is one of a classic EA that used to select users randomly with recurrent modification a population of individual solutions. In a dynamic learning and identification of the majority supported capability, GA plays a vital role in a dynamic adaptive content delivery which is more convenient for diversified mobile devices [34]. According to [35], GA is used as routing algorithm showing better performance in media applications. Hence, we believe that considering this algorithm with our scheme is more logical as one comparison schemes.

1. 3. PSO: The idea of this scheme is based on the social behavior of a swarm of bees and ants introduced by Eberhart and Kennedy in 1995 [36]. The algorithm is stable for communication to be established between the nodes; the nodes must be organized into groups called clusters. PSO is one of optimization techniques can be used to problems where finding an efficient solution is an NP-Hard problems. Also, it is more applicable for large search space communication among a considerable number of nodes and proposed in the selection of which solutions are mapped onto particles, and a fitness function considers the constraints in a penalty function [37]. This scenario is also more convenient to consider with our proposed scheme since the evaluation performances on similar parameters.

To assure the fairness of our comparisons, we apply mutation operators for diversity management, mapping and link selection strategies used as one fundamental parameters in all schemes during D2D content communication.

A. Simulation Setup

Here, the number of user devices in the network should be $U \geq 2$ to enable D2D communication. In the simulation, we have considered from 10 to 100 nodes located in the communication range r to share media content within possibly 250m of connectivity. We generated 2000 experimental for maximum iterations in MATLAB. Each node has various media services and can initiate requests for its interested media services by any demanding nodes. Here, each scheme was afterward instructed to find the maximum possible one and two factors of connection as the complexity of edges increases then we iteratively select the viable connection links of weighted MOS values. At each experimental sparks, we considered $G(x)$, whereas the $G(x)$ yields with the same matrix size as x with the original likelihood values of an extracted factor of the edges. We took the sum of the edges selected by solutions multiplied by the weight of the graph. The function is more of exploration in the communication set as $f(x) = P\left(\overline{g(x)}w\right)$where denotes to element-wise multiplication of two matrices with the same dimensions, and w is the original weight graph. The weight of MOS value is quality value of each link is between 1 and 5 based on prior studies. we considered the adjacency matrix of the node possesses the content to the other node as 1 and this validates the existence of a link between nodes. If the adjacency matrix of content possession status remains 0 it results with the quality of opinion score when the weight w $(i.e\ w < 2)$. Then, each algorithm was given 100 attempts to find the maximum the 1-factor and 2-factor graph functions with maximum graph size of 250. We set σ = 0.3 percent of connection chance to access the media content in the network scenario. In order to let the algorithms work, fitness functions were developed and compared. For each amount node, one graph was generated. Hence, our target is to minimize the number of lousy links explosion sparks as broadcast which is generated to provide sufficient information to all users in the communication environment to share media content.

B. Results and Discussions

Extensive simulations have been carried out to show the performance of our proposed scheme. Moreover, we did a comparison with other state of the art optimization schemes by considering various scenarios. The mean, minimum and maximum fitness values for each algorithm is generated where for 2000 function evaluations, where the mean value is considered for comparison of the schemes. As mentioned previously, the primary aim of the CEFA is to optimize the explosion sparks as broadcasting by propagating network information to weak communication among nodes generated through reducing the number of lousy links. The optimization function of the scheme is based on the function of mean fitness values in 1 and 2-factor graphs to address complexity. An important feature in the estimation and planning of radio networks is the computation of the effect of co-channel interference in radio links. The extent of interference that can be tolerated determines the required separation distance between co-channel cells. Also the efficiency of the network considering the path loss exponent while propagating content communication based on computing outage probabilities between devices in the cells. Any cellular operator uses topographic content communication to estimate outage probabilities in the area covered by the UEs, but results for idealized hexagonal cell layouts are nonetheless illustrative for the effect of the reuse distance and shadowing. Fig. 3 shows as path loss exponent increase the operator can change the outage probability with gradual decrements when the reuse distances become large.

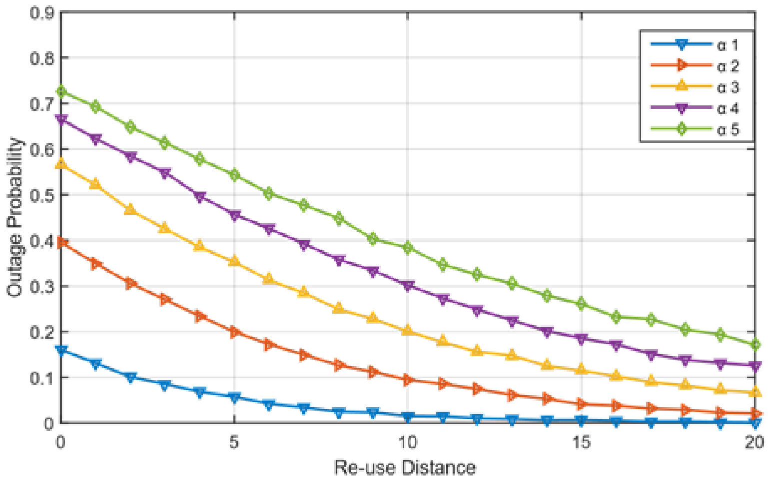

Figure 3. Signal outage probability versus the normalized re-use distance as path loss exponent changes with receiver threshold 10dB

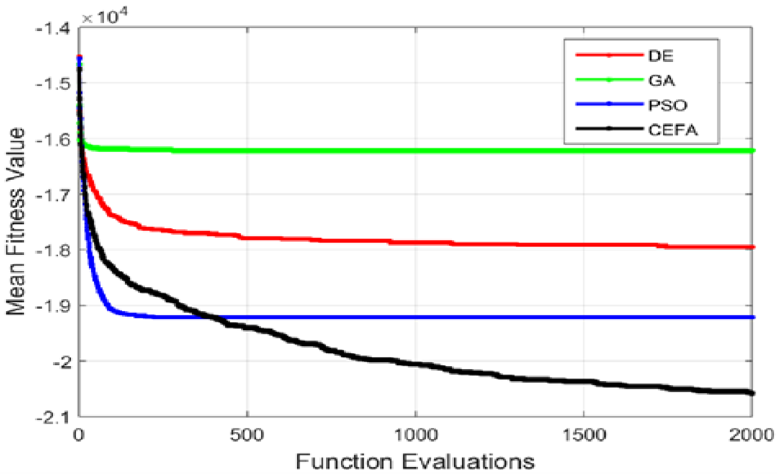

Figure 4. Mean fitness values over 2000 evaluations of 1 factor function.

To comprehend the simulation results, we consider the number nodes, runs of the experiment, and the iteration of evaluation. The Fig. 4 depicts the result of the mean fitness values over 100 runs with 10 nodes, where the CEFA scheme primarily shows gradual decrement for evaluations in mean fitness value as reuse distance increases than other swarm intelligent algorithms. Indeed, our scheme outperforms all other schemes within communication of 1-factor connection graph when communication broadcasted in the network.

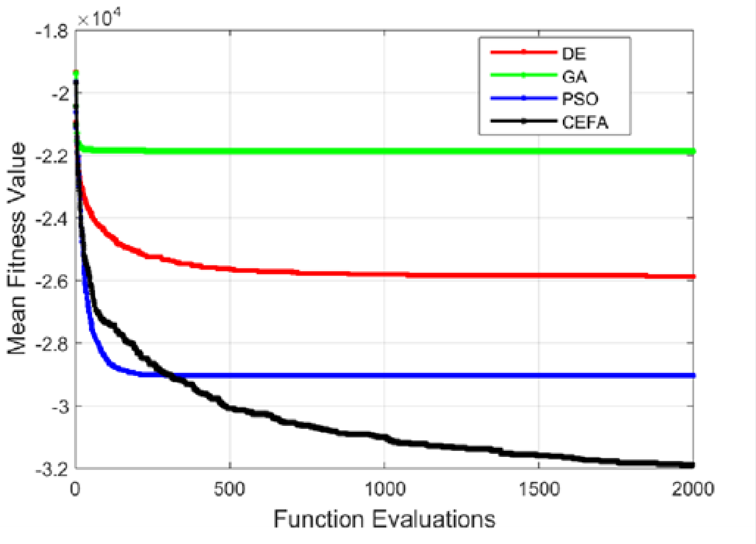

Figure 5. Mean fitness values over 2000 evaluations with 2 factor functions.

The observation of the simulation result in Fig. 5 shows as the complexity of links density increases as 2-factor of the graph with 10 number of nodes and 100 runs for each algorithm. In this result, we have seen that smaller improvement over 1- factor function at the beginning of our simulation. In addition, the Fig. 5 current values are minimized within 2000 evaluations which is showing better improvements. Therefore, in the communication system, we have observed that a minimal number of lousy links in the content communication network compared to other schemes of the function evaluation.

The Fig. 6 shows the evaluation of simulation result for mean fitness values for 25 nodes over 100 runs within 2000 evaluations. As observed from the result of the Fig. 6 our scheme performs sub-optimal at the beginning of evaluation compared to PSO scheme until 1200 evaluations, then for the remaining evaluations our scheme outperforms all other schemes for 1-factor graph function. Finally, we have seen that even we run more evaluations; our scheme shows the better output than other algorithms.

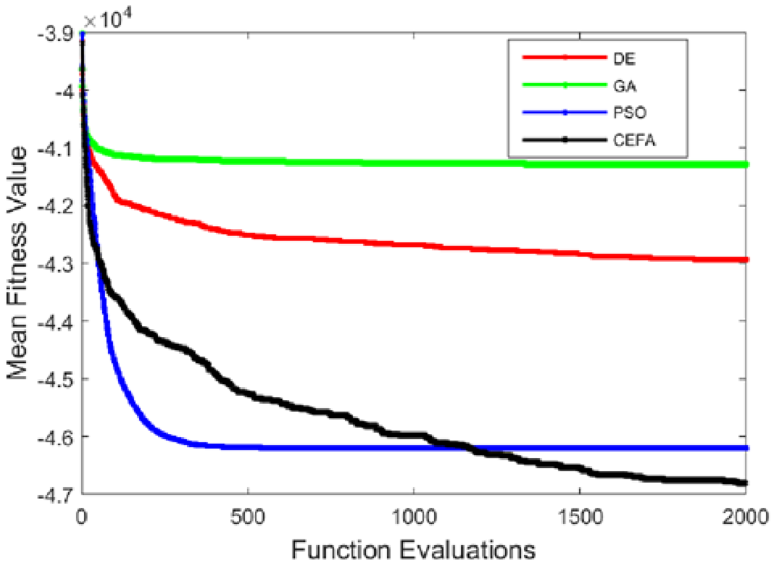

Figure 6: Mean fitness values over 2000 evaluations with 1-factor function

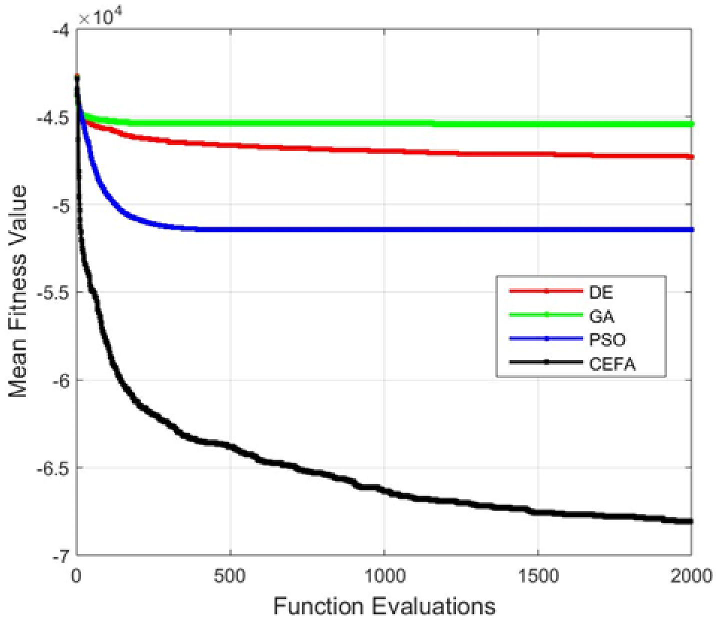

Figure 7. Mean fitness values over 2000 evaluations of 2-factor function

Fig. 7 shows the performance of the proposed scheme with the result of outperforming the other schemes as some evaluations rise. Here, 2-factor graph of fitness is better performing than 1-factor with the same 25 number of nodes in 100 runs of 2000 evaluations. Thus, a number of nodes increase in 2factor graphs, the complexity of communication also increases but our designed fitness function better coincides with our scheme showing better results than others. The Fig. 7 verifies as our scheme efficiently finds the connection nodes with the MOS weight values of links with better qualities as more number of incoming and outgoing edges connected in the network environment.

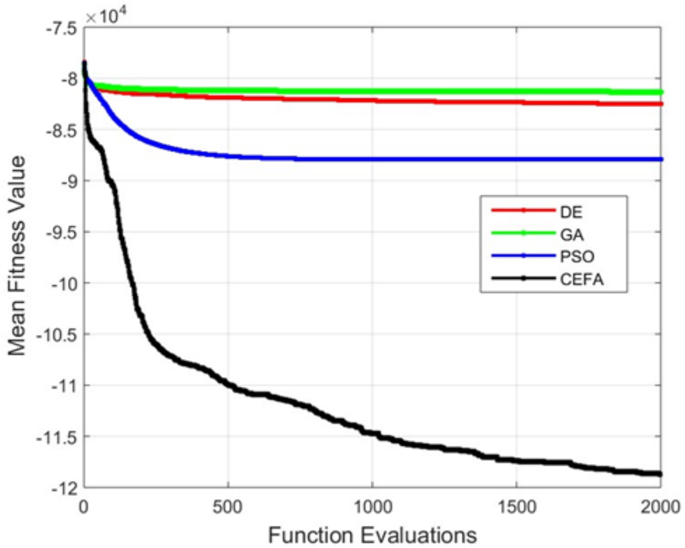

Figure 8. Mean fitness values over 2000 evaluations of 1-factor function

As we can see from the Fig. 8, the simulation result of our proposed method compared to the parameters with values of the mean fitness function. The scheme shows better performance at the beginning with gradual decrements as the number nodes increase to 50 over 100 experiment runs. Moreover, The proposed a scheme in the Fig. 8 showed changes with insignificant improvements at the beginning of evaluation compared to PSO algorithm after the evaluation of 1800.Here the PSO scheme performs better for most evaluations, Meanwhile for remaining more 200 evaluations; our scheme performs better than other schemes for the total of 2000 evaluations for 1factor graph functions.

In the Fig. 9, we compare the simulation output of 2000 evaluations to compare four different algorithms. From the Fig. 9, we have viewed changes as the number of nodes increases to 50 nodes over 100 runs to each algorithm; our scheme performs better than all other algorithms. The CEFA mean fitness values decrease as a result of better explosion sparks exists in the scheme of 2-factor graph which directly assures the existence of minimal lousy links of content communication in the network environment as some evaluation changes.

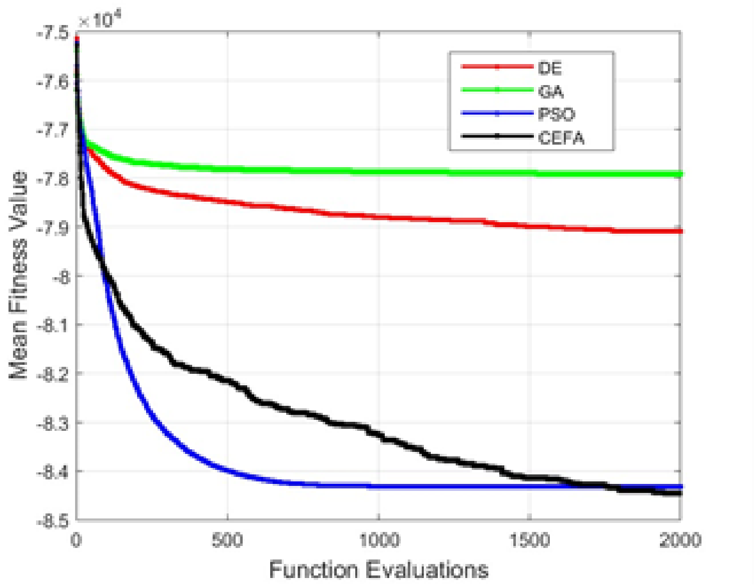

Figure 9. Mean fitness values over 2000 evaluations of 2-factor function

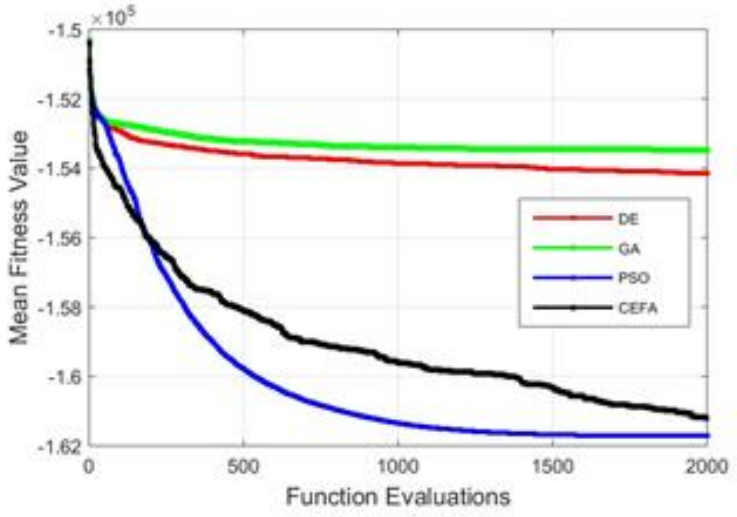

Figure 10. Mean fitness values over 2000 evaluations of 1-factor function

Fig. 10 demonstrates the communication of 100 nodes in the network with 100 runs over 2000 evaluations. In this figure, firstly the CEFA performs better at the beginning and than as evaluation changes the PSO scheme gradually performs better than all other schemes. Here the performance of PSO is compared with 1-factor graph as seen in our simulation result for specified parameters. Apparently, as the density in network changes with number of nodes increase the CEFA scheme preforms sub-optimal in 1-factor graph over 2000 evaluations following the PSO algorithm. Therefore, PSO shows better performance with a large number of nodes with the moderate complexity level of 1-factor graph than our scheme.

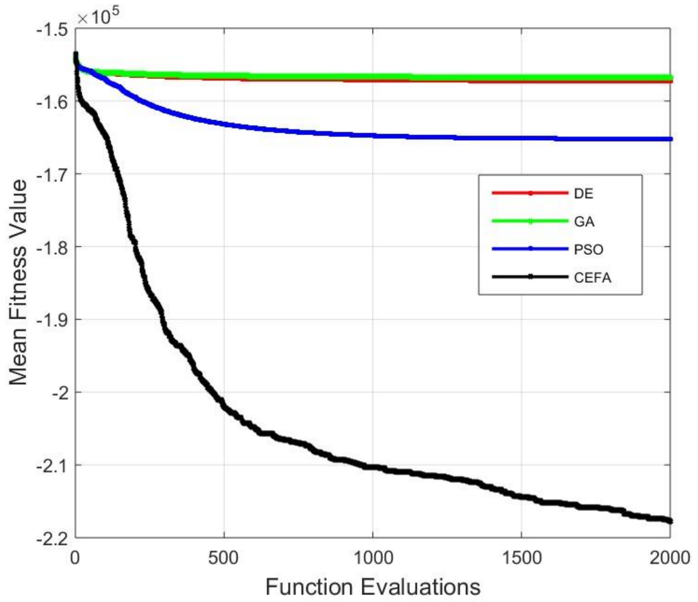

Figure 11. Mean fitness values over 2000 evaluations of 1-factor function

As shown in Fig. 11, the simulation provides results for communication of 100 nodes in the computation over 100 runs over four algorithms, were the DE and GA overlaps when we generate 2000 evaluations. Here, the figure shows improvements using CEFA than other schemes, but insignificant changes have seen using PSO as computation evaluation increase in 2-factor function performances. This result approves CEFA scheme have a fewer number of lousy links than other schemes in the computation of 100 nodes over 100 runs of 2000 evaluations. Finally, the scheme with a smaller number of lousy links shows that better communication and most nodes of the network are communicating in a proportional manner which results in better QoE of the network communication. The Fig. 11, shows as CEFA outperforms other schemes with a vast and complex communication scenario.

6. Conclusion

In this research, we proposed a new content communication technique named CEFA, utilizing network propagation and graph modeling to enhance collaborative communication through network reconstruction. Our method includes the emission of sparks as broadcast signals to evaluate communication nodes within the graph model. By assigning weights to graph connections and selecting communication paths based on user preferences, our approach enhances communication effectiveness in network settings. Through tailored fitness functions, our goal is to enhance mean fitness values throughout iterative assessments. In comparison to conventional algorithms such as DE, GA, and PSO, CEFA exhibits enhanced performance, particularly in extensive and intricate network setups.

Our approach integrates mutation and connection mapping operators to maintain information diversity within the search space. The spark explosions serve as indicators of network coverage breadth, assisting in the identification of viable communication pathways. This methodology is specifically advantageous for D2D communications, as it fosters effective user collaboration and assesses connections through multiple function iterations. Results from simulations underscore the efficacy of our approach in bolstering communication reliability for users, particularly in situations with a restricted number of subpar communication links. This enhancement in communication quality ultimately translates to an enhanced Quality of Experience (QoE) for users engaged in D2D content communication within expansive and intricate network landscapes.

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