Device-to-device based path selection for post disaster communication using hybrid intelligence

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ABSTRACT

Public safety network communication methods are concurrence with emerging networks to provide enhanced strategies and services for catastrophe management. If the cellular network is damaged after a calamity, a new-generation network like the internet of things (IoT) is ready to assure network access. In this paper, we suggested a framework of hybrid intelligence to find and re-connect the isolated nodes to the functional area to save life. We look at a situation in which the devices in the hazard region can constantly monitor the radio environment to self-detect the occurrence of a disaster, switch to the device-to-device (D2D) communication mode, and establish a vital connection. The oscillating spider monkey optimization (OSMO) approach forms clusters of the devices in the disaster area to improve network efficiency. The devices in the secluded area use the cluster heads as relay nodes to the operational site. An oscillating particle swarm optimization (OPSO) with a priority-based path encoding technique is used for path discovery. The suggested approach improves the energy efficiency of the network by selecting a routing path based on the remaining energy of the device, channel quality, and hop count, thus increasing network stability and packet delivery.

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1. INTRODUCTION

Communication is one of the biggest problems in disaster situations. In natural or human-made disasters, establishing an emergency wireless network is very important to save lives. Lack of communication between first responders and affected people has resulted in a catastrophic inability to effectively organize the rescue operation, leading to massive life loss. These circumstances lead to the need to utilize an opportunistic strategy of using all available communication devices, which might still be functioning [1]. The internet of things (IoT) is the network of intelligent physical entities. IoT is a promising technology used in several applications, including disaster management. In disaster management, the role of IoT is so essential and ubiquitous and could be life-saving [2], [3].

The catastrophic inability made it necessary to employ an opportunistic strategy to use the accessible communication equipment that was still functional. Wireless networks are the most needful structure for maintaining the flow of essential information in these circumstances [4]. Yet, available bandwidth, dependability, energy dissipation, and insufficient resources could harm wireless communications networks. Several research efforts have begun to overcome these circumstances, such as European Telecommunications Standards Institute (ETSI) terrestrial trunked radio (TETRA) [5] and M-urgency [6] an attractive solution that allows real-time crime/crisis positioning and live stream reporting. However, those proposed disaster management systems use existing network infrastructure, which may become totally or partially inaccessible after a disaster. Connecting people's devices located in a disaster area outside the transmission range of an available base station is inherently a complicated task. Natural disasters or other calamities devastate the traditional communication network partially or totally. Device-to-device (D2D) communication will improve rescue operations in such instances [7], [8]. An ad hoc system based on multi-hop D2D communication can enable seamless wireless connection between devices and links users in the non-coverage area to user terminals in coverage regions, which connect them to the functional wireless network.

D2D communication has a good advantage in network capacity, making it suitable for disaster situations. The D2D communication can be single-hop and multi-hop which can facilitate direct contact between the first responders and other rescue teams even if they are out of the coverage areas of the serving base station (BS). It is imperative to ensure the network's ability to connect all people in the disaster area with an optimum capacity to handle the information traffic while consuming less power. These factors are critical when designing such a network. The clustering technique has improved wireless network performance in throughput and power consumption. However, there are still difficulties when applying this technique to such a situation, essentially selecting cluster heads (CHs) and connecting them to the nearby functional base station. Sensor networks based on IoT have gained significant attention in several applications and research disciplines. Successful disaster management and rescue operations are dependent on powerful data exchange methods between first responders and catastrophe victims.

There are proposals for network designs by the government and academic research disciplines to create emergency solutions. Nishiyama *et al.* [9] developed a smartphone-based relay mechanism to send emergency messages from isolated locations utilizing multihop D2D communication simply via mobile phones. Individuals in disaster areas having damaged infrastructure could use this method to interact with one another via D2D communication. The movable and deployable resource unit (MDRU) is a system unit created by Sakano *et al.* [10] to offer network connectivity in disaster situations. The MDRU is transmitted to the disaster area and configured to provide network services to the victims. However, developing an MDRU is prohibitively expensive, and the installation of an MDRU may be impractical due to the scarcity of spectrum and energy resources in a catastrophe region. Smart victim localization (SmartVL) is presented in [11] where victims in a crisis region can use smartphones to detect the onset of a catastrophe utilizing the radio environment and shift to disaster mode to broadcast emergency messages to other smartphones in the vicinity. Instead of looking aimlessly for trapped patients, responders may search in specific locations based on the position coordinates of the devices using the long-term evolution-advanced (LTE-A) network. The authors presented an eNode-B framework that uses integrated virtual evolved packet core (EPC) to ensure service without a backbone network [12]. The eNode-Bs created a backhaul connection with one another to improve network range. It enhances the data transfer rate, but the effort did not fix the energy usage during the catastrophic situations. Masaracchia *et al.* [13] proposed a D2D-based paradigm that will incorporate connection from a catastrophe area into functional areas depending on critical parameters like position and energy level of user equipment (UE). The functional BS groups UEs into clusters. The multi-hop route through the CHs minimizes the end-to-end delay.

The unmanned aerial vehicle (UAV) and the mobile command center (MCC) were activated [14] to evaluate the link between devices in the disaster zone and the MCC in a signal interruption. There are several degrees of freedom for managing intra-cluster distances and the ability to reconstruct clusters with the provision of simultaneous wireless information and power transfer (SWIPT) at CHs. The optimization of attachment of the device to MCC or UAV before clustering can improve performance. Elshrkasi *et al.* [15] suggested the method for forming clusters and selecting CHs for an energy-aware critical wireless network connection. The connection of CHs to the relay node is using long-range communication links. Each group has two parts: the central cluster with CH and a sub-cluster with sub-cluster head (SCH). The algorithm selects CH and SCH depending on the residual energy of the node, thus improving the power consumption of the network. A rapidly deployable ad-hoc system for post-disaster management (RSDP) is proposed in [16]. This system deploys the server and relays in the disaster area. The server receives messages from the victims and the rescue team through the relay nodes. However, synchronization between the server, client, and relay nodes is necessary to identify the path to route messages. This coordination is through dynamic ID assignment and max-min neighbor strategies, which require exchanging many control messages. The phasor data concentrator (PDC) [17] protocol, in contrast, embeds the delay factor at every hop and chooses the path with the low delay unless that path includes a device with very little residual energy. It is because the route with minimum leftover energy is eliminated from the routing list despite having the least delay. Thus, it enhances the network performance by considering the device with a better life as a relay device. AOMDV [18] is an extension of an extension to ad hoc on-demand distance vector (AODV) [19], which shortens the route reconstruction by generating an alternative path for communication. The node with higher left-over energy and a smaller queue length of the media access control (MAC) layer interface is used to forward the packets toward the destination, reducing the delay in packet transmission.

During disaster recovery, the residual energy of the devices in the nonfunctional area plays an important role. The remaining energy of a gadget naturally decreases with time-the frequency of choosing a node for forwarding a packet impacts the fall rate. We apply the clustering strategy in our routing framework to increase the availability of nodes to relay packets and the network's stability. The path discovery chooses the node's remaining energy, link quality, and hop count. Multiple paths are discovered in advance to reduce the delay in packet transmission. While finding the parallel best possible route, the nodes in an already discovered routing path are avoided, thus reducing the number of exhausted nodes. In this study, we analyze a catastrophic scenario in which the cellular link is unavailable due to a defective BS due to a disaster's aftereffects. Our primary goal is to discover and link the detached nodes in the hazardous area by creating a D2D link, resulting in a robust D2D network. We introduce a network design that employs a relay station to extend the active base station network coverage. The design gives ample and sustainable connection between functional and non-functional zones. Because power consumption is an essential issue during a disaster, this technique is likely to improve the network's energy usage and longevity. The suggested method employs a hybrid cluster-based routing technique that uses oscillating spider monkey optimization (OSMO) in the clustering phase and oscillating particle swarm optimization (OPSO) for D2D path selection. The flow of the paper is as follows: section 2 discusses the work related to post-disaster management. Section 3 presents the proposed system model. Section 4 gives the performance analysis of the suggested method, followed by a conclusion in section 5.

2. PROPOSED SYSTEM MODEL

Deadly natural or human-made disasters have happened in recent decades, with catastrophic results. To mitigate the damage or loss of life, rescuers must monitor trapped persons and undertake relief activities as soon as possible. A disaster may cause partial or total damage to the traditional communications system (e.g., a landline or cellular network). IoT is a viable technology that tackles some of the difficulties described above. Figure 1 depicts a post-disaster scenario in which the BS fails. To preserve lots of lives, the nodes in the disaster region must communicate information to the designated destination. We presented a methodology based on cluster-based D2D communication that may well expand coverage from the adjacent operational region to the disaster area.

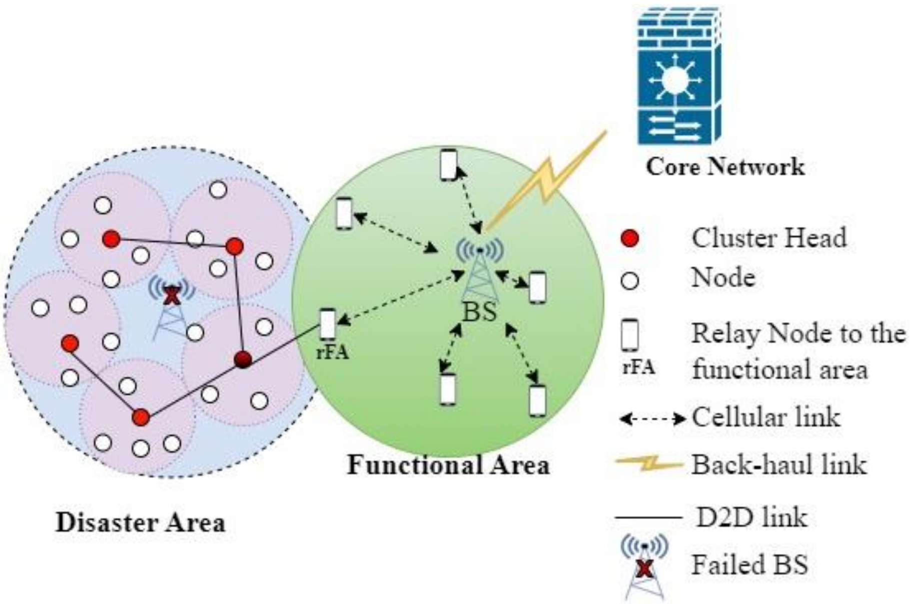

Figure 1. System model of proposed methodology

As cellular connectivity is unavailable in the disaster region, multi-hop D2D communication is the superior alternative for communication [20], [21]. A D2D communication and an ad-hoc network are developed during a typical network failure, with few devices acting as relay or gateway agents. When any active technologies such as Wi-Fi, satellite, or a functional classic cellular network become available, these relay agents will connect the impacted area with the rest of the world. The selection of relay agents may depend on the following factors [22]: i) device residual energy, ii) proximity to destination, and iii) end-to-end delay.

In this study, we suggest a clustering-based routing scheme to reconnect to the functional areas from the disaster zone using D2D relay communication through IoT. The clustering extends the stability of the network [23]. Clustering divides the entire disaster area into clusters, and CH leads each group which is selected based on the fitness function. We assume that all nodes in the network have a D2D relay feature [24]. The cluster members send data to the CH, which ships to the nearest BS through the relay node in a multi-hop D2D manner. The nodes in the disaster zone transfer the data packets through the active node (relay to functional area (rFA)) in the functional area. Thus, rFA is the destination node for the source node that sends data packets using D2D communication. The rFA carries out the transmission to the intended target. The fitness function to select CH considers the factors like residual energy, proximity to destination, and delay. The parameters like the remaining energy of the CH, link quality and hop count are the parameters for optimal path selection for D2D communication. We employ multi-hop D2D path selection, with an intermediary CH as a relay from the source to the destination node.

2.1. Event detection and mode switching

A device cannot simply comprehend the occurrence of an event unless it receives notification from the BS or another controlled trigger. The observable change in network activity or load may be a reliable indicator of the occurrence of an event. Due to the large number of devices initiating interaction, the network load fluctuates significantly during a disaster. In the LTE network, the device identifies the change in the load by monitoring the physical resource block (PRB). As shown by (1) is to defines the load of a device,

$$device_l = PRB_{allocated}/PRB_{total} \quad (1)$$

measuring the overall strength of the received signal indicator (RSSI) per PRB also determines the resource block allocation. The RSSI is the linear average of the total received power observed only in OFDM symbols carrying reference symbols by devices from all sources, including adjacent channel interference, and thermal noise. PRB is deemed allocated if the measured RSSI exceeds a predetermined threshold value; otherwise, it is vacant. The evolved universal terrestrial radio access (E-UTRA) carrier RSSI is the average total received power of the OFDM symbols containing reference signal 0 (RS0):

$$RSSI_k = \frac{1}{I}\sum_{i=kI}^{(k+1)I-1}(S\_P_i + N\_I_i) \quad (2)$$

in the t dimension, we measure over I OFDM symbols containing RS 0, numbered as $kI, \dots, (k+1)\,I - 1$. S_P_i is the total signal power; N_I_i is the noise and interference power in the i^{th} OFDM symbol containing RS0, both within the same measurement bandwidth over which RSRP is measured [25]. The assumption is that the estimation is always done every second up to S samples. We consider that the desired event has occurred when the accumulated result exceeds the chosen threshold value.

The assumption is that nodes in the disaster zone can switch their transmission mode based on the quality of the cellular link, energy level, and placement [26]. The nodes check the unavailability of the cellular link by confirming through the neighboring nodes. If the nearby devices indicate that the cellular connection is lost, switch to D2D disaster mode. The clustering process gets initiated to divide the network in the disaster zone into clusters and select the CHs. The D2D path selection follows the clustering phase. On receiving cellular connection by one device in the disaster area, it communicates with other nodes and the mode switches back to the cellular. Figure 2 depicts the creation and termination of a D2D network.

2.2. Selecting the destination for D2D communication

When there is a break in the network connection due to the disaster, the devices in the disaster area will activate disaster mode. When one device in a disaster area discovers rFA using communication technologies such as Wi-Fi, cellular, and so on, other nodes share the active link via that node using a multi-hop D2D connection. The source node relay on the subsequent CH nodes to reach the functional area. The destination for D2D multi-hop communication is the node with an active link to the operational network.

Usually, in post-disaster recovery, when BS goes down, the core network identifies the failure and instructs nearby base stations to extend their coverage [27] by allowing the edge cellular devices to connect to the devices in the disaster area. Now the rFA in the functional area broadcasts the message to introduce itself to the devices in the disaster area. The devices in the disaster area so identify the target node. When there is more than one destination node, the selection is on link quality and the remaining energy.

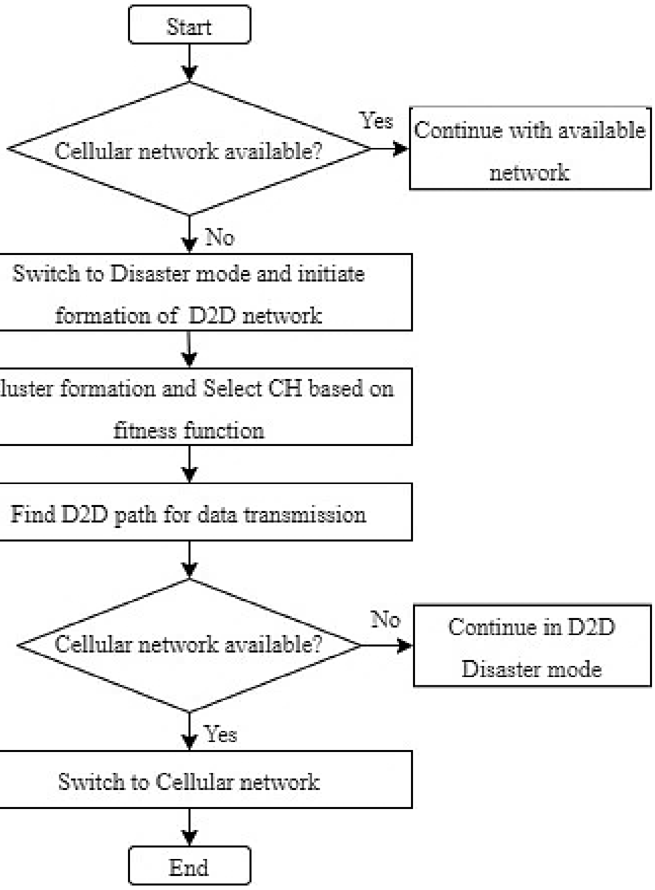

Figure 2. Flowchart of D2D network creation and termination

After locating the target node, a hybrid cluster-based routing approach based on spider monkey optimization (SMO) and particle swarm optimization (PSO) discovers the optimal D2D path from the disaster area to the functional area. The proposed system presents a new optimal routing technique using D2D communication as described in the algorithm 1. First, the OSMO method identifies the optimum CHs using the fitness function as in Figure 3. The primary research outcome of this work is the development of the second step, i.e., establishing a route for D2D communication. The identified prominent CHs are then made available to the routing phase, where OPSO is used to find the optimal communication path. The upcoming subsections describe each stage of the proposed methodology.

Algorithm 1. Cluster based path selection algorithm
Step 1: Initialize the network with size M×M
Step 2: Set the control parameters (local leader limit, global leader limit, perturbation rate (PR), inertia weight, and acceleration coefficients).
Step 3: Apply OSMO and OPSO, for clustering and D2D path selection.
Step 3.1:
- Measure the fitness of each individual.
- Find the global leader and local leader using greedy selection

```
while (no-of_grps<MAX_GRPS)
```

- Find the new positions of all individuals using local leader phase.

```
if (R (0,1)>=PR)
   Update the new position
else
   No changes
```

- Update the positions of local and global leader based on the fitness value.

```
   if (Local_Limit_count>local leader limit)
      Apply local leader decision phase
   if (Global_Limit_count>global leader limit)
      Apply global leader decision phase
end while
   (Set of cluster heads (CHs) selected is the population for D2D path selection)
```

Step 3.2:
Step 3.2.1:
- Initialize each particle in the population.
- Evaluate the fitness of each particle.

Step 3.2.2:

```
for each CHi
   Calculate fitness
      if (fitness of the CHi is good)
         Select CHi for data forwarding
      else
         Reject it
end for
      if optimal route is identified
         Update the path
      else
         Repeat the route selection process
return optimized D2D routing path
```

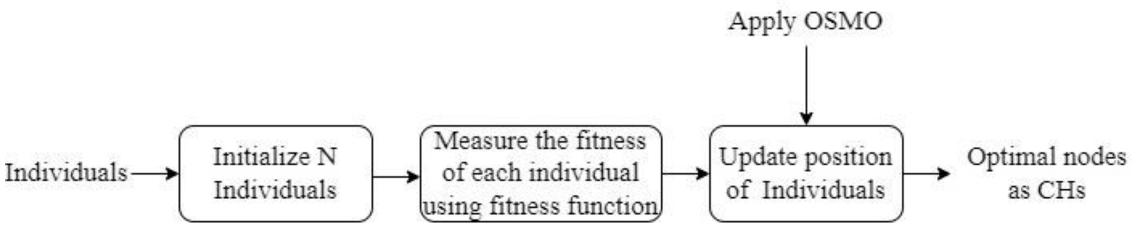

Figure 3. Optimal CH selection using OSMO technique

2.3. Cluster formation

2.3.1. Spider monkey optimization

Spider monkeys' social and foraging behavior are the driving forces behind the spider monkey optimization (SMO) algorithm. Fission-fusion social structure (FFSS) models SMO, in which monkeys divide themselves into groups from large to small and vice-versa. The following are the essential characteristics of FFSS in spider [28], [29]:

– All the spider monkeys maintain a group of 40 to 50 monkeys known as individuals in SMO.
– A global leader (GL) among the monkeys can divide the subgroups if the food is insufficient. Each group starts foraging independently.
– Each subgroup searches its food under a local leader (LL).
– The group members use a unique sound to interact with other group members.

In its mathematical design and implementation, SMO is derived from spider monkey foraging behavior. In SMO, there are six phases discussed in subsequent subsections. The flowchart in Figure 3 shows the different phases of SMO in selecting the CHs.

Let X_i be the i^{th} member of population *N*'s D-dimensional vector as $X_i = X_i^1, X_i^2, \dots, X_i^j, \dots, X_i^D$ and is initialized be (3).

$$X_i^j = X_{min}^j + r_1 \times \left(X_{max}^j - X_{min}^j\right) \quad (3)$$

r_1 is a random number such that $0 < r_1 < 1$, X_{min}^j and X_{max}^j lowest and higher limits of X_i respectively.

a. Local leader phase (LLP): During this phase, the update of each SM's current position is using information from local leader experience XL_k^j and local member's experience by (4) and based on the probability *PR* that is the perturbation rate.

$$X_i^1 = X_i^j + r_1 \times \left(XL_k^j - X_i^j\right) + r_2 \times \left(X_r^j - X_i^j\right) \quad (4)$$

XL_k^j is the k_{th} local group leader's position, and X_r^j is the r_{th} randomly picked SM from the k_{th} local group and $r_2 \in [-1,1]$.

b. Global leader phase (GLP): After LLP every member updates its location using (5) with the knowledge of GL (XG_j) and local members.

$$X_i^j = X_i^j + r_1 \times (XG_j - X_i^j) + r_2 \times (X_r^j - X_i^j) \tag{5}$$

c. Local leader learning phase: Evaluate the SM (i.e., solution) with the highest fitness value as the group's LL (XL_k^j). If there are no changes in the local leader for a long time, the local limit count (LLC) is increased by 1.
d. Global leader learning phase: In this case, best individual is declared as GL (XG_j). If GL fails to update its position, then global limit count (GLC) is increased by one.
e. Local leader decision phase: Based on the counter of local limit, this step basically randomly initializes or adjusts the location of all group members using (6),

$$X_i^j = X_i^j + r_1 \times (XG_j - X_i^j) + r_1 \times (X_r^j - XL_k^j) \tag{6}$$

f. Global leader decision phase: Based on the counter of the global limit, if the universal leader does not get organized to a predetermined global leader limit (GLL), the GL splits the overall population into smaller local units. A LL oversees each smaller local group. Until it reaches the maximum number of group (MAX_GRP) limit, local group formation continues.

2.3.2. OSMO based clustering

Extending the network lifespan by conserving the node’s energy is crucial in post-disaster management. Join surrounding nodes to form a cluster to preserve network energy, with the best node serving as the CH. One way to accomplish this is to organize the devices in a manner that is energy and computationally efficient. We could use SMO effectively for gathering individuals and finding the best group leaders. OSMO is a guided searching variant of SMO that finds the best solution. The destination calculates each node's fitness based on the information it receives. The best 'C' CHs are then selected using an OSMO-based clustering algorithm.

CH selection depends on several parameters. OSMO selects a node having more residual energy, less distance to the destination, and that takes less time to reach the packet to the destination as an optimal CH. After choosing the CH, other nodes join the neighboring CH using a potential function. In (7) computes the fitness of each node by considering three parameters residual energy, delay, and proximity to the destination.

$$f_{clustering} = \phi_1 \times f_E + \phi_2 \times f_{DT} + \phi_3 \times f_{DL} \tag{7}$$

Where $\sum_{i=1}^{3} \phi_i = 1$. The fitness of the node in terms of remaining energy, distance to the target and delay is calculated as follows. The node with the higher remaining energy is the better candidate to become a CH. The *(Initial energy of the node – residual energy) gives the energy consumed by the node.* The computation of energy dissipation during the transmission and reception of the data packets uses a first-order energy model [30]. The energy efficiency is computed as (8),

$$f_E = \frac{E_{consumed}(N_i)}{N} \tag{8}$$

Where N is total number of nodes in the search space and $E_{consumed}(N_i)$ is the energy consumed by the i^{th} node. The node should have a lesser value of f_E to be selected as a candidate for CH, which means energy consumption is less and has more left-over energy. The proximity between the node and the destination node in $m \times m$ search area is essential in CH selection. Transmission distance adversely affects the energy consumption of the node. Thus, the node nearer to the destination is the more likely to become a CH. The proximity to the destination is computed as (9),

$$f_{DT} = \frac{Dist(N_i, \ Destination)}{m} \tag{9}$$

The delay in the data transmission dissipates the node battery, so the node that transmits the data packets in less time to the destination is picked as a CH. Both the propagation delay and transmission delay are considered in (10) to compute the time the node takes to transmit the data packet to the destination.

$$f_{DL} = \frac{delay(N_i)}{N} \tag{10}$$

Thus, the node with maximum residual energy, minimum delay, and nearer to the destination is picked as a CH node. Thus, the node with maximum residual energy, minimum delay, and nearer to the destination is picked as a CH node.

Oscillating perturbation rate: The basic version of SMO has a linear increase in the perturbation rate. Recently, Yashoda and Shivashetty [30] used chaotic perturbation function in SMO for optimal D2D communication through IoT. This modification in perturbation taken advantage of the nonlinearity. The chaotic map to decide perturbation rate is illustrated by (11).

$$PR_{(t+1)} = 1 - PR_t \times \left(\frac{MAXiter - t}{MAXiter}\right) \times z_t \quad (11)$$

where $MAXiter$ is the number of maximum iterations and t denote current iteration.

The value of z is decided by (12),

$$z_{(t+1)} = \mu \times z_t \times (1 - z_t) \quad (12)$$

where $z_t \in [0,1]$ is a chaotic number at t^{th} iteration that reacts chaotically when the value of $\mu = 4$. Keeping these modifications in mind, we introduce oscillation in the perturbation rate to keep exploration and exploitation balanced. In OSMO, the rate of perturbation is updated as per its oscillating behavior, which can be implemented by (13).

$$PR(t) = \frac{(PR_{max} + PR_{min})}{2} + \frac{(PR_{max} - PR_{min})}{2} \cos\left(\frac{2\pi t}{T}\right) \quad (13)$$

Where:
$[PR_{min}, PR_{max}]$=[0, 1],
T: the oscillation period,
t: the t^{th} iteration.

We employ SMO with an oscillating perturbation rate to accomplish the clustering of nodes in the search space, which improves network performance by saving node energy. As a result, SMO finds the best location rapidly while avoiding premature convergence. The perturbation rate, an essential factor in SMO, governs the efficiency and convergence speed.

2.4. D2D path selection

2.4.1. Particle swarm optimization

PSO is a population-based method that imitates the behavior of flocking birds. Using a simple mathematical formula as in (14) and (15), it finds the best particle from a population of candidate solutions based on the particle's position and velocity. Each particle's personal best location (P_{best}) influences its movement, but it guides towards the best place (G_{best}) in the entire population. Other particles in the search space keep the G_{best} up to date when they find a better position. The velocity v_i^t and the current position are used to calculate the new position as (14) and (15):

$$v_i^{t+1} = \omega\, v_i^t + C_1 R_1 \left(P_{best,i}^t - x_i^t\right) + C_2 R_2 (G_{best} - x_i^t) \quad (14)$$

$$x_i^{t+1} = x_i^t + v_i^t \quad (15)$$

v_i^t is the velocity of i^{th} particle at t^{th} iteration, $P_{best,i}$ is the personal best of i^{th} individual, G_{best} is the best solution obtained so far, R_1 and C_2 are random numbers ϵ [0, 1] of size $1 \times D, C_1$ and R_2 are acceleration coefficients and ω is inertia of the particles that decides the exploration and exploitation of the search space.

2.4.2. OPSO based path selection

The OPSO based path selection enables the IoT nodes to learn the best neighbor relay node towards the destination node based on fitness. The path selection is through the CHs selected using OSMO. The picking of relay CH towards the destination depends on its fitness value computed by considering residual energy, link quality and hop count. The fitness of routing path is calculated using the objective function based on minimization of $f_{Routing}$ given in (16). Weighted parameters specify importance of objective in the main routing fitness function such that $\delta_1 + \delta_2 + \delta_3 = 1$. The solution that minimizes the value of $f_{Routing}$ is selected as the best D2D communication path to reach the peer device.

$$f_{Routing} = \delta_1 \times RE + \delta_2 \times LQ + \delta_3 \times HC \quad (16)$$

A neighbor CH with maximum battery (E), good link quality (LQ) and takes a smaller number of hops to travel to the destination is the better relay candidate in the path towards the destination. The calculation of energy consumption of the CH as in [30] and link quality is measured using the received signal strength indicator (RSSI) [29]. The fitness of the node in terms of remaining energy, link quality and hop count is calculated using (17), (19), and (20) respectively.

The node chosen as a relay node in the data transmission path is a neighbor CH node with the highest residual energy level. In route discovery, equation (17) selects the optimal CH as an intermediate node.

$$E = \frac{E(CH_i)}{\sum_{j=1}^{C} E(CH_j)} \quad (17)$$

Here, $E(CH_i)$ represents the energy consumed by the i^{th} CH. The power consumption by all CHs is computed using the denominator. The best route for D2D communication is the one that uses the least amount of energy.

A higher channel quality improves the average packet delivery ratio. The primary metric for determining link quality is the received signal strength indicator (RSSI). Formula (18) determines the channel's signal strength between two CHs is determined.

$$LQ(CH_i, CH_k) = \frac{RSSI(CH_i, CH_k)}{LRSSI} \quad (18)$$

$RSSI(CH_i, CH_k)$ is the RSSI value for the link from CH_i to CH_{kk} and $LRSSI$ worst RSSI among communicating pairs, and set to -70 dBm. The link quality improves with decreasing LQ. Formula (19) optimizes link quality by minimizing (18).

$$L = min\left(\sum_{\forall CH_i \in path} \frac{RSSI(CH_i, CH_{i+1})}{LRSSI}\right) \quad (19)$$

Hop count is the number of network nodes through which data is routed from source to destination, is calculated as (20),

$$H = \frac{N_C(Path)}{C} \quad (20)$$

where N_C is the quantity of CHs in the chosen path, and C is the network's total number of cluster heads. Lesser hops from source to destination reduce the end-to-end delay, resulting in energy-efficient D2D routing.

Oscillating inertia weight function: In basic particle swarm optimization (PSO), inertia weight is linearly increasing. We apply PSO with oscillating inertia weight to accomplish the path selection. The inertia weight governs how long a particle maintains its earlier velocity (i.e., speed and direction of the search). We introduce an oscillation in the inertia weight function to control the tradeoff between exploration and exploitation using (21).

$$\omega(t) = \frac{(\omega_{max} + \omega_{min})}{2} + \frac{(\omega_{max} - \omega_{min})}{2} \cos\frac{2\pi t}{T} \quad (21)$$

$$T = \frac{2S_1}{2+3k} \quad (22)$$

Where $[\omega_{min}, \ \omega_{max}]$=[0.1, 0.9], and T is the oscillation period. k is a constant integer value in the range of [1, 7]. S_1 is the count of iterations for which PR and ω oscillates and for the remaining iterations, its value is kept constant. This way, the oscillation is for S_1 number of iteration and then remains the same as other iterations.

Figure 4 gives the flowchart of optimal D2D path selection using a hybrid model. In this implementation, the SMO is combined with the PSO to form a hybridized algorithm known as OSMO-OPSO. It integrates the characteristics and functionalities of both algorithms. The hybrid approach is heterogeneous since it involves two different algorithms.

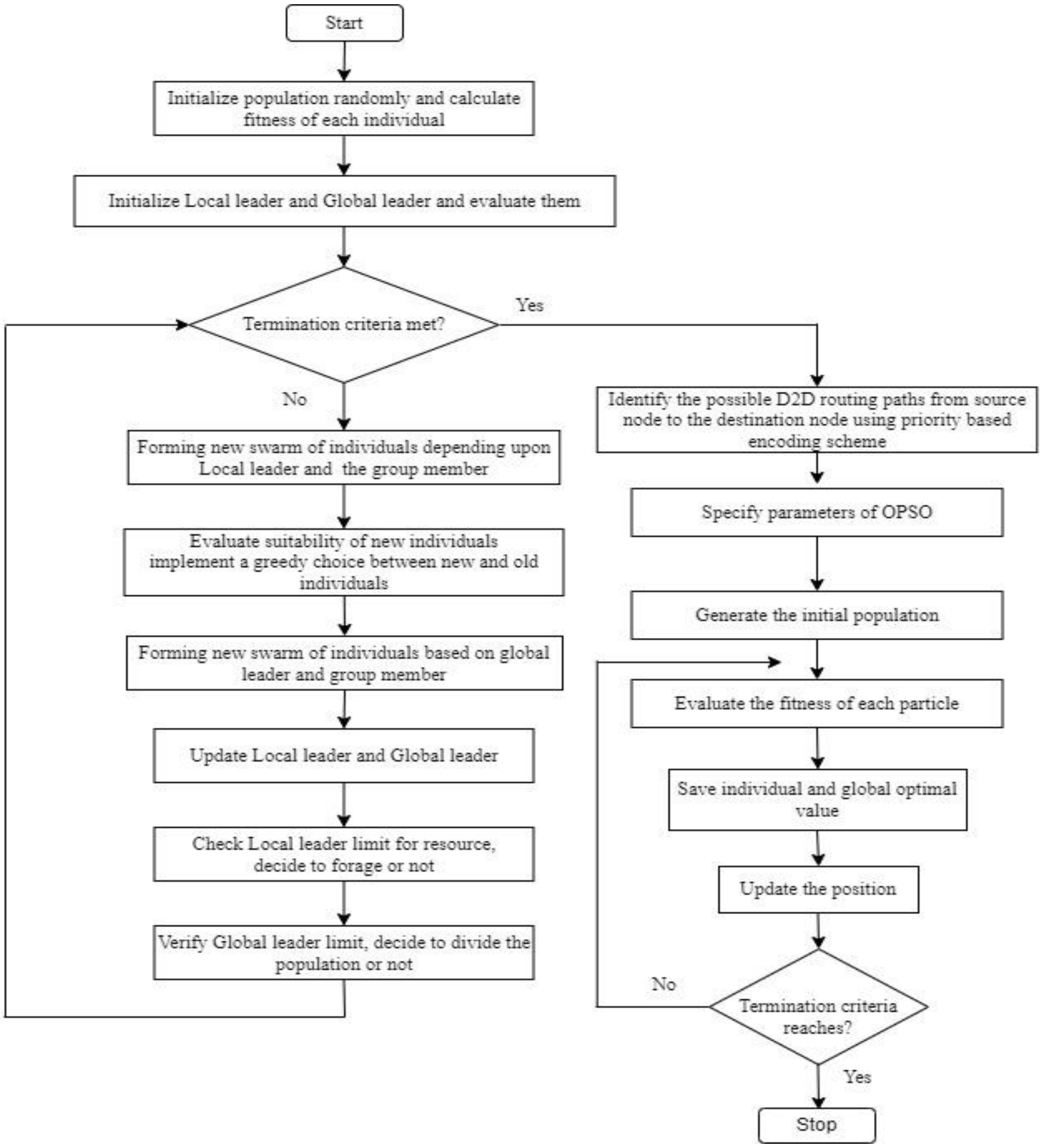

Figure 4. Optimal D2D path selection using hybrid model

3. D2D PATH DISCOVERY

The D2D communication path from the disaster region to the functional area is using OPSO with path encoding technique. We employ a priority-based encoding approach that relies on CH performance as a driving element in path selection across potential nodes toward the target. Instead of using random priority [31] we use the fitness value of the CH to select it as the next relay node toward the destination.

Assume the IoT network has 10 CHs, *C*1 to *C*10. So, the dimension of particles is *Np*=10. Consider the directed acyclic graph G (V, E) shown in Figure 5. The edge *u*→*v* suggests that *u* can transmit to *v*. Let us assume that a particle P_i is as in Figure 6. For the connectivity tree from *C*1 to *Destination*, the protocol will construct a D2D communication path from *C*1 to *Destination*.

To locate a link connecting C1 to the destination, identify neighbor nodes to C1. As indicated in Figure 6, such nodes to examine are [C2, C4, C6]. The priorities for them are [0.36, 0.23, 0.31]. Node C4 has the highest priority with the lowest fitness value likely to be selected as a relay node to C1, whose priority is updated to -N to avoid selecting it again in another route to reduce the transmission load. The possible nodes from C4 are [C5, C7], and the priorities of the node are [0.45,0.76]. Node C5 is selected as a relay node to C4 towards the destination and updates its priority to $-$N. This process continues till it reaches the D2D destination node. Figures 6(a) to (f) demonstrates this procedure.

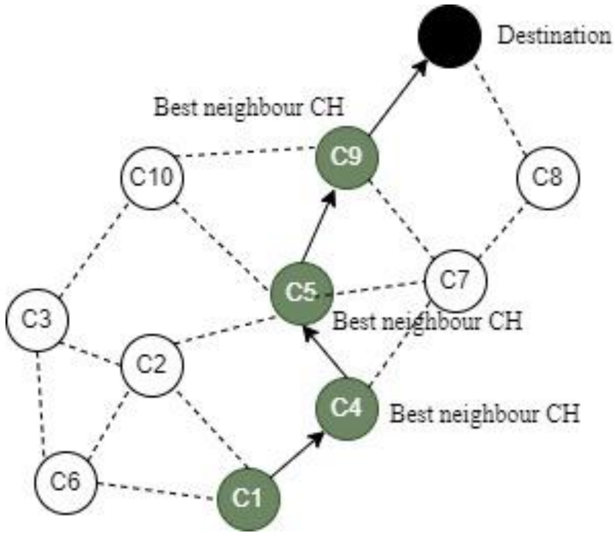

Figure 5. Network for D2D path selection

CH	1	2	3	4	5	6	7	8	9	10	Dest
Priority	0.81	0.36	0.52	0.23	0.45	0.31	0.76	0.31	0.42	0.18	0

(a)

CH	1	2	3	4	5	6	7	8	9	10	Dest
Priority	0.81	0.36	0.52	**0.23**	0.45	0.31	0.76	0.31	0.42	0.18	0

1

(b)

CH	1	2	3	4	5	6	7	8	9	10	Dest
Priority	0.81	0.36	0.52	-N	**0.45**	0.31	0.76	0.31	0.42	0.18	**0**

1 → 4

(c)

CH	1	2	3	4	5	6	7	8	9	10	Dest
Priority	0.81	0.36	0.52	-N	-N	0.31	0.76	0.31	**0.42**	0.18	**0**

1 → 4 → 5

(d)

CH	1	2	3	4	5	6	7	8	9	10	Dest
Priority	0.81	0.36	0.52	N	N	0.31	0.76	0.31	-N	0.18	**0**

1 → 4 → 5 → 9

(e)

CH	1	2	3	4	5	6	7	8	9	10	Dest
Priority	0.81	0.36	0.52	-N	-N	0.31	0.76	0.31	-N	0.18	**0**

1 → 4 → 5 → 9 → Dest

(f)

Figure 6. Example of priority based D2D path selection from arbitrary particle P_i (a) particle P_i encoding for network in Figure 5; (b) particle P_i after adding C1 to the routing path; (c) particle P_i after adding C2 to the routing path ; (d) particle P_i after adding C4 to the routing path; (e) particle P_i after adding C8 to the routing path; and (f) particle P_i after adding *Dest* to the routing path and finishing the path selection

4. RESULTS AND DISCUSSION

4.1. Simulation set up

A simulation based on ns-2 assesses the performance of the hybrid approach in a post-disaster scenario. The search space, spanning an area of 200 m^2, comprises a random distribution of nodes. The calculation of energy usage during transmission and reception is using first-order radio energy dissipation model. Table 1 gives the network parameters utilized in the experimentation. We assume that devices enter disaster mode after recognizing the existence of the catastrophic event, then we examine the effectiveness of post-disaster recovery through the simulation. The primary purpose of this research is to adopt an efficient routing method for D2D communication by reducing the overall energy use of network nodes. As a workaround in disaster mode, we use OSMO-based cluster creation and OPSO-based routing to build cluster-based routing. The decision of CH is by three node parameters: remaining energy, proximity to the target, and delay. The oscillating perturbation effectively manages the search space in finding ideal CHs. The OPSO technique selects the optimal path to connect the isolated area to the functional area using D2D communication based on the routing fitness function. We evaluate and compare this proposed method with some existing approaches like AODV [19], RSDP [16], PDC [17] and ad-hoc AOMDV [18] protocols. The metrics analyzed for communication protocols include residual energy, end-to-end delay, and network stability. Table 2 gives the control parameters used in OSMO and OPSO techniques.

Table 1. Network parameters

Parameter	Value
Simulation range	200×200 m
Initial Energy	100 Joule
Number of nodes	10-100 nodes
Simulation time	500 sec
E_{con}	50 nJ/bit
E_{fs}	10 pJ/bit/m^2
E_{mp}	0.001310 pJ/bit/m^4

Table 2. Control parameters used in optimization technique

Parameter	Value
OSMO	
LLL	5×N
GLL	N/2
$PR_{\min}$, $PR_{\max}$	[0, 1]
MAX_GRP	N/10
OPSO	
$\omega_{min}, \omega_{max}$	[0.1, 0.9]
C_1, C_2	[2, 2]

4.2. Energy efficiency and life of the network

With the number of energy-depleted nodes and residual energy, the OSMO-OPSO protocol performs as shown in Figures 7 and 8 with an increase in simulation time. Figure 7 illustrates how the OSMO-OPSO outperforms competing algorithms. Considering the device's remaining energy and energy consumption along the journey, are the reason for the high efficiency. Standard deviation of residual energy for different paths is calculated. Selecting a route with minimum standard deviation reduces the probability of failure of intermediate nodes. In this context, there are 100 devices each having a starting energy of 100 J. The total network energy is 10,000 J. Here we include an extension of AODV [18] (i.e., AOMDV) to compare the performance. The Improved AOMDV protocol performs better because it picks the nodes with more residual energy. It is expected for a device's remaining power to deplete over time. The probability of packet drops depends on the frequency of node selection to relay the packet. In our suggested approach, we take the route with a minimum standard deviation of residual energy and greater remaining power, which means we can utilize it for an extended period. Moreover, unlike other protocols during pathfinding, OPSO selects all possible paths from source to destination without repeating the same node (i.e., CH) in each route to relay the packets. The AODV and RSDP protocols ran out of power after the simulation period, but the recommended method had a remaining power reserve of one-half.

The network's longevity is determined by the residual energy of the CHs. Figure 8 shows the performance of the OSMO-OPSO protocol in terms of the number of energy-exhausted nodes with an increase in simulation time. As illustrated in the figure, the OSMO-OPSO protocol outperforms other protocols. This higher performance is attained by taking into account the device's residual energy along the route path, and the CHs are chosen by taking the distance to the destination into consideration as a key measure. The CH uses less energy to send packets when it is close to the target node. Figure 8 makes it evident that the proposed method still has 80% of the nodes alive at 500 sec.

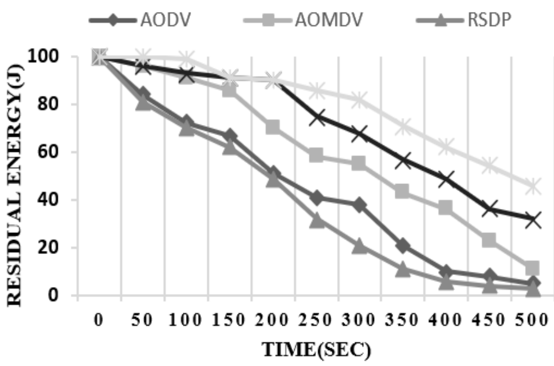

Figure 7. Residual energy of the network

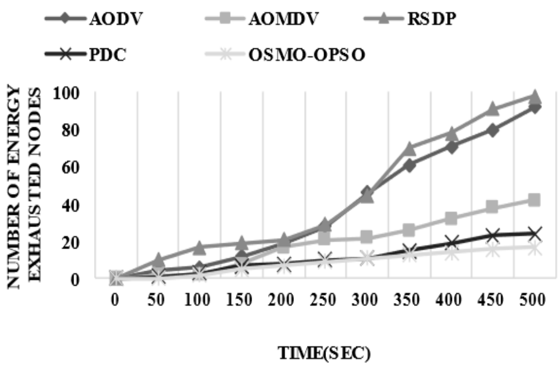

Figure 8. Analysis of number of energies exhausted nodes

4.3. End-to-end delay

In this part, we analyze the OSMO-OPSO routing algorithm's attainment by examining the end-to-end lag in the context of the number of devices with that of the AODV [19], RSDP [16], PDC [17] methods. We chose the above methods since they were to deal with post-disaster connectivity. Figure 9 gives the average end-to-end delay concerning the network's node count. According to the findings, the end-to-end delay for AODV and RSDP considerably rises as the device count increases. This technique's path selection does not account for route delay. A trustworthy cooperation between the source, destination, and relay devices is necessary for path discovery in RSDP. It achieves coordination by exchanging several control messages. OSMO and OPSO algorithms, on the other hand, incorporate the delay and proximity components at every hop. It chooses the route with the shortest delay, except when the path includes a device with low residual energy. The communication path with minimal residual energy gets removed from the routing list for a better network lifetime. OSMO-OPSO experiences overall lower end-to-end delay by 14%, 4%, and 21% when compared with AODV, PDC, and RSDP respectively.

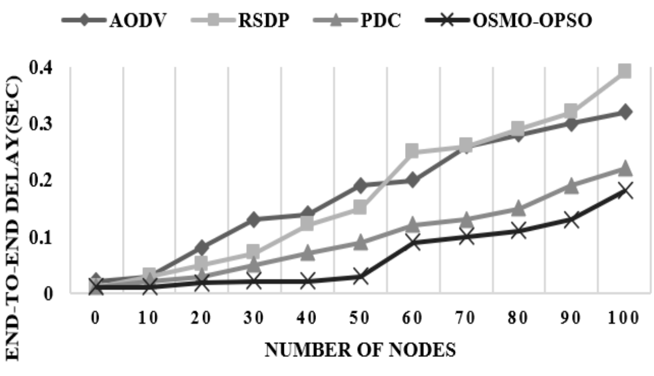

Figure 9. Analysis of end-to-end delay

5. CONCLUSION

This research suggested a D2D-based communication strategy for post-disaster communication and management. We briefly addressed public safety networks and the possible benefits of employing clusters and D2D connectivity. The objective is to find and link the catastrophe region to the functioning area by constructing a D2D network with a longer life using a hybrid optimization technique. In the immediate aftermath of a natural or artificial disaster, network performance will significantly deteriorate because of the disruption in power, traffic congestion, and infrastructure failure. It is critical in these circumstances to discover and save the victims in the isolated area as soon as possible by establishing a multi-hop D2D communication path between functional and nonfunctional regions. The nodes in the disaster zone switch from cellular to D2D mode and initiates the clustering process using the OSMO technique to make the ideal nodes available to relay the packets to the destination. The path discovery phase uses OPSO to locate the optimal path through the CHs selected from the clustering phase. Multiple ways are discovered from the source node to the destination node to reduce the delay in transmission. Several metrics, like residual energy of the node, proximity to the destination, link quality, and hop count, are considered during the clustering and path discovery phase to enhance the network performance. The suggested technique successfully lowers the node energy usage while increasing the total lifetime of the network.

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