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Energy-efficient device-to-device communication in internet of things using hybrid optimization technique

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ABSTRACT

Device-to-device (D2D) communication has grown into notoriety as a critical component of the internet of things (IoT). One of the primary limitations of IoT devices is restricted battery source. D2D communication is the direct contact between the participating devices that improves the data rate and delivers the data quickly by consuming less battery. An energy-efficient communication method is required to enhance the communication lifetime of the network by reducing the node energy dissipation. The clustering-based D2D communication method is maximally acceptable to boom the durability of a network. The oscillating spider monkey optimization (OSMO) and oscillating particle swarm optimization (OPSO) algorithms are used in this study to improve the selection of cluster heads (CHs) and routing paths for D2D communication. The CHs and D2D communication paths are selected depending on the parameters such as energy consumption, distance, end-to-end delay, link quality and hop count. A simulation environment is designed to evaluate and test the performance of the OSMO-OPSO algorithm with existing D2D communication algorithms (such as the GAPSO-H algorithm, adaptive resource-aware split-learning (ARES), bio-inspired cluster-based routing scheme (Bi-CRS), and European society for medical oncology (ESMO) algorithm). The results proved that the proposed technique outperformed with respect to traditional routing strategies regarding latency, packet delivery, energy efficiency, and network lifetime.

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1. INTRODUCTION

The incredible rise of the internet of things (IoT) throughout time has resulted in technological advancements that have far-reaching ramifications for our lives and societies. Due to significant advances in the area of IoT the dreams of connecting things around us to the worldwide network is rapidly becoming reality. Key participants in IoT are gadgets with some embedded intelligence, digital machinery, objects, and wearable devices [1]. The modern advances in IoT are making a significant contribution to the growth of small devices that can perceive, process, and wirelessly communicate over short ranges, which has resulted in an upsurge in the employment of IoT in a wide range of applications, including healthcare, agricultural, and weather monitoring [2]. Due to various impediments in its continuing adoption, the IoT has to achieve the enormous ongoing challenges such as security, energy efficiency communication, storing of IoT data, resource management, and data integration [3]. Device-to-device (D2D) communication is the direct communication between participating devices. Using D2D communication, energy-efficient communication in IoT can be achieved and also the devices can be connected without using a core network which minimizes the load on the base station and results in ultra-low latency, energy conservation, and higher data rate [4]. The battery limitations of hand-held D2D devices hamper the network's long-term viability. The adoption of D2D networks is in accord with the future concept of IoT technology as they are part of a larger IoT paradigm [5], [6]. D2D communication necessitates the development of novel routing algorithms that can take advantage of optimization techniques to customize the use of network resources to the needs of various IoT applications.

One of the driving forces for the popularity of D2D technology is energy efficiency [7]. Devices in an IoT network are battery-powered with finite energy. For the longevity of battery-powered IoT network, it is necessary to conserve IoT devices [8]–[10]. Topology management is a core necessity in ad hoc type massively distributed IoT networks to improve the efficiency of the network [11]. Routing in such networks by region (cluster) based node deployment will give promising results. Clustering arranges the nodes in the search space under groups, and selecting an optimal cluster head (CH) by considering several performance metrics. Each cluster member transmits the packets to the specified destination through the CH. Thus, the clustering-based routing technique will conserve node energy and improve the network lifetime [12]. Many studies show that bio-inspired routing algorithms provide an optimized route selection for communication in wireless sensor networks (WSN) and IoT networks [13]–[17].

IoT-based sensor networks has received considerable attention in a variety of applications and research fields, such as in the field of commercial [18], medical [19], and surveillance systems [20], [21]. Because the sensors or devices in such network possess low resources and it is important to have connectivity that doesn't drain the battery. In the situtation where recharging and reinstalling IoT devices are impossible then we we need temporary communication network which can be established using D2D communication. As a result, in this circumstance, sustaining energy is challenging. Studies in the literature proposed a solution to this issue by grouping nodes into clusters to help prolong the life of wireless networks. In addition, routing algorithms are used in cluster wireless networks to discover an optimal route from source to destination by picking efficient CHs, thereby elongating the network lifetime.

Elhoseny *et al.* [13] particle swarm optimization (PSO) is used to pick CHs, whereas gray wolf optimization (GWO) for routing process. The algorithm chose CH based on the node's energy and vicinity, but it experiences communication delays. In [14] cluster formation method is proposed based on ant colony and bee colony optimization. The use of bee colony optimization is to tackle ant colony optimization (ACO's) early convergence problem, but artificial bee colony (ABC) suffers from convergence delay. Seyyedabbasi and Kiani [15] introduced multi-agent pathfinding based on the ant colony optimization (MAP-ACO), an ACO-based pathfinding solution for wireless sensor network (WSN) and IoT. The node's residual energy, buffer size, traffic rate, and distance are considered during destination selection. The novel method proposed gives good results over other ACO-based routing techniques in network lifetime and energy consumption. However, it is susceptible to falling into the trap of local optima. The authors used the hybrid algorithm GAPSO-H for cluster-based routing in WSN [16]. CH selection is through genetic algorithm (GA) and data transmission using PSO. The repeated calculation of fitness makes it computationally expensive. The PSO uses a linear inertia weight function, which results in premature convergence. adaptive resource-aware split-learning (ARES), an ACO-based algorithm [17], is suggested to find an energy-efficient shortest path for data transmission in IoT. Calculations are performed at the node level to decrease data transfer overhead. It may lead to a reduction in the network lifetime.

Tilwari *et al.* [22], describe a better routing strategy for improving service quality in IoT-based networks. It considers the mobility of the nodes, link quality, and the battery as the critical parameters to select the route for D2D communication. To increase the WSN's resource efficiency, [23] proposes a hybrid routing protocol built on Naive Bayes and PSO. Experimental findings demonstrate that it excels conventional approaches by taking into account the load on the sensor node and the distance to the destination as the main energy efficiency considerations. Using a graph coloring strategy, Bastos *et al.* [24] devised a network-assisted navigation and deployment method for D2D communication in a fifth-generation (5G) cellular framework that allocates new resource blocks to increase the D2D coverage. Table 1 summarizes the related work.

According to the study, it is evident that no research has combined different device measurements into a single fitness function for the best routing mechanism for D2D communication. Figure 1 presents the path discovery mechanism of the proposed oscillating spider monkey optimization-oscillating particle swarm optimization (OSMO-OPSO) system that works in two tiers. In the first phase, topology management is through the clustering technique using OSMO by considering the device's residual energy, distance to the destination, and delay as the key parameters. The ideal CHs from the first phase serve as a population for the routing phase using OPSO, which takes CH's remaining energy, link quality, and hop count as the metrics to select the optimal route. The enhancement introduced in the social media optimization (SMO) and PSO technique effectively balances the exploration of the search space and exploitation and improves the network reliability. The research work aims to find an energy-efficient path for D2D communication, thus maintaining network reliability. It reduces the energy consumption of the sensor nodes through clustering for overall packet transfer to the destination. The proposed study employs multi-objective spider monkey optimization with oscillating perturbation rate (OSMO) for clustering and particle swarm optimization with oscillating inertia function (OPSO) for finding the optimal routing path for packet transmission from source to destination. The purpose of using a hybrid strategy is to obtain the most notable benefits from both methodologies. Outline of the paper: section 2 presents the formation of clustering and routing problem. Section 3 gives an overview of spider monkey optimization and particle swarm optimization algorithms, and section 4 presents the proposed model; section 5 gives the experimental results and conclusion in section 6.

Table 1. Summary of related study

Reference	Year	Algorithm used	Demerits
[13]	2020	PSO, GWO	Experiences communication delay
[14]	2018	ACO, ABC	Delay in convergence
[15]	2020	MAP-ACO	Stagnation problem
[16]	2021	GAPSO-H	Computationally expensive
[17]	2021	ARES	Node level calculations reduces network lifetime.
[21]	2022	MBLCR	Experiences communication delay
[22]	2022	HRA-NP	Constant inertia weight in the routing face may lead to premature convergence.

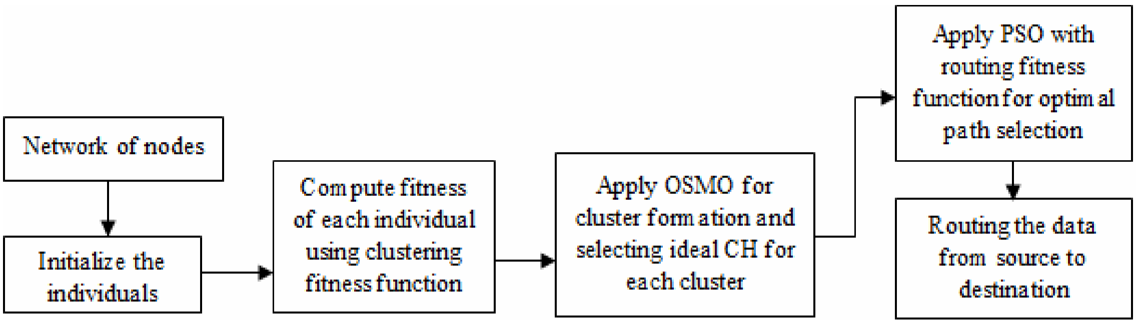

Figure 1. Proposed clustering and routing method

2. PROBLEM FORMULATION

We consider an IoT network with two tiers with *N* number of nodes, *C* number of CHs, and one destination. Each sensor node has a unique ID, and the destination ID is 0. During the cluster construction process, each CH acts as a CH for just one cluster and each IoT node contributes to only one CH. The suggested method includes two algorithms: one for selecting the CH and the other for finding routing paths over the network from source to destination. The optimal CH selection using European society for medical oncology (ESMO) and the optimal route to transmit the data to the destination is using OPSO shown in Figure 1. Through CH selection, the proposed algorithm attempts to improve the sustainability of IoT networks. As a result, we looked at factors that can influence energy consumption. For network performance optimization, the optimal CH is determined by taking into consideration many aspects such as latency, the distance to destination, and residual energy of the node.

The proposed framework includes 100 nodes randomly placed within an area of 200×200 m square with an unconstrained energy sink that does not alter throughout the simulation. The initial distribution of the individuals (i.e., Nodes) in the search space is shown in the Figure 2 with the node ‘0’ as the sink.

The following elements are used to build the system model: i) In the search space, *N* nodes are distributed at random while their positions are set; ii) Each sensor node has its own identifier; iii) In terms of starting energy, all of the sensor nodes are very comparable; iv) A non-rechargeable battery is used to operate each node; v) Once the destination has the CH selection criteria, the effective CH selection algorithm chooses the node with the most energy, the fewer loads, the shortest delay, and the shortest distance to the destination as the ideal CH; vi) The path between the source and the destination is then determined using the routing method.

This section describes the formulation of clustering and routing problems in IoT networks. Multi-objective fitness function is constructed using weighted sum approach (WSA) in both clustering and routing. Table 2 gives the notations used in the formulation of clustering and routing problem.

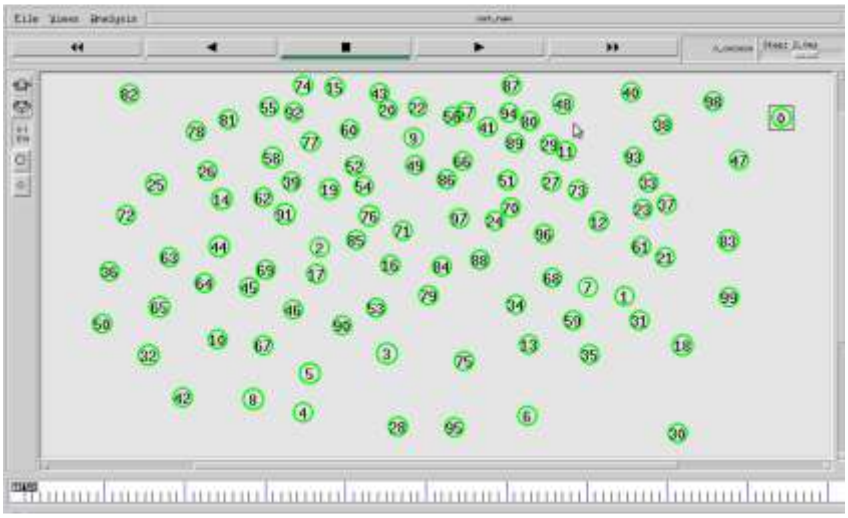

Figure 2. Proposed clustering and routing method

Table 2. Notations used

Notation	Meaning
N	Total number of IoT nodes
M×M	Sensing area
C	Total number of cluster heads (10% of N)
E (N_i)	Energy of i^{th} IoT node
E (CH_j)	Energy of j^{th} CH
RSSI (CH_i, CH_k)	RSSI value for the link from CH_i to CH_k.
leastRSSI	Worst RSSI among communicating pairs, and set to -70 dBm.
c_1, c_2, and c_3	Weighted parameters specify importance of objective in the main clustering fitness function. Where $\sum_{i=1}^{3} c_i = 1$.
r_1, r_2 and r_3	Weighted parameters specify importance of objective in the main routing fitness function such that $r_1+r_2+r_3=1$.

2.1. Formulation of clustering problem

Clustering is one of the most popular techniques for network topology management. A clustering technique organizes nodes into groups based on predefined criteria such as proximity to the target, optimizing resource consumption, and network load balancing. Each cluster has one CH which gathers data from cluster members and sends the data directly to the destination or using intermediate nodes. In this implementation the IoT nodes which minimize the cost of fitness function are selected as the best CHs for the longevity of the IoT network. The proposed SMO aims to optimize the combined effect of the following properties:

2.1.1. Energy efficiency

The remaining energy of the IoT node could be the basis for choosing a better CH. A node with better energy is the best candidate to extend the network lifetime and data aggregation. The function to calculate the fitness of node in terms of energy efficiency is:

$$EE = \frac{E_{consumed}(N_i)}{N} \tag{1}$$

for any value of i, the energy consumed by the node is computed as $E_{consumed}(N_i) = E_{initial}(N_i) - E_{remaining}(N_i)$. $E_{initial}(N_i)$ and $E_{remainin}(N_i)$ are the initial and remaining energy of the i^{th} node respectively. The energy dissipated during transmission and reception of data is calculated using first order energy model [25].

2.1.2. Transmission distance

The goal is to lower the average distance between CHs and the destination. CHs that must send huge data packets will use less energy if their transmission distance (TD) is lower. The (2) gives the formula to calculate the distance between a node to the destination, where (N_i, Destination) is the euclidian distance between an i^{th} node and the destination.

$$TD = \frac{Dist(N_i, Destination)}{M} \quad (2)$$

2.1.3. Delay

The objective is to minimize the time to deliver the packet to the destination. The (3) calculates the delay experienced by IoT devices during data transmission to the destination. The numerator denotes the time to transfer data from node to destination. The lower the number of individuals in each cluster recompenses delay.

$$DL = \frac{delay(N_i)}{N} \quad (3)$$

The final fitness function (FF) for clustering that has to be minimized once the above objectives are computed is:

$$FF_{clustering} = c_1 \times EE + c_2 \times TD + c_3 \times DL \quad (4)$$

The stronger the weighted value, the greater the importance of the associated objective word.

2.2. Formulation of routing problem

A routing technique is needed for sending the data between the sensor nodes and the base stations to establish communication. The routing problem leads to a decreased network lifetime with increased energy consumption. In this paper, the efficient routing path is selected depending upon the cost of the routing fitness function. The proposed OPSO aims to enhance the overall impact of the attributes listed below.

2.2.1. Energy efficiency

A CH having high energy is a better relay node contender for inclusion in the routing path. Routing-wise, the (5) is used to choose the best CH as a relay node.

$$E = \frac{E(CH_i)}{\sum_{j=1}^{C} E(CH_j)} \quad (5)$$

Here, $E(CH_i)$ is the energy consumed by the i^{th} node. The denominator computes the energy consumed by all the CHs in the routing path. The path with minimum energy consumption is the optimal path for D2D communication.

2.2.2. Link quality

Better link quality maximizes the packet reception ratio. Received signal strength indicator (RSSI) [26] is the key to measure the link quality. The quality of the link between two CHs is found by (6).

$$LQ(CH_i, CH_k) = \frac{RSSI(CH_i, CH_k)}{leastRSSI} \quad (6)$$

The lower the LQ, the best is the link quality. The following equation maximizes the quality of the link by minimizing (7),

$$L = min\left(\sum_{\forall CH_i \in path} \frac{RSSI(CH_i, CH_{i+1})}{leastRSSI}\right) \quad (7)$$

2.2.3. Hop count

Hop count gives the number of nodes the source relay on towards the destination node. It is regarded as a fundamental distance between source node to the destination node. The number of hops in a routing path is calculated as (8),

$$H = \frac{N_C(Path)}{C} \quad (8)$$

where $N_C(Path)$ is the number of CHs in the selected path. The delay in data transmission depends on the number of hops from the source node to the destination node. The smaller number of hops from source to sink, results in energy-efficient D2D routing. The FF for routing that has to be minimized once the above objectives are computed is (9).

$$FF_{routing} = r_1 \times E + r_2 \times L + r_3 \times H \tag{9}$$

3. OPTIMIZATION USING SMO-PSO

3.1. Spider monkey optimization

The spider monkeys' (SM) sociability and hunting habits are the driving forces behind the SMO algorithm. Whenever there is a shortfall of food, the monkeys will disperse themselves into subgroups and vice versa. They adhere to a social structure based on fission and fusion [27] that includes five standard steps. The significant features of fission-fusion behavior in spider monkeys are as: i) in SMO, all spider monkeys keep a cluster of 20 to 40 individuals; ii) when there is a food shortage, the global leader (GL) divides the entire group into subgroups, with each group exploring individually; iii) each subgroup searches the food under a local leader (LL); iv) to socialize with other group members, they employ a distinct sound. Let X_i be the i_{th} member of population of size N, whose D-dimensional vector as X_i=$X_i^1, X_i^2, \ldots, X_i^j, \ldots, X_i^D$ and is initialized using (10).

$$X_i^j = X_{min}^j + r_1 \times \left(X_{max}^j - X_{min}^j\right) \tag{10}$$

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. After population initialization, the algorithm undergoes following phases.

3.1.1. 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 (11) and based on the probability PR that is the perturbation rate. Fitness of each SM is calculated at new position, if it is better than the old value the position gets updated.

$$X_i^1 = X_i^j + r_1 \times \left(XL_k^j - X_i^j\right) + r_2 \times \left(X_r^j - X_i^j\right) \tag{11}$$

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 $r_2 \in [-1,1]$.

3.1.2. Global leader phase (GLP)

After LLP every member updates its location using (12) with the knowledge of GL (XG_j) and local members. The SM updates its position based on the probability which is the function of fitness i.e., $P_i=0.9*(fitness_i/Max\_fitness)+0.1$.

$$X_i^j = X_i^j + r_1 \times \left(XG_j - X_i^j\right) + r_2 \times \left(X_r^j - X_i^j\right) \tag{12}$$

Here XG_j is the bets solution among the entire population.

3.1.3. Local leader learning phase (LLLP) and global leader learning phase (GLLP)

The LLLP and GLLP 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. In the GLLP, the best individual is declared as GL (XG_j). If GL fails to update its position then global limit count (GLC) is increased by one. These phases identify the stagnation problem which can be resolved in following phases to avoid premeture termination.

3.1.4. Local leader decision phase

If the LL does not get reorganized based on the counter of local limit, this step basically randomly initializes or adjusts the location of all group members using GL experience through the perturbation rate PR through (13).

$$nX_i^j = X_i^j + r_1 \times \left(XG_j - X_i^j\right) + r_1 \times \left(X_r^j - XL_k^j\right) \tag{13}$$

If the LL is not updated for long time, to be away from the stagnation area, we make the LL to move towards randomly selected member. Thus, in the above equation the coefficient is taken as non-negative.

3.1.5. Global leader decision phase

Here the position of the GL is monitored. 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. Each time in this phase local leader learning is initiated to elect the local leader in newly formed groups.

3.2. Particle swarm optimization

PSO mimics the social behavior of flocking birds and schools of fish. There is a velocity and position connected with each particle/bird. To find food particles they adjust their speed, which causes them to change location. Each particle remembers the best spot it has found. Particles share information with their neighbor about the optimal solution they have discovered. Velocity of the particle is modified by using: i) flying experience of the particle and ii) flying experience of the group. The (14) and (15) govern the new solutions. Particle velocity is given by (14),

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

where v_i is velocity of i^{th} particle, W is inertia of the particles, C_1 and C_2 are acceleration coefficients, R_1 and R_2 are random numbers ϵ [0, 1] of size $1x\ D$, $P_{best,i}$ is personal best of i^{th} particle, $G_{best,i}$ is global best, x_i is position of i^{th} particle. The velocity v_i^t and the current position are used to calculate the new position as (15),

$$x_i^{t+1} = x_i^t + v_i^t \tag{15}$$

The momentum part $W v_i^t$ serves the memory of the previous flight of the particle and prevents the drastic change in the direction. The cognitive function $C_1 R_1 \left(P_{best,i}^t - x_i^t\right)$ draws the particles to their own best position, and the social part $C_2 R_2 (G_{best} - x_i^t)$ draws towards the location identified by the entire group.

4. PROPOSED PROTOCOL

For D2D communication in IoT, the proposed solution introduces a new clustering and routing strategy. Using SMO with an oscillating perturbation rate (OSMO), the approach first finds a collection of optimal CHs. The routing phase finds the routing path for D2D communication through the optimal CHs. A PSO with oscillating inertia weight (OPSO) discovers an energy-efficient routing path from the source to the destination. Each round has two phases the set-up phase and the steady-state phase. Network configuration is in the first phase, and the destination picks the optimal CHs as a relay node in the following steps.

Step 1: Every node in the network sends out a HELLO packet that includes its unique ID to neighboring nodes. Each node updates its neighbor table with the ID included in the packet with the RSSI value.

Step 2: After discovering neighbor nodes, it broadcasts the data about itself, including ID, neighboring table data, and the values of node parameters until it reaches the destination node.

Step 3: The destination configures the network once it receives control packets from all nodes. The destination node uses OSMO to find the best CHs and OPSO for optimal routing paths for D2D communication in the IoT network.

Step 4: Finally, the destination broadcasts the configuration information to all the nodes. On receiving the configuration packet from the destination node, each node updates its status as either CH or cluster member. CH updates its next hop to destination and cluster member to its respective CH.

Cluster members submit data packets to their respective CHs during the steady-state phase. CH chooses the best route to convey data to its destination.

4.1. Oscillating perturbation rate and inertia weight

Exploration and exploitation are two crucial phases in meta-heuristic algorithms in finding an optimal solution and free from stagnation problems. *PR* and *W* are the two main parameters that balance exploration and exploitation in SMO and PSO. With the iterations, these are generally a linearly rising value which may lead to divergence from the optimal solution. This study introduces oscillation in *PR* and *W*, which dramatically impacts the precision and rate of convergence. Bansal *et al.* [28], proposed ESMO with chaotic *PR* for D2D communication. This enhancement in SMO has taken advantage of the nonlinear perturbation rate. The fluctuating inertia weight in PSO [28] is an inspiration for the novel oscillating PR and inertia weight proposed in this study. This improvement successfully strikes a balance between the utilization of the search space and exploration, increasing network reliability.

4.1.1. Modified perturbation rate

Perturbation rate PR governs the accuracy and pace of convergence, a significant parameter in SMO. The perturbation rate of the basic SMO is linearly rising. Because real-world problems are nonlinear, nonlinearity in the perturbation rate can help SMO perform better. The new oscillating perturbation rate is as in (16).

$$PR(t) = \frac{(PR_{max}+PR_{min})}{2} + \frac{(PR_{max}-PR_{min})}{2}\cos\left(\frac{2\pi t}{T}\right) \quad (16)$$

Where PR_{min} and PR_{max} are the range of oscillation of *PR;* t^{th} iteration is represented by t and T is the oscillation period.

4.1.2. Modified inertia weight

In PSO inertia adoption technique is the factor that drives particle velocity as they fly in the search space. The use of an oscillating inertia weight steers the swarm toward global and local search. The inertia weight function $W(t)$ oscillates between W_{max} and W_{min} as in (17).

$$W(t) = \frac{(W_{max}+W_{min})}{2} + \frac{(W_{max}-W_{min})}{2}\cos\frac{2\pi t}{T} \quad (17)$$

A joint stipulation is that the method must start at PR_{max} or W_{max} with strong exploration capabilities and finish at PR_{min} or W_{min} with high exploitation preferences. As a result, a wave function of this type should complete $(3/2)+k$ cycles in a single run of the algorithm, where k is a parameter that regulates the oscillation frequency, whose value is 3 in this experimentation. In both (16) and (17), T is the oscillation period given by $2I/(3+2k)$, and I is the number of iterations for which PR or W oscillates.

4.2. Oscillating SMO based clustering

The nodes used in the IoT network are battery-powered and energy-constrained. The aforementioned indicates that energy and power usage are the prime considerations. Internet-based communication consumes significantly more energy, causing these low-power gadgets to drain quickly, and requiring optimized connectivity through minimum communication. One approach to achieve this is to group the devices in a way that is efficient in terms of energy consumption and computational cost. SMO is one such approach that can be applied efficiently for grouping the devices and selecting optimal group leaders. OSMO is a guided searching variation of the SMO technique that discovers an optimal solution. Based on the information received, the destination computes the fitness of each node. Then it runs OSMO based clustering algorithm to select the best '*C'* CHs. The proposed CH selection approach is as:

a) Let D be the decision variables for the selection of the best CH.
b) Set the N individuals in the population to an arbitrary value between 0 and 1. The dimension of an individual solution is equal to the number of factors D as in (18).

$$X_i = X_i^1, X_i^2, \dots, X_i^j, \dots, X_i^D \quad (18)$$

c) Initialize limits of GL, LL and PR.
d) Compute each individual's fitness using the clustering fitness function in (4).
e) Apply the OSMO algorithm to discover the most suitable individuals as CHs.

4.2.1. Position updating of spider monkeys

After the initial configuration of SMs, evaluate them using the fitness function. This assists in the classification of the population and the selection of global and local leaders. We utilize the fitness function developed previously (4) to evaluate the SM. Choose the SM with the best fitness as a universal leader. In the local leader phase, the oscillating perturbation rate PR (16) decides the position update of individuals. The PR oscillates between PR_{min} and PR_{max}. As a result, exploration remains at its peak. Calculate the probability Pi of each SM, and if the randomness of the global leader $r_1<Pi$, the new positions are updated for all group members. The greedy selection technique based on fitness selects global and local leaders. The exploration begins to avoid stagnation if the local leader's location does not update for a predefined limit. The global leader divides the population into groups if it is position is not updated a specified number of times.

4.3. Oscillating PSO based routing

After identifying the best set of CHs, the destination node runs OPSO to find the best D2D communication routing path. Each solution represents a mapping of one CH to another or the destination node. The dimension of the population is equal to the total number of CHs (C). The solution establishes a path from each CH to the destination via the network's subsequent CHs. The node appending technique creates the route that starts at the source node and ends at the destination node. At each step of this process, a node can pick the best next-hop out of several neighbor nodes. Yao *et al.* [29] used priority as a guiding factor in determining the routing direction. They utilized the position vector of the particle to determine the priority.

The suggested encoding method uses CHs fitness value to represent the node's significance in generating a path across candidate nodes. Let $P_i=[Y_{i,1}, Y_{i,2...} Y_{i,C}]$ be the i^{th} solution where each component $Y_{i,d}$, $1<d<C$ represents the nodes (i.e., $N_{d)}$ priority to selects it as a relay node towards destination. Since the objective of the method minimizes the fitness function, the CH with the least fitness value is the best neighbor to be selected.

As shown in Figure 3, each CH transfers data packets to another CH in the direction of the destination, not backward, establishing a directed acyclic network *G (V, E)*. *V* denotes the set of all CHs, and *E* denotes the set of all links between the CHs in the routing path leading to the destination. From Figure 3, it is clear that the CH 5 (C5) can select any of the CH among {C4, C6, C7} as the next CH to forward data towards the destination. As a result, neighbor of C5 is Nbr (C5)={C4, C6, C7}. Table 3 shows the neighboring CHs for all CHs based on Figure 3. Out of three neighbor nodes C4, C6, and C7, the fitness of C4 is better than C6 and C7; thus, next (C5)=C4. Therefore, C4 gathers packets from C5 and works as a relay node toward the destination. This process continues until the routing path reaches the destination. Thus, the final routing path from C5 to the destination is C5→C4→C8→Dest. Similarly, discover all feasible pathways to the target node by choosing the next fittest CH. When selecting a route, assign the relay CH in the path the utmost priority, therefore less chance to pick that node again. In the worst case, if a node is selected again, the concerned route can be treated as an invalid route and is assigned a high penalty value.

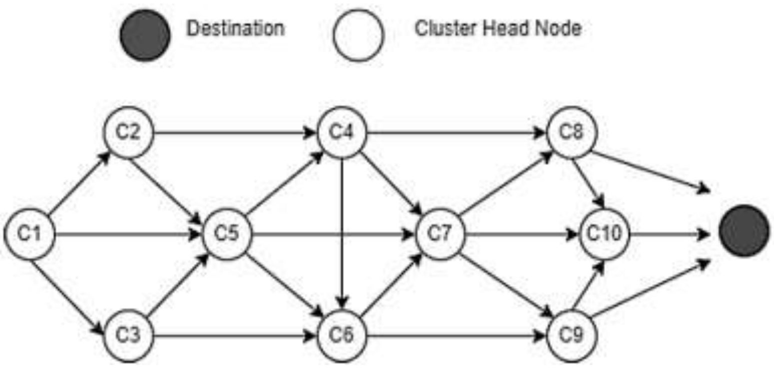

Figure 3. The network for routing phase

Table 3. Network information for routing phase

CH	Nbr (CH)	No. of Neighbor	$Y_{i,d}$	Next (CH)
C1	{C2,C3,C5}	3	0.81	C2
C2	{C4,C5}	2	0.36	C4
C3	{C5,C6}	2	0.52	C6
C4	{C7,C8}	2	0.23	C8
C5	{C4,C6,C7}	3	0.45	C4
C6	{C7,C9}	2	0.31	C9
C7	{C8,C9,C10}	3	0.76	C10
C8	{C10,Dest}	2	0.31	Dest
C9	{C10,Dest}	2	0.42	Dest
C10	Dest	1	0.18	Dest

4.3.1. Position and velocity updating

Following the initialization of the particles, evaluate the routing path formed by the decoding process using the fitness function (9). The global best and personal best of all particles are determined. Each particle needs to update its position depending upon the velocity of the particles to reach the optimal solution. Compute the speed of each particle, and the new location is updated. Following the allocation of the new position, re-evaluate all the paths using the fitness function, and global best and local best places are updated accordingly.

5. RESULTS AND DISCUSSION

5.1. Simulation set up and performance analysis

The sensor nodes are randomly distributed in the 200 m^2 sensing region. The first-order radio model is used to calculate the node transmission power loss. The list of network parameters utilized in the simulation is in Table 4. Table 5 gives the control parameters for OSMO and OPSO. A fitness function used by OSMO to select CH is of five parameters that are crucial for optimal communication. The source node can communicate with the destination using the path through optimal adjacent CH through OPSO based routing algorithm. The simulation results of the proposed scheme is compared with existing swarm intelligence (SI) based algorithms like GAPSO-H [16], ARES [17], bio-inspired cluster-based routing scheme (Bi-CRS) [30], ESMO [27] based on performance metrics like packet delivery ratio (PDR), delay, residual energy, and network lifetime. Under this section, the above metrics are investigated by altering number of nodes in each simulation.

Table 4. Network parameters

Parameter	Value
Simulation range	200×200 m
Initial Energy	100 Joule
Number of nodes	100-500
MAC protocol	IEEE 802.11
Packet size	1,000 bits
E_{fs}	*10 pJ/bit/m²*
E_{mp}	*0.0013 pJ/bit/m⁴*
E_{con}	*50 nJ/bit/m²*

Table 5. Control parameters for OSMO and OPSO

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

5.1.1. PDR

PDR is the percentage of data packets successfully communicated to the intended destination. It is the number of packets received at the receiver to the data packets sent by the node, given by (19). Table 6 shows the PDR of proposed method and existing algorithms. Figure 4 shows that the proposed method delivers data packets successfully, ranging from 100% at 100 nodes to 99.5% at 500 nodes. PDR drops with an increase in the nodes due to the increased hops and varied link quality. The suggested method provides superior PRD by limiting the number of relay nodes used to carry data packets to their destination that are at an optimal distance.

$$PDR = \frac{\sum Number\ of\ packets\ received}{\sum Number\ of\ packets\ sent\ by\ the\ node} X100 \tag{19}$$

5.1.2. Residual energy

The remaining energy in a node is critical to the network's long-term viability. All nodes start with 100 J of energy, which drains over time. Nodes consume energy in the transmission and reception of data packets. As indicated in Figure 5, the proposed cluster-based routing method is energy efficient and can improve the network lifespan compared to other optimizing techniques. The proposed OSMO effectively selects the CH using a multi-objective fitness function, and OPSO uses neighbour CH with the highest remaining energy as a relay to the destination. Table 7 gives the residual energy of different optimization techniques. In (20) calculates the average residual power of the network, where E_i is remaining energy of i^{th} node in the network.

$$Average\ residual\ energy\ = \frac{\sum_{i=1}^{N} E_i}{N} \tag{20}$$

5.1.3. End-to-end latency

This measure indicates the time taken to transmit the data packet to the designated place. The transmission of data packets from source to destination in less time improves system performance. Both transmission delay (D_t), and propagation delay (Dp) are used to calculate end-to-end latency. D_t depends on the size of the data packet and the bandwidth available on the network, whereas D_p on distance and speed. As the CH puts the data packet on the outgoing link, we cannot claim that a data packet has arrived at its destination until the final piece of the data packet spans the whole connection, known as D_p. As a result, both D_t and D_p are used to determine the network's communication latency. Table 8 shows the time taken by proposed and existing optimization techniques to transmit the data from source to destination. Figure 6 compares the proposed method's communication delay with existing methods. OSMO selects the best CH based on the most critical metric: closeness to the target. The shortest distance between CH and destination allows quicker data transfer.

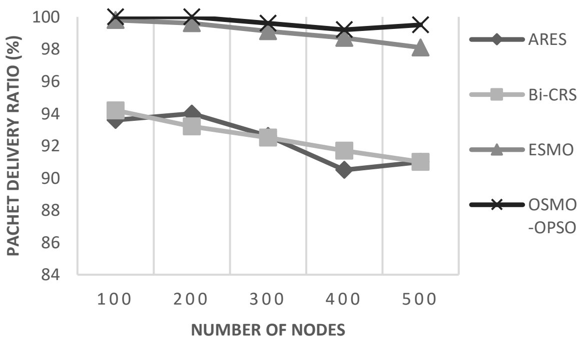

Figure 4. Packet delivery ratio at varied network size

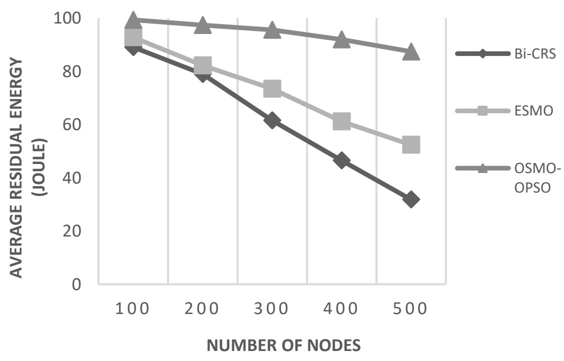

Figure 5. Residual energy at varied network size

Table 6. PDR for different optimization techniques

No. of Nodes	ARES	Bi-CRS	ESMO	OSMO-OPSO
100	93.6	94.2	99.8	100
200	94	93.2	99.6	100
300	92.6	92.5	99.1	99.6
400	90.5	91.7	98.7	99.2
500	91	91	98.1	99.5

Table 7. Residual energy for different optimization techniques

No. of Nodes	Bi-CRS	ESMO	OSMO-OPSO
100	89.06	92.73	99.32
200	78.92	82.19	97.34
300	61.52	73.48	95.5
400	46.54	61.19	91.99
500	31.79	52.35	87.4

Table 8. Delay for different optimization techniques

No. of Nodes	ARES	Bi-CRS	ESMO	OSMO-OPSO
100	0.042	0.016	0.0109	0.0101
200	0.045	0.019	0.0115	0.0104
300	0.044	0.025	0.018	0.0162
400	0.05	0.024	0.0213	0.0112
500	0.052	0.03	0.0294	0.0186

5.1.4. Network lifetime

The longevity of a network is a measure of its performance. We tested the proposed methods for a different number of iterations. The stability of the network depends on the number of live nodes. The nodes consume energy on packet transmission, reception, and aggregation. The node energy dissipates with iterations, and the network lifetime reduces. Figure 7 shows that the proposed method has a longer network lifespan than all the protocols studied. The improvement introduced in both the clustering and routing phase explores the search space effectively to select the energy-efficient solution using the multi-objective fitness functions.

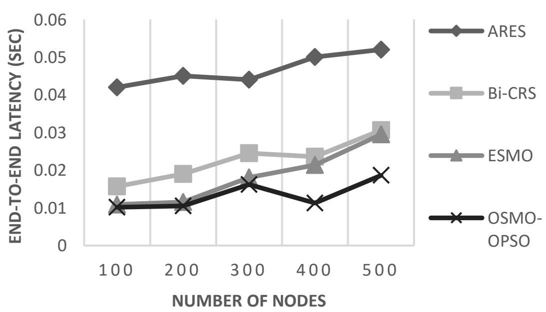

Figure 6. End-to-end latency at varied network size

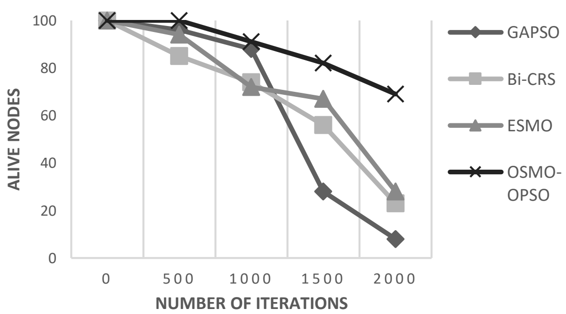

Figure 7. Performance analysis based on stability

From the experimental results, it is clear that the novelty introduced in the technique enhanced its performance. In Bi-CRS, the inertia weight was linearly increasing; the values of acceleration coefficients manage the exploration and exploitation in selecting the optimal solution. The success of a metaheuristic algorithm depends on the selection of step size. The introduction of chaotic perturbation rate in position update in ESMO shows better results than Bi-CRS. The decision concerns the global best position; hence the approach performs better. OSMO-OPSO is the hybrid version that takes advantage of both SMO and PSO. Compared to the chaotic perturbation rate, oscillation gives better efficiency and accuracy. In the oscillation-based technique, a proper balance between exploration and exploitation better updates the ideal solution. In addition to that, OPSO uses priority-based relay selection to route the data to the destination. Thus, from the comparison, it is clear that the hybrid OSMO-OPSO shows promising performance for D2D communication. The proposed hybrid methodology intelligently selects the ideal CHs and routing path from source to destination using multi-objective fitness functions. When the load on the IoT node is well balanced, the distance to the destination is smaller, and there are more alive nodes, the energy consumption remains optimal. The modified perturbation rate introduced avoids the local optima and allows quick convergence.

6. CONCLUSION

This research suggests a hybrid energy-efficient routing strategy for D2D communication in IoT. The technique introduces a nonlinearity-based SMO algorithm to divide the IoT network into clusters and find the CHs. To make it a viable protocol for D2D communication, it joins a routing mechanism that determines network pathways using PSO. The proposed method creates and maintains an optimal routing path that connects sensor nodes and the destination. The non-linearity in both algorithms successfully balances the exploration and exploitation stages and eliminates stagnation issues. The result shows the promising improvement over state-of-art techniques in packet delivery ratio, residual energy, end-to-end latency, and stability.

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