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Implementation of Enhanced Spider Monkey Optimization for D2D Communication through IoT

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Abstract. The rapid magnification of connected devices and a massive rise in mobile data have introduced the Internet of Things (IoT) technology. Device-to-Device (D2D) communication is a standard for future IoT networks that aims to achieve high data rates, ultra-low latency, and energy efficiency. Topology management is critical for energy-efficient D2D communication, and cluster-based topology management is better for enhancing the network's performance. Choosing the best Cluster Head (CH) by considering the communication metrics will extend the network's lifetime. We present an Enhanced Spider Monkey Optimization (SMO) algorithm based on a multi-objective fitness function to choose the best CH and routing path for effective D2D communication. Experimental findings reveal that enhanced SMO improves packet delivery ratio, average energy consumption, and end-to-end latency compared to similar protocols.

Keywords. Cluster head, device to device communication, IoT, multihop routing, swarm Intelligence

1. Introduction

The Internet of Things (IoT) is a pioneering technology that is getting traction over the next generation of technological networks, introducing the idea of the interconnecting range of physical things or objects. IoT refers to the online connection of widely dispersed physical items with inbuilt electronics, software, sensors, or actuators to gather information and exchange it for management and surveillance. Various communication may be found in IoT (Bello and Zeadally 2016), like Device-to-Device (D2D), Device-to-User (and vice versa), and Device to Distributed Storage. D2D communication is gaining propulsion as a means of facilitating peer-to-peer networks. Thus D2D communication technology is projected to play a role in the IoT (Pawar et al., 2019). D2D communication is a standard for future IoT networks that aims to achieve high data rates, ultra-low latency, and energy efficiency. Its application is for neighbourhood services, emergency communication, and IOT advancement. D2D communication enables devices to route the data to each other instead of using the core network, thereby reducing the load (Oteafy et al., 2012). D2D communication necessitates novel routing strategies that employ effective optimization methods to customize network resources to the needs of various IoT applications. IoT growth mainly depends on the effective use of network resources. The available techniques use rigid and inefficient routing, which dissipates network and device resources. Optimal use of network resources is crucial to the growth of IoT.

D2D technology's popularity is motivated by its ability to conserve energy (Höyhtyä et al., 2018). Ad-hoc IoT networks use battery-powered devices with limited power. It is vital to save the energy of IoT devices to ensure the network's long-term viability (Yarinezhad 2019). The energy consumption of devices in such a network is influenced by many factors, including data transmission, receiving and aggregation, end-to-end delay, computation load on the device, and temperature, to mention a few. There is a need for a good topology management strategy for effective network administration (Yarinezhad 2021). Thus, the clustering-based topology management technique will yield favourable outcomes. The clustering technique divides the search space into clusters of nodes or devices. An effective clustering technique selects the best Cluster Head (CH) for each cluster. The nodes in a given cluster route data only through their CH. Thus the network's overall energy utilization is lowered, and its lifetime is improved.

For topology management in Wireless Sensor Network (WSN), a variety of clustering algorithms are presented, to name a few LEACH (Heinzelman et al., 2000), HEED (Younis et al., 2004), TEEN (Manjeshwar et al., 2001). There are cluster-based studies that differentiate and evaluate WSN clustering approaches and their efficacy, but they didn't assess their goals or, more crucially, relevance (Xu 2017). Clustering methods based on swarm intelligence are reliable and commonly employed in optimization challenges that include protocols based on Particle Swarm

Optimization, Ant Colony Optimization, and Artificial Bee Colony, to list a few. Spider Monkey Optimization (SMO) (Bansal 2014) is a recently proposed method that mimics the behaviour of spider monkeys searching for food. It accurately discovers suitable solutions compared to other swarm intelligence-based optimization algorithms. SMO has been utilized in several trials to select CH (Gui et al., 2019; Mittal et al., 2018).

By combining different objectives, the proposed study increases the original SMO's ability to choose the best CH for the node to route the data to the destination. This study adopted a fitness function with several aims to find the best CH. The destination node notifies all nodes about the CHs, and the nodes are assigned to the CH using the potential function. Finding the optimal routing path for D2D communication follows the clustering phase. Routing the data packets is through the selected CHs to improve the stability of the network. The source CH selects neighbour CH as a relay node towards the destination depending on its remaining energy and link quality.

2. Related Work

In a Wireless Sensor Network (WSN) and WSN based IoT; minimizing energy usage is a goal and can be accomplished through effective routing techniques. Energy conservation during communication plays a role in extending the network lifespan. Clustering-based network management plays a vital role in balancing energy between sensor nodes. Various routing algorithms have been presented in the previous decade to use resources effectively in energy-constrained IoT networks. They employed different strategies to achieve the objectives. This section discusses some of the most recent excellent works.

To enhance the performance of traditional LEACH, Wang et al., (2019) presented a protocol LEACH-Impt. The computation of the optimal path depends on various parameters like hop count and left-over energy and shows improvement on traditional LEACH. But the random selection of CH from a set of nodes reduces the network lifetime. Younis et al., (2004) proposed a hybrid energy-efficient approach HEED for ad-hoc networks. The remaining energy of the node is considered a parameter during clustering. HEED cannot assure optimal CH selection as the distance to the base station is not considered. The computation ability of bio-inspired algorithms has made them useful in solving optimization problems. PSO-C is the first PSO-based algorithm used for clustering in WSN (Heinzelman et al., 2000). The algorithm does not account for the proximity between the CH and the Base Station (BS), so energy consumption is not controlled during CH to BS transmission.

The authors proposed a dynamic clustering strategy that relies on a genetic algorithm (GA) to improve WSN network longevity (Yuan et al., 2016). When designing an ideal dynamic network layout, the remaining energy, proximity of nodes, and distance to the base station are considered. They created more clusters to maintain the energy level when the sensing field is far from the base station. This may result in more computations and a decrease in network performance. Gupta et al., (2018) applied the cuckoo search approach to select the CHs. The load on the CH is not uniform as the delay is not optimized.

Lipare et al., (2019) devised a GWO technique for clustering and routing in WSN that tackles the energy hole issues around the BS. Two decision variables, overall distance covered and hops distance, are considered while evaluating the fitness function. But, because of the high traffic load, the energy of gateway CHs nearer to the base station depletes rapidly. An optimized clustering approach based on a genetic algorithm (GAOC) introduces additional sink nodes to reduce the transmission distance between the cluster and the sink (Verma et al., 2019).

Ahmed et al., (2019) presented a new PSO to speed up data transfer while lowering energy consumption. Yogarajan et al., (2019) proposed a clustering method based on the Ant Lion optimization (ALO) technique. Uneven consumption of energy at the nodes affect the network lifetime. Spider monkey optimization (SMO) (Bansal et al., 2014) based SMO-C is proposed to locate the CH (Gui et al., 2016). The evaluation of the CH node is through two fitness parameters CH power and node to CH distance. The results demonstrate no significant differences between similar procedures.

The majority of proposed clustering algorithms in the literature involve only a few parameters when addressing the energy conservation challenge for communication in wireless networks. The best choice is to partition the nodes in the network and select the CH for each partition. D2D communication is a standard for future IoT networks that aims to achieve high data rates, ultra-low latency, and energy efficiency. In D2D communication, there has to be an intelligent selection of relay CH towards the destination node. The proposed improved SMO considers residual energy, proximity to the destination, and end-to-end delay of the node to decide the node's fitness to be CH; neighbour CH's battery status and link quality to find the best path for D2D communication. Table I gives the summary of the related study.

Science and technology advancements have enabled the monitoring of potentially dangerous or inaccessible situations. Each innovation has its mix of benefits and drawbacks. The computational power and energy of IoT devices are confined, so the energy utilization of the network has to be optimized (Gomez et al., 2018). Because Smart objects are battery-powered and gather and distribute data continually, there is high demand for energy efficiency. Because device energy depletes quickly, the energy consumption of IoT nodes must be managed (Reddy et al., 2018). The use of energy optimization techniques extends the network's lifespan. We present a cluster-based enhanced SMO routing approach for an IoT-enabled wireless network that uses a multi-objective fitness function.

The rest of the paper shows related work in section II, the proposed routing method in section III. Section IV contains a detailed performance analysis of the work, and section V concludes the study.

Table 1: Summary of related study

Reference	Year	Algorithm used	Clustering Parameter	Demerits
(Heinzelman et al., 2000)	2000	LEACH	Random	Random selection of CH does not consider other parameters, thus energy depletion is more if the CH is far away from the destination
(Younis et al., 2004)	2004	HEED	Residual energy	Cannot guarantee for optimal control node selection in term of minimizing energy consumption and network longevity
(Elhabyan et al., 2015)	2015	PSO-C	Energy, Link quality	Hard to find optimal set of CH
(Yuan et al., 2016)	2016	GA	Residual energy, distance	Getting optimal network structure is challenging
(Gupta et al., 2018)	2018	Cuckoo Search	Node degree, Energy, Distance,	Load on the CH is not uniform
(Lipare et al., 2019)	2019	GWO	Distance, hop count	CH near to the base station drains quickly due to heavy load
(Verma et al., 2019)	2019	GAOC	Energy. distance	Shorter network lifetime
(Ahmed et al., 2019)	2019	PSO	Distance	Packet loss rate results in more energy consumption
(Yogarajan et al., 2019)	2019	ALO	Distance, Energy	Uneven energy consumption at the nodes greatly affects the network lifetime
(Elhoseny et all., 2020)	2020	PSO+GWO	Energy, Node location	Experiences communication delay
(Maddikunta et al., 2020)	2020	MFO+WOA	Energy, delay, distance, load, temperature	Network load is not optimized

3. Proposed Clustering based Routing Technique

(A) Network Model

IoT nodes are deployed at random in search space. G= {V, E} illustrates a multi-hop network, with V representing a sensor node and E representing the link between the nodes. Fig. 1 shows the network model. The following is the network model for energy-efficient route discovery:

- *N* sensors are spread through *M X M* search space;
- Each sensor is identified by a unique number;
- Each node is powered by a battery that is non-rechargeable;

- Sensor node locations are fixed once deployed;
- All nodes have the same starting energy;
- The sensor nodes are connected via bidirectional communication lines;

(B) Energy Model

The energy model utilized in this model is based on Behera et al., (2019). The transmitter provides energy to the radio circuit and a power amplifier, while the receiver is only on a power amplifier. When the distance between the transmitter and receiver 'dist' falls below the threshold d0, the energy loss in the free space model is square of distance 'dist2'. While dist>=d0, the energy loss in the multipath fading model is 'dist4'. So the energy consumed to transmit a packet of l bits is given E_T as in Eq. (1).

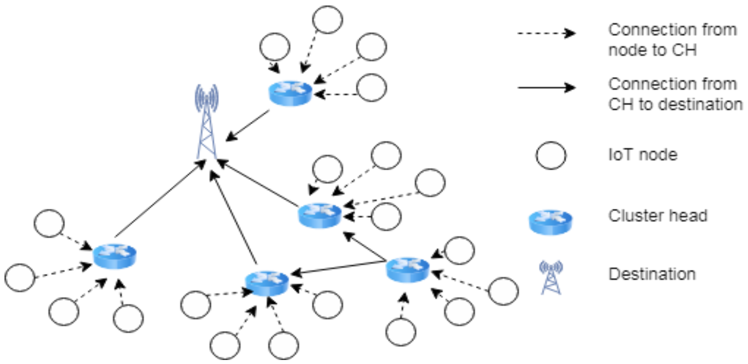

Fig. 1: The network model

$$E_T = l \times \begin{cases} E_{con} + E_{fs} \times dist^2, \ dist < d_0 \\ E_{con} + E_{mp} \times dist^4, \ dist \geq d_0 \end{cases} \quad (1)$$

Where E_{con} is energy dissipated at transmitter or receiver node. E_{fs} and E_{mp} are energy to transmit a bit through free space or multipath channel respectively. The threshold distance d_0 *is* figured out using Eq. (2).

$$d_0 = \sqrt{E_{fs}/E_{mp}} \quad (2)$$

The energy consumed to receive a packet of l bits is given as E_R in the Eq. (3)

$$E_R = l \times E_{con} \quad (3)$$

(C) Background of SMO

SMO is a meta-heuristic algorithm modelled based on the food-finding activity of spider monkeys inside the dense forest. Each Spider Monkey (SM) symbolizes a sensor node in the study. At first, select a Global Leader (GL) as a potential solution based on performance. When food becomes scarce, GL divides the population into subgroups. A Local Leader (LL) is in charge of each sub-group. The group members discuss their findings after one investigation cycle, and the leader goes to the region

Algorithm 1: Cluster Head Selection Using SMO Algorithm.

Step 1: Initialization of the population, Local Leader Limit, Global leader limit, Perturbation rate (PR)
Step 2: Calculate Fitness (i.e. individual nodes fitness using (9))
Step 3: Select Global Leader and Local leader using greedy selection.

loop (termination condition is not satisfied)
- (i) Find new positions for all individuals using local leader phase. [Refer (5)].
- (ii) Using fitness values, apply the greedy selection process.
- (iii) Calculate the probability P_i for all the group members using (7).
- (iv) Produce new positions for the all the group members, using global leader phase.[Refer (6)]
- (v) Based on the fitness, update the position of local and global leaders.
- (vi) If any Local group leader is not updating its position after a specified number of times, then start exploration using (8).
- (vii) If Global Leader is not updating position for a specified number of times then divide the group into smaller groups.

end loop

with the most plentiful food resources (i.e., optimal result). As a result, the global leader shifts to the perfect location in the overall exploration findings, while local leaders move to the best position within their local groups. Working with local groups speeds up foraging. As a result, SMO finds the best location rapidly while avoiding convergence to local optima. Exploration consists of seven stages in the suggested SMO initialization, local leader phase, global leader phase, local-leader learning phase, global-leader learning phase, local-leader decision phase, and global-leader decision phase (Bansal et al., 2014). Algorithm 1 shows the steps of the multi-objective cluster-based routing technique.

1. Initialize the Nodes

The initialization of the population is the first step in the exploration process. Node deployment uses Eq. (4), SM represents a node in the search space ranges from 1 to N.

$$SM_{ij} = SM_{minj} + r_1 \times (SM_{maxj} - SM_{minj}) \qquad (4)$$

SM_{ij} is i^{th} spider monkey in j^{th} dimension, r_1 is a random number: $0< r_1 <1$, SM_{minj} and SM_{maxj} are search space's lowest and higher limits.

2. Local Leader Phase

By utilizing local leader experience and social experience update SM's current position. Using the fitness function calculates the fitness of the new location if the new solution fits better than the old one, it is updated. In this phase, the positional gets updated using the formula provided below.

$$SM_{newj} = SM_{ij} + r_1 \times (LL_{kj} - SM_{ij}) + r_2 \times (SM_{rj} - SM_{ij}) \qquad (5)$$

SM_{ij} is the i_{th} SM's current location, LL_{kj} is the k_{th} local group leader's position, and SM_{rj} is the r_{th} randomly picked SM from the k_{th} local group and $r_2 \in [-1, 1]$. If $r_1 > PR$, (5) is evaluated; where PR is the perturbation rate as in (16).

3. Global Leader Phase

This phase follows the Local Leader Phase. SM's position is updated here based on GL experience, social experience, and perseverance. In this phase, the positional update formula is provided below:

$$SM_{newj} = SM_{ij} + r_1 \times (GL_j - SM_{ij}) + r_2 \times (SM_{rj} - SM_{ij}) \qquad (6)$$

GL_j holds the position of global leader. In this stage, the SM's position is updated based on the probability P_i computed from the fitness value. As a result, the superior candidate has a better probability of receiving an upgrade.

$$P_i = 0.9 \times \frac{fit_i}{\max\_fit} + 0.1 \qquad (7)$$

The fitness of i_{th} SM is fit_i, and the maximal fitness value in the cluster is max_fit. The new position of the SM is created and fitness is calculated only when $r_1 < P_i$. The new fitness value is compared to the previous one, and if the new value is better, the new position is taken.

4. Local Leader Learning Phase

The position of the local leader is updated using the greedy selection. SM with the highest fitness value is the group's local leader. If the location of the local leader doesn't get updated for a long time, the Local Limit Count (LLC) is increased by 1.

5. Global Leader Learning Phase

The position of the global leader is updated using the greedy selection. Choose SM with the highest fitness value as the universal leader of the population. If the location of the global leader doesn't get updated for a long time, the Global Limit Count (GLC) is increased by 1.

6. Local Leader Decision Phase

If the local leader does not get organized to predetermined Local Leader Limit (LLL), the members of that group update their positions either by random initialization or using the information of global leadership experience through PR given by,

$$SM_{newj} = SM_{ij} + r_1 \times \left(LL_{kj} - SM_{ij}\right) + r_1 \times \left(SM_{rj} - LL_{kj}\right) \tag{8}$$

To avoid stagnation, this phase enables members of the local group to explore further.

7. Global Leader Decision Phase

If the global leader does not get organized to a predetermined Global Leader Limit (GLL), the global leader splits the overall population into smaller local units. A local leader oversees each smaller local group. Local group formation continues until the maximum number of groups MAX_GRP.

(D) Cluster Head Selection using Multi-objective Fitness Function

The network is separated into multiple zones to prevent node energy degradation and BS load. Multiple criteria decide an ideal CH for each zone or cluster. By sending data packets through the best CH, cluster-based routing will help the IoT network last longer. The CH is identified based on several decision variables: remaining energy of the node, latency in sending data to the destination, and the proximity to the destination. So the node with maximum leftover energy, low delay, and lesser distance to the destination is considered the CH. Multiple objectives formulate the fitness function to select the optimal CH as the weighted sum approach given in Eq. (9).

$$F_{CH} = v_1 \times obj_E + v_2 \times obj_{DST} + v_3 \times obj_{DL} \tag{9}$$

Where v_1 to v_3 are weights satisfying the condition, $v_1 + v_2 + v_3 = 1.$ Weights can be modified as per the importance of the decision variables. The CH is the node that meets maximum or all objectives. The following part discusses the computation of decision variables for optimal CH selection.

The remaining or residual energy is critical for determining the CH for the cluster. CH is chosen as the node with the most remaining energy. The computation of the energy consumed by the node is given by,

$$E_{consumed} = E_{initial} - E_{RE} \tag{10}$$

E_{RE} *is* residual energy of the node and $E_{initial}$ is the initial energy of the node. The energy dissipated by the node during packet transmission and reception is computed using (1) and (3).

The destination uses following function to calculate fitness of a node in terms of energy efficiency:

$$obj_E = \frac{E_{consumed}(N_i)}{N} \tag{11}$$

Where $E_{consumed}(N_i)$ is the energy consumed by the i^{th} node. The node having more remaining energy is the better candidate to be selected as the CH.

The node's energy usage is proportional to the proximity between CH and the destination. The time it takes to transport a data packet increases as the distance between them grows, consuming more energy. Thus, pick the node nearest to the target as the CH. The Second objective is as given in Eq. (12) below.

$$obj_{DST} = \frac{Dist(N_i,\ Destination)}{M} \tag{12}$$

Where $Dist(N_i, Destination)$ is the distance between i^{th} node and destination. The CH node should have minimum distance to the destination.

As the time to transmit data increases, so does the workload on the node, which requires more energy. Sending packets of data from the sender to the receiver in a less time improves system performance. The third objective is described in Eq. (13). The numerator assumes that data is being transferred from CH node to the destination.

$$obj_{DL} = (Delay(N_i)/N \tag{13}$$

The delay at the node is calculated using both transmission delay and propagation delay. The CH node should transmit packets in less time to the destination.

(E) Modified Perturbation Rate

Exploring and exploiting are critical aspects in a meta-heuristic algorithm's quest for an optimal solution and escape from the dilemma of stagnation. The perturbation rate, an essential parameter in SMO, influences stability and continual optimization. The perturbation rate of the classic SMO increases linearly. Because real-world problems are nonlinear, nonlinearity in the perturbation rate might allow SMO to function better. In the proposed enhanced SMO, rather than using the linear behavior, the chaotic behavior of the PR function is being used. A chaotic-driven approach to SMO allows it to escape local optima and converge quickly. This nonlinearity lends itself to global optimization. This study uses a logical mapping-based chaotic function that reacts when it exceeds a specific value of $\mu = 4$ [24]. Eq. (14) illustrates the logical mapping.

$$z_{(t+1)} = \mu\ x\ z_t\ \times\ (1 - z_t) \tag{14}$$

$z_t\ \in [0,1]$ is the chaotic number at t_{th} iteration. The proposed perturbation rate is changed according to the chaotic behavior as in Eq. (15),

$$PR_{(t+1)} = (1 - PR_t) \times \left(\frac{MAXiter-t}{MAXiter}\right) \times z_t \tag{15}$$

Where t is the current iteration, $MAXiter$ are maximum number of iterations and PR is set to a range between 0 and 1 at random.

(F) Path Selection and Routing

Data transmission from CH to the destination necessitates the most efficient path possible. The selection of neighbour CH during path selection depends on its fitness rating. The optimal neighbour CH for data forwarding is selected based on two fitness factors: remaining energy and channel quality. CH's remaining energy is calculated as,

$$E_{RE} = E_{intitial} - E_{Consumed} \tag{16}$$

Connection quality of the link depends on the received signal strength indicator (Shu et al., 2017). The neighbour CH with higher remaining energy and good link quality is selected as relay node towards the destination for D2D communication. The data transmission procedure begins after finding the optimum path. The CH dissipates on data transmission and reception, which may cause the CH to die. Before starting the data transfer, the algorithm frequently examines the routing path. An alternative route is selected when a node fails to send the data packets.

4. Performance Evaluation

(A) Simulation Set Up

We simulate the proposed technique in ns - 2.35 to select the optimal CH and the routing path. Table II lists the network parameters utilized in the experimentation. A first-order radio model is used to calculate the node transmission power loss. The proposed SMO with a chaotic perturbation rate handles exploitation and exploration effectively. Table 3 gives the control parameters for SMO. The enhancement introduced in SMO with multi-objective fitness function finds an optimal path for D2D communication. The source node can communicate with the destination using the route selected through optimal adjacent CH. The proposed scheme compares simulation results with existing swarm intelligence (SI) algorithms like ALO (Yogajaran et al., 2019), PSO (Elhabyan et al., 2015), GWO (Lipare et al., 2019), and GA (Yuan et al., 2016) based on performance metrics like packet delivery ratio (PDR), Delay and residual energy.

Table 2: Network parameters

Parameter	Value
Simulation area	200 m x 200 m

Parameter	Value
Initial Energy	100 Joule
Number of nodes	100 - 500
E_{fs}	10 pJ/bit/m^2
E_{mp}	0.0013 pJ/bit/m^4
E_{con}	50 nJ/bit/m^2
Packet size	1000 bits

Table 3: Control parameters for SMO

Parameter	Value
LLL	5 x N
GLL	N /2
PR	[0,1]
MAX_GRP	N / 10

(B) Performance Analysis

Throughout the simulation, the initial energy of the node is 100J. The simulation is carried out for different network sizes (100-500 nodes). Evaluation of the proposed method based on the performance metrics residual energy, packet delivery ratio, stability and delay is as follows.

1. Performance Analysis based on Packet Delivery Ratio (PDR)

It denotes the proportion of data packets successfully transmitted to the destination node, is given by Eq. (16)

$$PDR = \frac{\sum Number\ of\ packets\ received}{\sum Number\ of\ packets\ sent} X100 \qquad (16)$$

Table 4 shows the PDR of proposed method and existing algorithms.

Table 4: PDR for different optimization techniques

No. of Nodes	PSO	ALO	GA	GWO	PROPOSED
100	94.2	95.7	94.6	96.8	99.8
200	93.2	95.2	94	96.3	99.6
300	92.5	94.4	93.6	95.8	99.1
400	91.7	93.8	92.7	95.1	98.7
500	91	93.1	92.2	94.3	98.1

The comparison of PDR of proposed approach with other is shown in Fig. 2. Results shows that proposed study delivers packets at a faster rate.

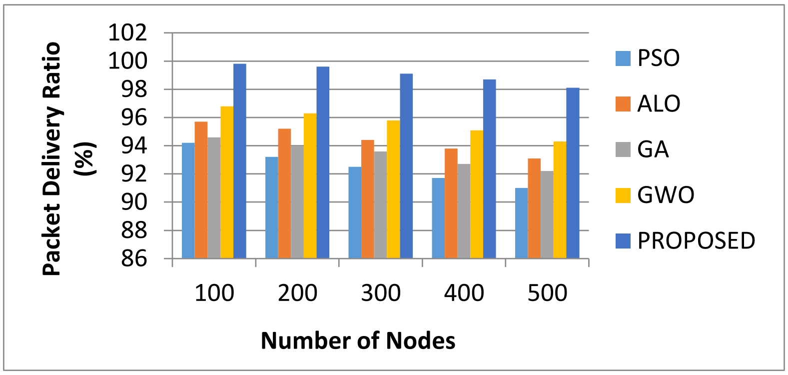

Fig. 2. Performance analysis based on Packet delivery ratio

2. Performance Analysis based on Residual Energy

The amount of remaining energy in a node is crucial in determining the network's longevity. Initially, all the nodes have the highest battery, which dissipates as the number of iterations increases. During experimentation, the source node sends a data packet to its CH then CH transmits data to the destination. The transmission and reception of data packets consume some amount of energy. CH utilizes more if the proximity between CH and destination is long. The proposed method effectively balances the energy consumption at CH by choosing it using a multi-objective fitness function. The residual energy is calculated using Eq. (17), and E_i is the remaining energy of i^{th} node in the network.

$$Average\ residual\ energy = \frac{\sum_{i=1}^{N} E_i}{N} \tag{17}$$

As illustrated in Fig. 3, existing techniques consume significantly more energy than the suggested approach. Table 5 gives the residual energy of different optimization techniques.

Table 5: Residual energy for different optimization techniques

No. of Nodes	PSO	ALO	GA	GWO	PROPOSED
100	81.4	85.4	81.8	87.2	92.733
200	58.8	73.4	66.3	72.3	82.188
300	45.3	50.6	42.7	53.1	73.476
400	27.2	38.1	33.9	34.6	61.188
500	10.7	29.4	18.5	16.4	52.347

The chaotic perturbation rate efficiently balances the exploration and exploitation phases of the proposed method. As a result, the nodes nearer to the destination are picked as a CH, resulting in reduced energy consumption.

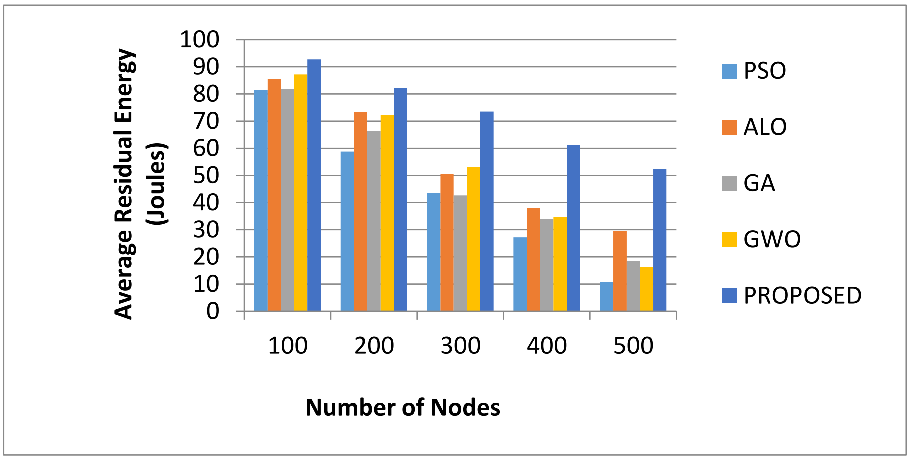

Fig. 3: Performance analysis based on residual energy

3. Performance Analysis based on End-to-End Latency

This metric denotes the time taken to deliver the packet to the destination. Communicating packets of information from source to destination in the shortest time is essential for enhancing system performance. End-to-end latency considers both the transmission delay and propagation delay. Table VI shows the time taken by proposed and existing optimization techniques to transmit the data from source to destination.

Table 6: Delay for different optimization techniques

No. of Nodes	PSO	ALO	GA	PROPOSED
100	0.026	0.029	0.028	0.010904
200	0.035	0.034	0.037	0.011534
300	0.043	0.047	0.035	0.018029
400	0.051	0.041	0.044	0.021387
500	0.064	0.054	0.057	0.029479

Fig. 4 compares the proposed method to existing methodologies in terms of delay. When compared to previous algorithms, the proposed technique has a faster response time because the separation between the ideal CH and the destination is less.

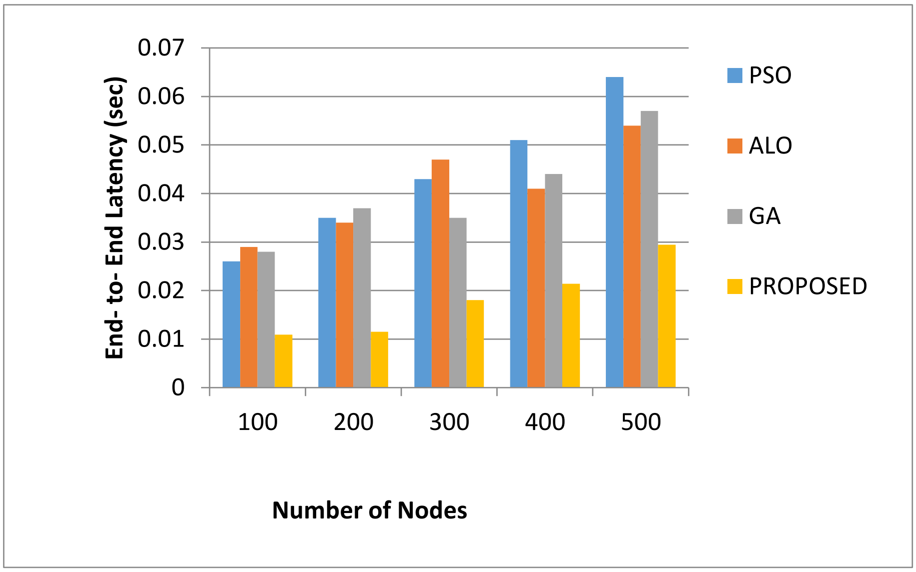

Fig. 4: Performance analysis based on latency

4. Performance Analysis based on Stability

Alive nodes are decisive for network sustainability. The live nodes consume energy on packet transmission and reception. As the number of iterations increases, node lose their battery and die. Live nodes keep the network stable by distributing the load evenly and reducing the delay in packet transmission. Fig. 5 shows the stability of the network depending upon the number of alive nodes.

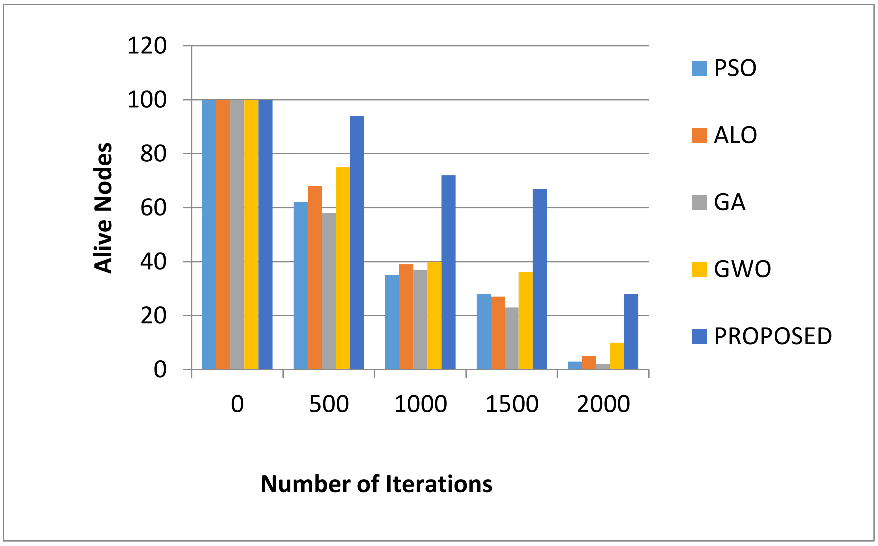

Fig. 5: Performance analysis based on stability

The proposed enhanced SMO intelligently selects the ideal CH for packet transmission from source to destination using the fitness function. 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 chaotic perturbation rate introduced in the method avoids the local optima and allows quick convergence.

5. Conclusion

The Internet of Things is a network of devices or nodes that use a non-rechargeable and irreplaceable energy source. As a result, it requires wise usage of node energy to ensure network endurance. This study introduced a multi-objective cluster-based routing method based on spider monkey foraging behaviour with a chaotic perturbation rate to address the routing challenge of D2D communication in IoT networks. Device-to-Device communication is a future IoT network standard that aspires for high data speeds, ultra-low latency, and energy economy. Enhanced SMO employs an effective clustering based routing algorithm that considers node parameters like residual energy, latency, and closeness to the target. It improves the D2D path selection by considering the link quality of the relay CH to the target node. Instead of selecting a CH based on its location, this method uses a multi-objective fitness function to pick a CH depending on the node's performance. The new methodology has a longer network lifespan and exhibits progress to PDR, residual energy, and delay

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