RESEARCH ARTICLE

A Multi-Objective Metaheuristic Approach Based Adaptive Clustering and Path Selection in IoT Enabled Wireless Sensor Networks

Pallavi Joshi

Department of Electronics and Communication Engineering, National Institute of Technology Raipur, Chhattisgarh, India
pjoshi.phd2017.etc@nitrr.ac.in

Ajay Singh Raghuvanshi

Department of Electronics and Communication Engineering, National Institute of Technology Raipur, Chhattisgarh, India
asraghuvanshi.etc@nitrr.ac.in

Abstract – The application-oriented Internet of Things (IoT) systems that exhibit the use of wireless sensor networks (WSNs) have energy constraint issues. The nodes in the WSN are driven by batteries that cannot be used for a very long time and thus the network is unable to combat the energy efficiency challenge. Also, the energy of the nodes drains rapidly with time as a result of a steady sensing task. Moreover, there are several intermediate tasks performed by the wireless network from sensing to sending the data to the destination. The traditional wireless models can accomplish the task of sensing and transmitting but are unable to avoid the tradeoff between many quality-of-service matrices such as network latency and throughput. So, there is a need to employ optimization techniques with a multi-objective paradigm. In this paper, a model for both choosing the cluster head and selecting the efficient path in a WSN for IoT applications has been proposed. The cluster head selection which is a part of clustering is done using a multi-objective rider optimization algorithm (ROA) which considers 3 objectives namely energy, distance, and delay. The routing is performed by selecting efficient and optimal paths using the multi-objective sailfish optimization algorithm (SFO). The results reveal that the proposed model proves itself superior to other similar existing works when compared based on execution time, energy depletion, network delay, throughput, packet delivery ratio, alive nodes in the network, and increase in dead nodes. The experimentation is done on a dense sensor network and it is observed that the proposed work can mitigate up to 30-40% of energy utilization and 40-60% of delay when compared with similar multi-objective techniques for routing and clustering. The intensification in the network lifespan and throughput is also marked by the proposed multi-objective technique which makes it profitable to be used in various IoT applications.

Index Terms – IoT Enabled WSN, Multi-Objective Optimization, Clustering, Quality-of-Service, Rider Optimization, Sailfish Optimization.

1. INTRODUCTION

Internet of things (IoT) technology has manifested itself as mandatory technology in many wireless-based applications like monitoring of residential areas, forests, hilly areas, military surveillance, etc.[1]–[3]. The sensors deployed within the objects such as RFID tags, actuators, mobile devices, and many more in the IoT framework, are treated as the things which collect useful data, process it, and updates it to the destination user or central controller. They can communicate with other objects in the IoT framework. With full internet access, the IoT framework at one site can be connected with the other site with different or same applications in case of huge networks covering a considerably big area. For instance, residential area which is on a plain ground can be connected with the areas of high altitude or hilly or forest. The IoT enabling technologies consists of cloud computing, embedded systems, big data analytics, wireless sensor network (WSN), and various protocols for wireless communications. Figure 1 represents an IoT-enabled framework. WSN is the system of homogeneous and/or heterogeneous sensors and actuators known for their self-organizing nature, which transmits the data collected by each node to a controller following some routes using a high data rate mechanism. WSN forms a key constituent of the IoT framework for collecting, aggregating, and transmitting the data. It is also responsible to magnify the total performance of the IoT network by employing various efficient and optimized algorithms. The WSN gives access to remote areas like marshy lands, in the air, valleys, etc. which are quite unreachable for humans. To design a large WSN compatible with the IoT structure is quite a challenging task. The challenges are due to the resource constraints of the sensor network like the battery power. The lifespan of a

RESEARCH ARTICLE

network depends on the life of every node. To answer these challenges, some solutions should be adopted. One of the major issues is data aggregation. The best solution to it is clustering. Much research has been done in this field to achieve efficient and reliable aggregation and data gathering in the sensor networks using clustering-based approaches[4]–[10]. Although the WSN are self-organized networks, some issues like network load balance, topology control still exist in the case of large WSN.

The clustering technology may help to overcome these problems. By decentralizing large WSNs, and creating the clusters of nodes based on some aspects like node density, distance, etc. high scalability and network lifetime can be achieved. The introduction of machine learning techniques and optimization approaches has proved to be a revolutionary step in clustering.
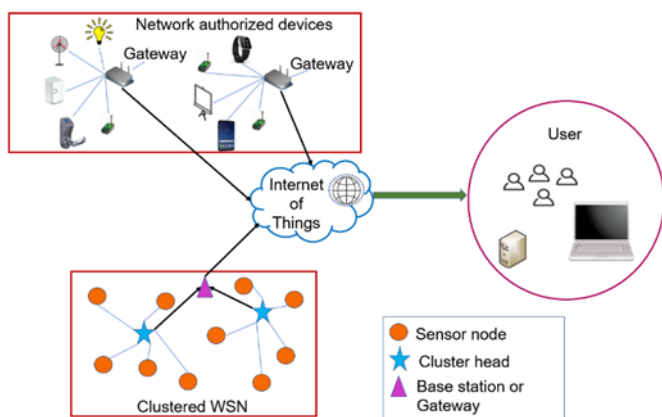

Figure 1 An IoT Enabled Framework

The introduction of optimization and machine learning has proved to be a revolutionary step in clustering. The cluster head selection, creation of optimized clusters and inter-cluster, and intra-cluster communication can be efficiently performed using optimization algorithms. Many optimization algorithms for instance Particle swarm (PSO) optimization[11], Grey wolf technique of (GWO) optimization[12], Genetic algorithm[13][14], Cuckoo search optimization[15], Chicken swarm optimization[16], Ant lion optimization[17][18]etc.

The multi-objective approach in optimization has not been inspected much in the whole clustering process and there are very little research and findings in this domain. In [19] and [20] authors used a multi-objective optimization approach to design efficient and optimized routes for reliable communication between nodes and BS. Thus, the multi-objective aspect for making both the optimal cluster head selection along with optimal path selection for routing in order to enhance the QoS and reliability of clustering in WSN and IoT networks is the source of motivation for this paper. The contributions to the paper are as follows:

- The combined problem of cluster head selection and route path selection is performed in an optimized way by considering 3 objectives simultaneously i.e., node energy, delay, and distance for selecting the cluster heads and for optimal routing a fitness function based on throughput, remaining energy, and link quality is optimized.

- The cluster head selection has been performed on large WSN using a multi-objective rider optimization algorithm to ensure efficient and reliable clustering. To ensure load balancing, the cluster heads are changed after certain iterations centered on the power, distance, and delay of the nodes in the network.

- The selection of route path for inter and intracluster communication has been performed by a multi-objective sailfish optimization algorithm. The route path keeps on changing as soon as any of the elite cluster heads is found dead or inactive. This function of SFO acts as a self-healing property for the proposed model.

- Both the approaches are combined and the enhancement in the performance of various QoS metrics is noted when compared with other pre-existing approaches.

The flow of the paper is sequentially explained in further sections. Section 2 consists of a brief review of the recent articles dealing with the application of optimization in the clustering of WSN/ IoT networks. Section 3 deals with defining the problem and gives the system model for the proposed approach. In Section 4, multi-objective rider optimization for cluster head selection and optimal path selection procedure based on sailfish optimization are described in detail. Section 5 gives the detailed working and algorithm of the proposed work. In Section 6, experimentation based on graphical and quantitative analysis is carried out for proposed work and other similar existing techniques. Section 7 gives a summary of the outcomes of the paper and concludes it by presenting a viable future scope.

2. RELATED WORK

Several studies have investigated cluster head selection in clustering and route path establishment. One of the basic techniques is low energy adaptive clustering (LEACH) hierarchy protocol that selects cluster heads temporarily depending on probability $\left(P_j(t)\right)$ at which a node 'j' is suitable to be a cluster head at round 'k' and is given by the following equation:

$$P_j(t) = \begin{cases} \dfrac{g}{N - g(k \bmod \frac{N}{g})}, & G_j(t) = 1 \\ 0, & G_j(t) = 0 \end{cases}$$

Where N is the quantity of nodes in the network, $G_j(t)$ is the term that tells whether a node 'j' is a cluster head or not. 'g'

RESEARCH ARTICLE

expresses the expected cluster heads for the present ongoing round. In [21], the authors proposed a variant of LEACH called LEACH for achieving efficiency in energy utilization in multi-hop wireless sensor networks (EEM-LEACH). This multi-hop scheme with low communication cost is established to inflate the lifetime of the WSN. The nodes that consume minimum energy and have high residual energy are declared as cluster heads. The nodes in the vicinity of the sink are able to communicate directly with the sink to mitigate the cost of communication. Miranda et al. [22] give an extensive comparison among 3 optimization approaches namely S-Metric Selection Evolutionary Multi-objective Optimization algorithm (SMS-EMOA), Non-dominated sorting genetic algorithm II (NSGA-II), and an evolutionary multi-objective genetic algorithm based on decomposition (MOEA/D) for cluster head selection problem. In [11] authors have used PSO in clustering so that all nodes can be covered and no individual node remains after clustering also it mitigates the overhead of the cluster head.

An optimized LEACH is proposed in [13] which uses a genetic algorithm to find an optimal route path to route data from source node to the sink node. Prasad et al. [23] proposed a differential evolution-based multi-objective PSO (MOPSO-DE) for efficient clustering in WSN. the cluster heads are chosen using differential evolution scheme based on genetic algorithm. The experimentation shows that the MOPSO-DE surpasses multi-objective particle swarm (MOPSO) optimization, PSO, and LEACH algorithms on grounds of average end-to-end delay, number of alive nodes, and packet delivery ratio. The literature [4], [5][24]–[36]presents various ways of selecting the cluster head in a cluster-oriented WSN. [19], [20], [37]–[46] propose path selection techniques using optimization approaches to achieve low energy consumption and low communication overhead. An attempt to achieve both clustering and routing using multi-objective approach is suggested in [47]. The proposed joint clustering and routing based on the genetic (GA) algorithm for multi-objective (CRMOGA) optimization mainly focuses on reducing the energy usage and amplifying the network lifetime. CRMOGA uses an evolutionary GA approach to form optimal clusters as well as to set up routing paths. It outperforms LEACH and a two-level approach for clustering called TLC.

In [35], the authors attempt to search for optimal route paths using PSO and tabu search methods called TabuPSO for a multi-hop clustered WSN application. Li et al. [48] propose an improved non-dominated sorting PSO (INSPSO) which uses multi-objective functions for making clusters and optimal route paths. Xu et al. [49] give an elaborated survey on various clustering methods used in WSN and 5G IoT applications. An efficient emergency message delivering technique based on clustering of dense vehicular networks is proposed in[50]. The method uses two MAC broadcasts protocols for reliable transmission of emergency messages. It compares three routing protocols that use the IEEE standards 802.11p and 802.11 and models for mobility. The results for proposed method against clustering algorithm based on direction for data dissemination in vehicular (DBCADD) networks method [51] are compared on the basis of broadcast time, delay, throughput, message delivery ratio, and overhead. Table 1 gives recent works in the field of clustering in which the cluster head selection and optimal path establishment have been done using various metaheuristic multi-objective optimization approaches. The issues are identified and the advantages are described in the table. Some multi-objective approaches aim to reduce energy requirement, some reduce network latency. Our proposed method is efficient in optimizing energy expenditure, throughput, link quality, delay, distance and enhances packet delivery ratio and network life. Thus, the proposed approach claims to overcome the drawbacks of the above-mentioned works.

Literature	Technique used	Advantages	Limitations
Hoang et al.[52]	Harmony search algorithm-based clustering	Lifespan improvement and suitable for real-world experiments	Adaptive coefficient in fitness function creates temporary clustering
Ahmed et al.[53]	Multi-objective whale optimization algorithm (MOWOA)	Good for prolonging network life of large-scale WSN & lowering the energy consumption.	Depends only on the sink node positions which are sometimes unable to cover the whole network area and may increase the cost of the network
Mehta et al.[54]	Multi-objective sailfish optimization, proposed method is termed as Multi-objective Cluster	Optimizes energy, cost, distance, and coverage while selecting cluster head and route path.	Not very much suitable for large WSNs. Also, with a large count in rounds the quantity of dead nodes increases.

RESEARCH ARTICLE

	Head based Energy-aware Optimized (MCH-EOR) Routing		
Preeth et al.[39]	Adaptive fuzzy multi-criteria decision-making approach+ Immune-inspired optimization	Almost all QoS parameters are improved	Efficient inter-cluster communication is not focused, and is not suitable for more BS.
Hacioglu et al.[55]	Non- dominated sorting genetic (NSGA-II) algorithm-II	High accuracy	High computational cost and not good for multi-hop routing.
Gupta et al.[15]	Cuckoo search + Harmony search algorithms	Efficient routing and cluster head distribution enhances alive nodes and mitigates energy depletion.	Cannot handle faulty nodes, delay is more.
Elhabyan et al.[56]	NSGA-II + Speed-constrained multi-objective particle swarm (SMPSO) optimization	Reduces average energy expenditure per node, low execution time, and high throughput.	Cannot address network interference issue because nodes transmit data at high power.
Yogarajan et al.[17]	Ant Lion optimization	Reduces individual node creation.	Not suitable for heterogeneous WSNs.
Sert et al.[57]	Multi-objective fuzzy clustering (MOFCA) algorithm	The more total remaining energy, a high number of half node alive and first node dies with increase in rounds.	Not suitable for varying node locations (mobile nodes).
Kaswan et al.[58]	Multi-objective particle swarm (MOPSO) optimization	Well planned path design for routing, good network life, and low standard deviation as compared to other approaches	Multiple mobile sink problems.

Table 1 Multi-Objective Optimization Approaches for Clustering and Route Selection in WSN and IoT Applications

3. PROBLEM DESCRIPTION AND SYSTEM MODEL

3.1. Problem Formulation

The clustering and routing issues when addressed simultaneously may show a degrading influence on the performance of QoS parameters like delay, throughput, etc. since these two issues cannot be efficiently solved using traditional algorithms. Moreover, the nodes in a sensor network or IoT network have limited energy sources which makes them function in a time constraint manner. So, a model which can work with energy, time, cost, and other QoS constraints is very essential for dense WSN for its high performance.

The proposed method takes the multi-objective paradigm of the optimization approach into consideration to combat these problems. Below written points are the goals of the proposed work:

- Three objectives to maximize the throughput and network life while minimizing the energy usage per node and end-to-end delay in network are simultaneously achieved.

RESEARCH ARTICLE

- Efficient clustering and the choice of cluster head to avoid residual energy node problems. The clustering works efficiently till the energy of the nodes gets depleted completely thereby making energy usage to its fullest.

- Ensuring reliable data transmission using the link quality of the links for data transmission between the cluster heads.

3.2. System Model

The proposed model considers a sensor network just like the one which is depicted in figure 2 with 'Y' number of sensor nodes, 'm' cluster heads (AN), and a base station. The locations of each node are determined by the global positioning (GPS) system. The GPS collects the latitude and longitude of the node and calculates the distance. This paper adopts the Haversine distance method given in [59] to find the distance of each node from the base station (BS). Every node has a unique identification (ID) and the ID for BS is 0.
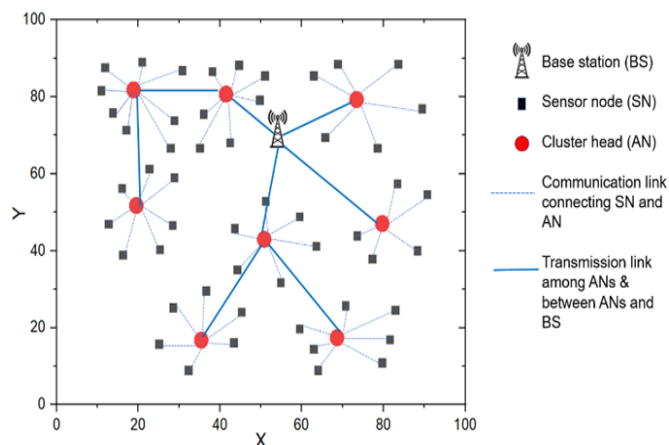

Figure 2 A Clustered WSN with Cluster Heads and a Base Station

The following assumptions are taken into consideration while proceeding with the proposed algorithm:

- The number of BS is set to 1 since the network has only one BS.

- All cluster members are in the transmission range of the cluster head of the corresponding cluster.

- Each cluster head has its communication range such that other neighboring cluster heads come in its range.

- All cluster members send the information to their corresponding cluster heads in every iteration.

- Only cluster heads are allowed to communicate with the base station and other nodes cannot directly send data to the BS.

- The nodes are assumed to be mobile and the locations of cluster heads are updated with every iteration.

The energy dissipation at both transmitter and the receiver [60]follows the multi-path fading model. The energy dissipation for sending 'b' bits if packet when distance 'd' between the source (sender) and the sink (receiver) is less than threshold 'th' is given as:

$$E_s = b * (E_{el} + E_{free} * d^2)$$

And when 'd' signifies a value greater or equal to the threshold 'th' then the energy for sender node 'E_s' is given by:

$$E_s = b * (E_{el} + E_{mfad} * d^4)$$

Where 'E_{free}' is energy consumption for free space, 'E_{el}' energy for electronic circuit simulation, 'E_{mfad}' is the energy spent in multipath fading. The threshold 'th' is given by:

$$th = \sqrt{\frac{E_{free}}{E_{mfad}}}$$

The energy utilized for receiving 'b' bits of packet is given by:

$$E_r = b * E_{el}$$

Each cluster head spends energy which is given by:

$$E_{AN} = E_{ANagg} * b * n$$

Where 'n' is the number of messages and 'E_{ANagg}' is the energy spent for collecting a bit of packet.

4. CLUSTER HEAD AND OPTIMAL PATH SELECTION MODEL

This section manifests a detailed description of both the approaches i.e., rider optimization and sailfish optimization along with the usage of a multi-objective framework to select cluster head during the clustering process and selecting optimal path during the routing process.

4.1. Multi-Objective Rider Optimization (MROA) for Selecting Cluster Head

Binu et al. [61] proposed a novel rider optimization algorithm (ROA) in 2019 which was employed for finding faults in the analog circuitry. In order to solve various issues related to energy consumption, delay, etc. the sensor network in an IoT-enabled WSN must opt for optimization methods to choose the cluster heads carefully and efficiently while clustering the nodes. There have been many approaches modeled for this purpose. One of the latest and highly convergent approaches is the rider optimization approach for cluster head selection. This algorithm uses groups of riders (nodes) that aim to reach a target location and become a winner. There are 4 groups in

RESEARCH ARTICLE

this approach namely Bypass rider, follower, attacker, and overtaker. The follower axially follows the leader's position, bypass rider tries to bypass the leader's path to achieve the target, the attacker uses its high speed and searches fast to occupy the position of the leader for attaining target and the overtaker traces the locations in rider's proximity to get to the target thereby achieving faster convergence.

It considers 3 objectives to find the best fitness for evaluating the success rate as well as for updating the locations of bypass rider, follower, overtaker, and attacker in the method. The clusters in the network tend to change and the fittest node among them is chosen to be the cluster head (AN) based on the objective functions and the rider optimization output. Therefore, a multi-objective strategy is used with ROA in which the cluster heads are picked on the basis of fitness values based on the energy, delay, and distance between the nodes. Figure 3 depicts the node representation for AN selection using the multi-objective rider optimization method.

Furthermore, the important factors for a rider to get to the target are steering, proper use of accelerator, gears, and brake. The rider varies its position with time to attain the target location using these factors. Depending on the success rate, the rider repeats the whole process until it attains the maximum time 'qi_{off}' after which the rider reaching the target is announced as a winner also called a cluster head in the WSN. Figure 4 represents the flowchart of the MROA for cluster head selection. A multi-objective optimization approach with three objectives is considered to evaluate the fitness of riders in ROA. These objectives are energy consumption of nodes, delay, and distance among sensor nodes, cluster heads, and base station.

The reason behind taking these three objectives is that during clustering energy of the node is a very significant factor. After multiple transmission of data packets, the energy of nodes reduces with time in that case the clustering can be made efficient by considering the cluster members of low energy level and a cluster head possessing higher energy among other nodes. The transmission of packets is governed by the time it takes to get delivered from one node to another and the more optimal the distance is between the nodes the lesser will be the delay in the network during transmission. Equations (1) to (4) display energy consumption, $OF_{energy}(x)$ is the energy for nodes in a cluster except maximum energy node and $OF_{energy}(y)$ is the energy of node with maximum energy. 'X' signifies total nodes in one cluster, r denotes a constant ranging between 0 and 1. $E(SN_k)$ represents the energy of kth node and $E(AN_l)$ symbolizes the energy of lth cluster head (AN).

$$OF_{energy} = \frac{OF_{energy}(x)}{OF_{energy}(y)} \tag{1}$$

$$OF_{energy}(x) = \sum_{l=1}^{X} rE(l) \tag{2}$$

Where

$$rE(l) = \sum_{k=1; k \in l}^{X}(1 - E(SN_k) * E(AN_l)) \; ; 1 \leq l \leq X \tag{3}$$

In equation (3) the iteration occurs through all nodes except 'AN' with 'k' ranging from 1 to X. the energy in equation (4) is considered as maximum energy for k^{th} node.

$$OF_{energy}(y) = X * \max_{k=1}^{X}\left(E(SN_k) * \max_{l=1}^{X} E(AN_l)\right) \tag{4}$$

In the equation (5), OF_{delay} lies in interval [0,1] and is the ratio of 'AN' in WSN to the total number of sensor nodes (Y). The delay should be minimum which can be attained by lowering the quantity of nodes in a cluster.

$$OF_{delay} = \frac{\max_{l=1}^{X}(AN_l)}{Y} \tag{5}$$

Equation (6) represents the distance model, $OF_{distance}(x)$ represents distance among AN to BS and sensor nodes to AN. This distance lies in the range of interval [0,1]. $OF_{distance}(y)$ is the distance between two sensor nodes.

$$OF_{distance} = \frac{OF_{distance}(x)}{OF_{distance}(y)} \tag{6}$$

$$OF_{distance}(x) = \sum_{k=1}^{Y}\sum_{l=1}^{X}\|SN_k - AN_l\| + \|AN_l - BS\| \tag{7}$$

$$OF_{distance}(y) = \sum_{k=1}^{Y}\sum_{l=1}^{X}\|SN_k - SN_l\| \tag{8}$$

In equation (1), OF_{energy} is the objective function for energy and is defined by equations (1) to (4). The aim is to select maximum energy nodes so that they act as AN in the network and also the delay and distance should be made minimum to ensure fast data transmission. Equation (9) shows the relation between the objective functions for energy, delay, and distance. The fitness value calculated in equation (9) should be maximum to ensure the best solution.

$$\text{Fitness value for AN selection} = \text{Max (OF)} = OF_{energy} + \frac{\lambda}{OF_{distance}} + \frac{(1-\gamma)}{OF_{delay}} \tag{9}$$

Here, λ and γ are constants. The experimentation shows that to achieve maximum value of the fitness function both values should be taken less than 1. Here, 0.3 and 0.9 are chosen for λ and γ respectively which gives the best results as compared to other values.

The group of riders is initialized using equation (10)

$$R^{qi} = \{R^{qi}(u,v)\}; 1 \leq u \leq A; 1 \leq v \leq B \tag{10}$$

$R^{qi}(u,v)$ signifies the position of uth rider in v^{th} size at qi^{th} time instant. 'A' is the count of riders. 'B' is the number of coordinates or dimension.
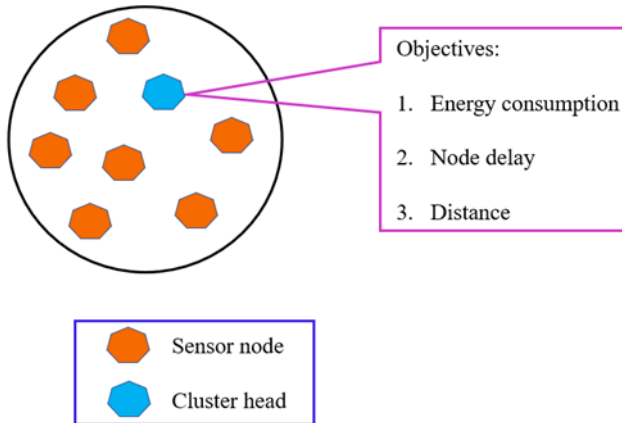
RESEARCH ARTICLE

Figure 3 Node Representation for a Selection Using Multi-Objective Rider Optimization Method

The success rate is represented in equation (11) where R_u is the position of uth rider and qi_t symbolizes target location. The success rate is determined by making reciprocal of the distance between the riders (nodes) which is taken as a fitness value from one of the objective functions expressed in equation (6). The distance is made minimum and thus the success rate can be maximized.

$$SR = \frac{1}{\|R_u - qi_t\|} \qquad (11)$$

The count of riders' 'A' is expressed as:

$$A = BPi + FOi + OTi + ATi + RB \qquad (12)$$

Where BPi is the bypass rider, FOi is the follower, OTi represents overtaker, ATi signifies attacker and RB is the rag bull rider. The steering, location, and vehicle coordinate for u^{th} rider is denoted as $\theta i_{(u,v)}^{qi+1}$, ϕ_u and χ respectively. As described earlier the major factors of vehicle[43] for u^{th} rider are brake br_u, accelerator ac_u, and gear G_u. The value for gear lies between 0 and 4 while that for the accelerator and brake lies between 0 and 1.
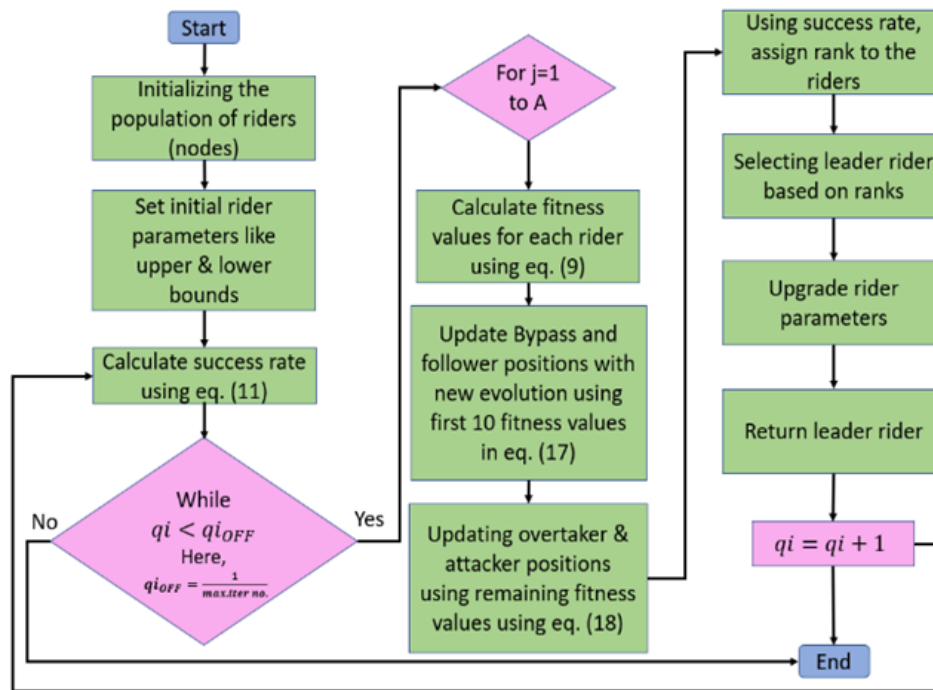

Figure 4 Flow Chart for MROA

Once the initialization of the rider and its parameters is done, the success rate value is used in each iteration to update all riders to establish the leader rider or optimal rider which has the highest value of success rate among other riders and is in close proximity to the target. The contribution of the attacker is to locally convergence the algorithm whereas global convergence can be achieved using the directional indicator while updating the overtaker position. In the arbitrary search, the follower uses the multi-directional space for searching the position. Initially, the bypass rider ignores the leader's path and follows a normal route, then the group's position is updated using equation (13). Here β and ω are the arbitrary numbers ranging from 0 to 1 of size 1×B. 'q' and 'a'

RESEARCH ARTICLE

represent a random number between 1 to A. To get the target, it is important to update the bypass rider's location.

$$R_{qi+1}^{BPi}(u, v) = \beta \left[R^{qi}(q, v) * \omega(v) + R^{qi}(a, v) * [1 - \omega(v)] \right]$$
(13)

Based on the leading rider position, the follower location is updated which is expressed in equation (14). R^{Pi} indicates the location of the leader rider, 'Pi' symbolizes the index of the leader rider, $\theta i_{u,v}^{qi+1}$ represents the steering angle for u^{th} rider in b^{th} coordinate, and $g i_u^{qi}$ specifies the distance required for u^{th} rider to cover. $g i_u^{qi}$ can be evaluated by multiplying the rate and velocity of the off-time for the rider.

$$R_{qi+1}^{FOi}(u, b) = R^{Pi}(Pi, b) + \left[\cos\left(\theta i_{u,b}^{qi+1} * R^{Pi}(Pi, b) * g i_u^{qi}\right) \right]$$
(14)

Equation (15) represents the position update of the overtaker which is responsible to promote the success rate. Here, $Di_{qi}^{li}(u)$ symbolizes the directional indicator.

$$R_{qi+1}^{OTi}(u, b) = R_{qi}(u, b) + \left[Di_{qi}^{li}(u) * R^{Pi}(Pi, b) \right]$$
(15)

The attacker seeks to grab the leader's place by following the update process of the leader which is expressed in equation (16).

$$R_{qi+1}^{ATi}(u, v) = R^{Pi}(Pi, b) + \left[\cos\left(\theta i_{u,v}^{qi+1}\right) * R^{Pi}(Pi, v) \right] + g i_u^{qi}$$
(16)

Equations (9) gives the fitness value which is used to update the positions of bypass rider, follower, overtaker, and attacker using equations (13) to (16) respectively. For example, if there are 20 fitness values then first 10 are used to update the bypass rider and follower's position, and the next 10 values are used to update the overtaker and attacker positions as shown in the below equations (17) and (18).

$$R_{qi+1} = \frac{R_{qi+1}^{BPi} + R_{qi+1}^{FOi}}{2}$$
(17)

$$R_{qi+1} = \frac{R_{qi+1}^{OTi} + R_{qi+1}^{ATi}}{2}$$
(18)

4.2. Multi-Objective Sailfish Optimization (MSFO) for Route Selection and Data Transmission

Shadravan et al. [62]proposed a metaheuristic population-based approach called sailfish optimization (SFO) in 2019 for solving engineering problems with constraints like truss, beam, gear design problems, and many more. It is a novel optimization approach that mimics the hunting strategy of sailfish. The sailfish has a bill in the front consisting of small teeth this helps it in injuring and then capturing the sardines swimming in a school. The steps in SFO approach are listed below:

Step 1 Initialization: The search space consists of the position of sailfishes which are scattered randomly in one, two, or hyperdimensional space. The school of sardines helps to update the best position of the sailfish. When a sardine is injured, its position is taken by a sailfish thereby upgrading the old position and obtaining a better solution.

Step 2 Elitism: The selection of elite sailfishes avoids the risk of losing good solutions. In this step, the fittest solution of sailfish is kept reserved in every iteration and is called "elite". These elite sailfish are responsible to injure the sardines and the injured sardine position is considered to be the best target for hunting. Both the elite sailfish position and injured sardine position are called in this step.

Step 3 Alternate attack strategy: The sailfish hunt in a group by encircling the prey school. Either a sailfish attacks with respect to an elite sailfish and updates its position substituting the injured sardine or it occupies any empty position while encircling the prey. The attacks are coordinated temporally such that one sailfish attack at one time thereby enhancing the success rate. However, there are also more chances for sardines to escape the sailfish attacks because the energy and speed of sailfish reduce with time.

Step 4 Hunting: The sailfish bills help them to injure the sardine school by removing their scales and tissues. The speed of motion of sailfish is quite high and they hunt their prey by slashing their rostrum. With time more and more sardines get injured which affects their speed and maneuverability which ultimately makes them an easy target to capture for sailfish. It is observed that the capture success rate is in a positive correlation with the number of injuries caused to the sardine school.

Step 5 Catching: With frequent attacks of sailfish, the energy and maneuverability of the prey reduce. Eventually, the sardines will get more vulnerable to be attacked by sailfish's bill and can be captured easily and quickly. When sardines become more suitable than their corresponding sailfish, the sailfish substitutes their position with the position of wounded sardine, this enhances the possibility of catching new sardines.

The search space of SFO contains the position of sailfish and sardines as variables in a matrix. In this paper, we consider 2-dimensional search space where j^{th} cluster head or aggregator node 'AN' in the path 'l' has position $AN_{jl} \in \Re (j = 1,2, \dots m)$

$$AN_{pos} = \begin{bmatrix} AN_{1,1} & AN_{1,2} & \cdots & AN_{1,m} \\ AN_{2,1} & AN_{2,2} & \cdots & AN_{2,m} \\ \vdots & \vdots & \vdots & \vdots \\ AN_{d,1} & AN_{d,2} & \cdots & AN_{d,m} \end{bmatrix}$$
(19)

Where 'm' represents number of cluster heads (AN), 'd' is the number of paths and $AN_{j,i}$ is the dimension of jth cluster head. The fitness function for finding fitness of AN in every path

keeping 3 objectives in consideration i.e., throughput (Th), link quality (LQ), and energy of nodes is calculated as:

Fitness value of AN = f(AN)   (20)

$$Th = \sum_{j=1}^{m} AN_j \left[V_{AN_j} \left(P_{AN_j}, P_{BS} \right) \right] \text{ bits/sec} \qquad (21)$$

Equation (21) gives the throughput equation in which data transmission speed of AN location of AN and location of BS. Here, in a particular path, the energy of each cluster head is evaluated instead of calculating the energy exhibited by the nodes. The link quality is calculated in terms of the received signal strength (RSS) of the neighbor cluster head. Table 2 gives the benchmark of link quality with respect to the value of RSS.

Link quality	Range of RSS
Excellent	< -10dBm
Acceptable	< -20dBm
Poor	< -40dBm
Very poor	< -60dBm

Table 2 Link Quality Selection Based on a Range of RSS

The fitness for every AN in each path of the network can be shown in the following matrix:

$$AN_{fit} = \begin{bmatrix} f(AN_{1,1} & AN_{1,2} & \cdots & AN_{1,m}) \\ f(AN_{2,1} & AN_{2,2} & \cdots & AN_{2,m}) \\ \vdots & \vdots & \vdots & \vdots \\ f(AN_{d,1} & AN_{d,2} & \cdots & AN_{d,m}) \end{bmatrix} \qquad (22)$$

The fitness value for AN is given by:

$$f(AN) = x_1 \times Th + x_2 \times E_{rem} + x_3 \times LQ \qquad (23)$$

'x' is the weight factor that ranges between 0 & 1. To select the best path, the best neighbor cluster head AN_{elite}^j has to be identified with the best fitness value and is updated with other cluster head's position $P_{AN_{old}}^j$.

$$P_{best} = AN_{elite}^j - \alpha_j \times \left[rnd \times \left(\frac{AN_{elite}^j + P_{BS}}{2} \right) + P_{AN_{old}}^j \right] \qquad (24)$$

In equation (24), AN_{elite}^j is the newly found AN position. $P_{AN_{old}}^j$ is the previous AN position and 'rnd' represents a random number lying between 0 & 1, α_j is the coefficient of jth iteration and is given by the equation (25).

$$\alpha_j = 2 \times rnd \times D_p \qquad (25)$$

D_p is the density of path in the network which is defined by equation (26)

$$D_p = \frac{N_{AN}}{N_{AN} + N_{BS}} = \frac{N_{AN}}{N_{AN} + 1} \qquad (26)$$

N_{AN} is the number of cluster heads and the base station is one so the quantity for the base station (N_{BS}) is taken as 1. Once the best path is searched by SFO, the data communication starts. During the transmission, the cluster heads may become dead or inactive due to energy consumption. The inactive nodes are removed from the transmission paths and some other path is selected to promote the mitigation in the end-to-end delay.

$$R_{alt} = NewP_{best} \text{ if } E_{rem} = (AN_j) < \min\_Th \qquad (27)$$

The new alternate path among the available paths is found using equation (24) with the threshold (Th) condition in equation (27). Here, $\min\_Th = E_{req}(AN_j, AN_i)$ and $E_{req}(AN_j, AN_i)$ represents the energy required for transmitting the information from the present cluster head (AN_j) to the next cluster head (AN_i). Figure 5 shows how the path is selected using AN_{elite} and by removing dead ANs.
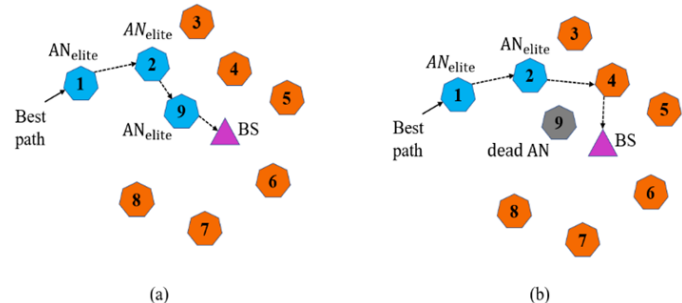

Figure 5 Optimal Path Selection Using MSFO

5. PROPOSED WORKFLOW

Generally, the WSN in the IoT framework is modeled as a clustered network with clusters of different node density and each cluster has its own cluster head that works as a coordinator. These coordinators collect data from all sensor nodes and finally send their information to the base station. The selection of the coordinator node is very critical and must be done in an organized manner because the wrongly selected coordinator or aggregator may lead to the inefficient working of the network resulting in various issues.

In our model, the choice of cluster heads is done by the rider optimization algorithm (ROA) and the route selection for data transmission is performed using sailfish optimization (SFO). Figure 6 demonstrates the block diagram explaining the full model proposed in this paper. The algorithm for the proposed combined clustering and routing model using multi-objective optimization is written below. The algorithm shows the flow of how both approaches are used for accomplishing two different tasks. Initially, the population of nodes is taken as rider count. The success rates are evaluated and

RESEARCH ARTICLE

simultaneously the fitness function based on the three objectives described in the section for each rider is also calculated. Now the process is started till the stopping criteria are achieved. The locations of bypass rider, overtaker, follower, and attacker are updated on the basis of the fitness function values and the ranking is given to the riders based on the rates of success. The highest-ranked rider becomes the leader rider. These leader riders are chosen in every iteration for left out nodes and the clusters are also formed based on the distance objective. The collection of all cluster heads is taken as the input to the sailfish optimizer where the optimal path is searched among the cluster heads also called AN_{elite}

which are responsible to lead the data further to the base station. Here, the path is established depending on the value of energy of node, throughput, and link quality depending on RSS values. The path which is in charge of the data transmission directs from the source to the destination node. If any AN_{elite} fails due to energy depletion, an alternate AN_{elite} is searched and is included in the existing route thereby saving time for the algorithm. The proposed model works effectively for multi-dimensional data (search space). The proposed multi-objective optimization-based clustering and routing algorithm is shown in algorithm 1.
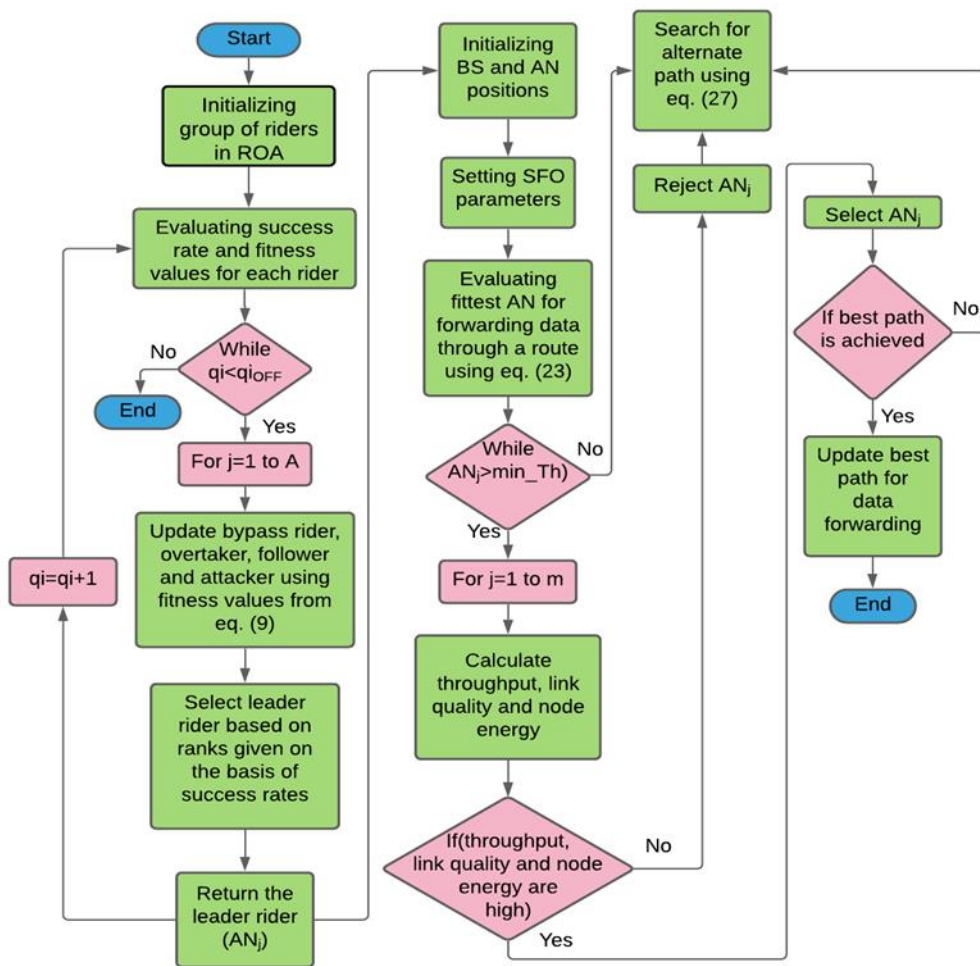

Figure 6 Flow Schema for the Proposed Model

BEGIN

(A) Selection of 'AN' using Rider optimization algorithm (ROA)

Input: Random rider positions

Output: Leader rider or cluster head

Initializing the population & rider parameters like brake (br_u), accelerator (ac_u) etc.

RESEARCH ARTICLE

Evaluate success rate (SR)

While $qi < qi_{OFF}$

Evaluate the fitness values using eq. (9)

For i=1 to A

Updating follower & bypass rider locations using the first 10 best fitness values in eq. (17)

Updating overtaker & attacker locations using remaining 10 fitness values in eq. (18)

Ranking of riders from 'SR' values using eq. (11)

Selecting a leader rider with maximum 'SR' value.

Update rider parameters

Return leader rider as cluster head (AN)

qi=qi+1

End For

End While

(B) Route path selection using Sailfish optimization algorithm (SFO)

Input: Number of all feasible routes from all clusters including selected 'ANs' to BS

Output: Optimized route from source to BS

Considering ANs positions from ROA & a fixed BS position

Initialize SFO parameters

Evaluate the fitness of each AN to become a data forwarder on route to BS

While $(AN_j) > min\_Th$

For j=1 to m

Evaluate throughput, link quality (LQ), and node energy of AN_j

If (throughput is high && node energy is high && LQ is good) **then**

Select AN_j as AN_{elite} for data forwarding

Else

reject AN_j

End If

End For

If (best path is achieved) **then**

Update that path as a route to BS

Else If (any AN_{elite} become dead or exhausted of   energy in the selected path) **then**

Search for alternate path by employing eq. (27)

RESEARCH ARTICLE

End If

End If

End While

Return best optimal route to BS

END

Algorithm 1 The Proposed Multi-Objective Optimization-Based Clustering and Routing Algorithm

6. RESULTS AND COMPARATIVE ANALYSIS

The proposed model has been tested on MATLAB software for dense WSN scenarios. It is validated on grounds of energy consumption, throughput, delay, network life, etc. with some existing techniques CRMOGA[47], MOPSO-DE[23], INSPSO, [48] and EEM-LEACH[21]. The parameters used during the implementation of the proposed approach are specified in table 3. The execution time of the proposed work has been compared with other methods in table 4. The running time for the proposed technique is less among other methods but it increases with the increment in the count of nodes. EEM-LEACH records the highest execution time and CRMOGA performs better than other approaches except for the proposed method. Table 7 gives a comparison on the basis of various features for the existing methods discussed in the results and the proposed method.

Network Parameters	
Network area	200 m X 200 m
Number of Nodes	500 (dense network)
Clusters	Variable
Packet size	5000 bits
Maximum rounds	5000
Initial node energy	2 J
BS position	(40,60)
E_{el}	5 nJ/bit
E_{free}	10 pJ/bit/m^2
E_{mfad}	0.0013 pJ/bit/m^4
E_{ANagg}	5 nJ/bit/signal
Communication radius	2 m
Cluster radius	15 m

Mobility	Random waypoint
ROA parameters	
Rider count (A)/ number of populations	500
Number of gears (G_u)	5
Maximum iterations	5000
SFO parameters	
Rate between sardines and sailfish (N_sail=N_sar * population)	0.25
A (coefficient to decrease attack power)	5
ε (coefficient to decrease attack power)	0.001

Table 3 Parameters Along with their Values Used During the Simulation

Network size	Proposed method	[47]	[48]	[23]	[21]
200	17.4	21.2	38.7	49.5	64.9
400	30.2	43.6	51.8	74.1	106.3
600	53.7	87.3	97.4	154.9	184.7
800	98.3	151.9	145.6	207.4	218.2
1000	130.8	198.5	190.3	257.6	305.1

Table 4 Running Time (in seconds) for Various Multi-Objective Methods and Proposed Method

6.1. Energy Consumption

The energy utilized by a node in a network is given by:

$$E_c = \left[\sum_{m=1} AN_E(m) + \sum_{A=1} u_E(A) \right]$$

RESEARCH ARTICLE

AN_E symbolizes the energy of cluster heads, u_E denotes energy of riders or sensor nodes, m expresses the number of cluster heads and A specifies quantity of sensor nodes. Figure 7 shows the energy consumption per node measured in millijoule (mJ). The energy consumption is recorded highest for EEM-LEACH as this approach does not exhibit any optimization mechanism for optimal selection of clusters and routes. The proposed method indicates an increase of energy consumption of 100 to 500 nodes by 0.509 mJ. The percentage increase in energy usage for CRMOGA, INSPSO, MOPSO-DE, and EEM-LEACH as compared to the proposed approach is 27.2%, 38.8%, 42.4%, and 45.9% respectively.
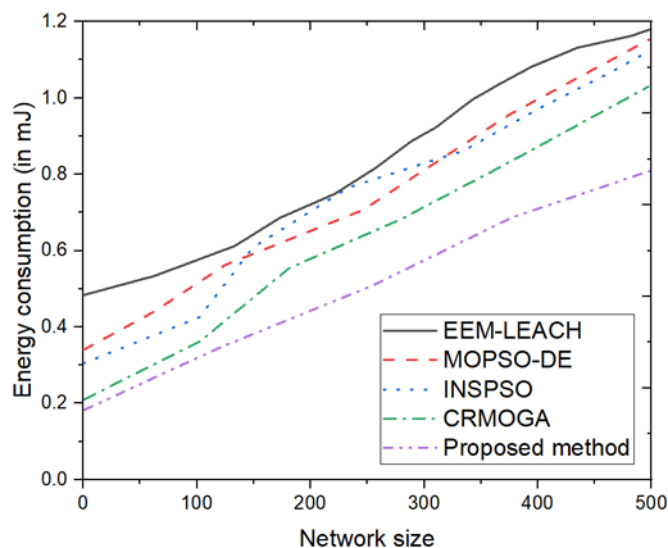

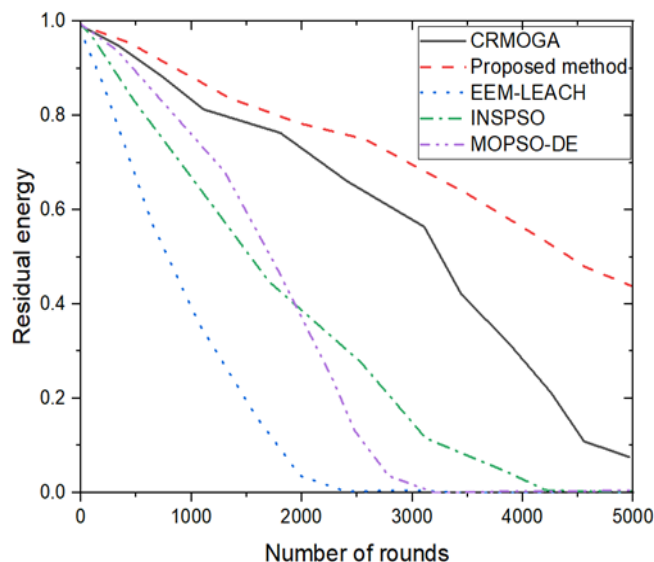Figure 7 Energy Consumption Versus Number of Nodes Evaluated in Millijoule

Figure 8 Residual Energy Left with Number of Rounds

Figure 8 depicts the residual energy in mJ with each round of simulation. It decreases slowly as the iteration count enhances in each round the cluster head selection and optimal path is chosen and the node position also changes with respect to the optimized clustering. The residual energy remains 0.437 mJ at 5000th round for the proposed method which is high in contrast with the other 4 methods. The multi-objective technique for both clustering and route selection in the proposed approach makes it possible to prevent energy depletion in the nodes. The simulation shows that for the residual energy goes low or near to zero after 4205, 3212, and 2400 rounds for INSPSO, MOPSO-DE, and EEM-LEACH respectively. For CRMOGA the value of residual energy continues to be greater than zero and is noted to be 0.0752 mJ even at 5000th round.

6.2. Throughput

Throughput indicates the rate at which data is successfully sent to the base station and is given by:

$$\text{Throughput} = \frac{\text{packets delivered} * \text{size of packet}}{\text{time taken in delivering the packets}}$$

A higher value is desirable for throughput. The throughput analysis has been done in figure 9 which shows the throughput for proposed method and the 4 pre-existing similar methods with increase in rounds. There is a 2% increase in the throughput of proposed method when compared to its immediate rival method CRMOGA. The graph reveals that the EEM-LEACH has the lowest throughput due to the congestion caused by the individual nodes which are not included in the clusters. This problem has been solved in the proposed method by applying objective functions for various factors like energy, distance link quality, etc. The throughput increases by 8%, 29%, and 47.3% for proposed scheme as compared to INSPSO, MOPSO-DE, and EEM-LEACH respectively for 5000 rounds.
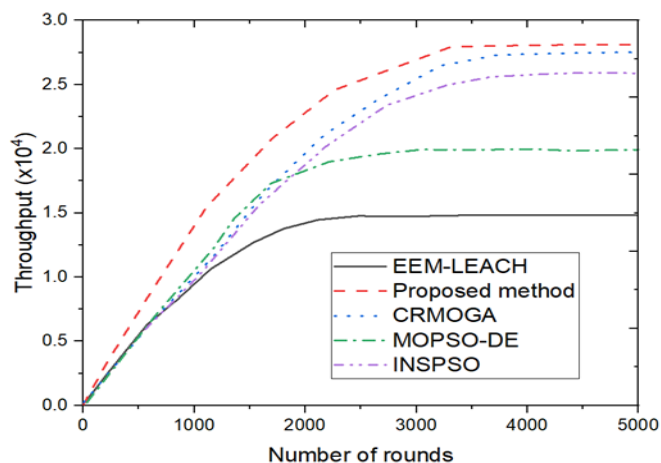

Figure 9 Throughput Value with Increase in the Number of Rounds

RESEARCH ARTICLE

6.3. Number of Alive Nodes

This parameter depends on the residual/remaining energy of nodes. When the nodes exhibit high energy value for data transmission and other tasks then the value of alive is more to ensure more network lifespan i.e.,

$$A_{alive}^{j} = E_{rem}^{j}(n) > 0$$

Where $E_{rem}^{j}(n)$ is the energy remaining by the node in jth round, 'A' is the total nodes in the network i.e., 500. Figure 10 gives the alive node count with the number of rounds for four approaches and the proposed method. Nearly 14% of nodes are sustained after 5000th rounds in case of the proposed method making it a more reliable and higher lifetime possessing method. The count of alive nodes drops to nearly zero at 4800th, 3737th, and 3448th rounds for INSPSO, MOPSO-DE, and EEM-LEACH protocols. The CRMOGA performs better after the proposed model and records 6% of alive nodes even after 5000 rounds.
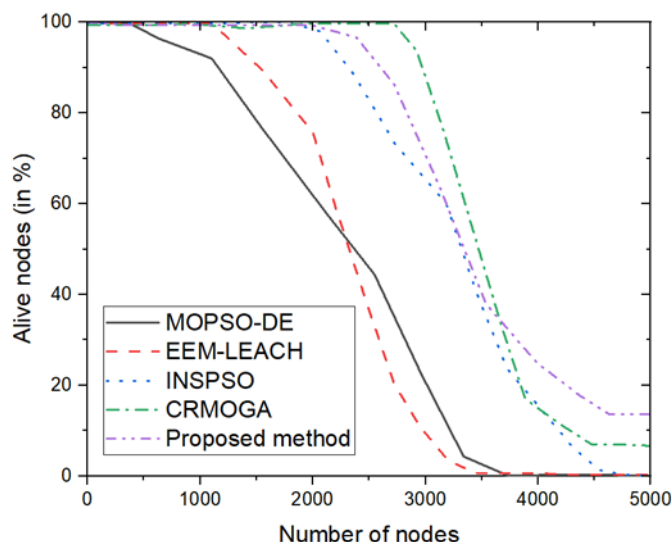

Figure 10 Number of Alive Nodes Versus Number of Nodes

6.4. Network Lifetime (Netlife)

Network lifetime basically gives the count number for the rounds for which the network performs its task without depleting the energy of nodes. The high value of network lifetime is desirable. It is given by:

$$Netlife = \min_{j}\left[\frac{\sum_{i=1} Co_{ij} * T_{i}}{S_{j}}\right]$$

Where Co_{ij} signifies coverage matrix with value 1, when a sensor node identifies the target, otherwise, it possesses value 0. S_{j} gives the number of nodes in a coverage area. T_{i} is the life of the ith node and is given by the ratio of sensor node's initial energy to rate of expenditure of energy by the sensor

node. In figure 11 the graphical representation for network lifespan evaluates the life of the network for each method against the count of nodes in the network in terms of number of rounds. The bar graph is the plot of table 5 and shows the superiority of the proposed method over other methods in case of network lifetime. The network life is achieved highest in case of proposed model i.e., 1200 rounds even for a dense network with 500 nodes whereas the other protocols have the lifetime less than 1000 rounds for 500 nodes.

Network size	Proposed method	[47]	[48]	[23]	[21]
100	1700	1550	1480	1499	1430
200	1601	1430	1390	1360	1305
300	1540	1280	1220	1050	1000
400	1370	1070	1100	950	870
500	1200	900	850	800	750

Table 5 Network Life Time in Rounds for Proposed Method and Four Other Similar Methods
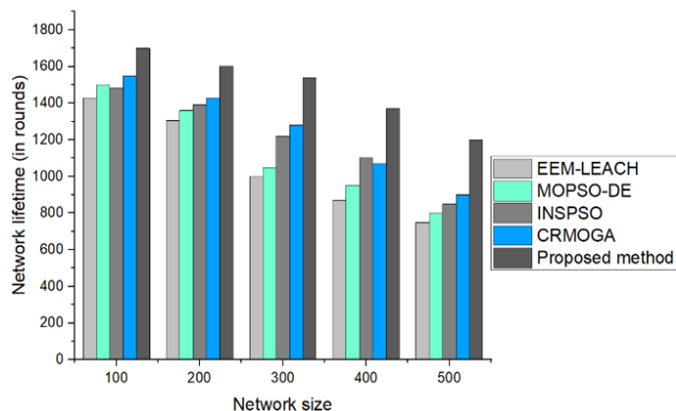

Figure 11 Comparison of Network Life for Various Approaches against the Increase in the Size of the Network

6.5. Packet Delivery Ratio (PDR)

It represents the ratio of total packets received by BS to the number of packets sent by all nodes. It is generally measured in percentage and the high value of PDR is considered best. The packet delivery ratio for the proposed method is high since the throughput for it is also large. Figure 12 shows a graphical comparison for PDR among different clustering and routing techniques employing multi-objective optimization. The highest PDR is attained by the proposed method for 100 nodes. It gives a low decrease of PDR i.e., 0.269 when the nodes increase from 100 to 500. The percentage increase in PDR for proposed methodology is by 6%, 27%, 22%, and

RESEARCH ARTICLE

60% when compared to other four methods that are CRMOGA, INSPSO, MOPSO-DE, and EEM-LEACH. It can be clearly noticed that MOPSO-DE outperforms INSPSO method because of the differential evolution method which is implemented in the MOPSO-DE method for selecting optimal cluster heads.
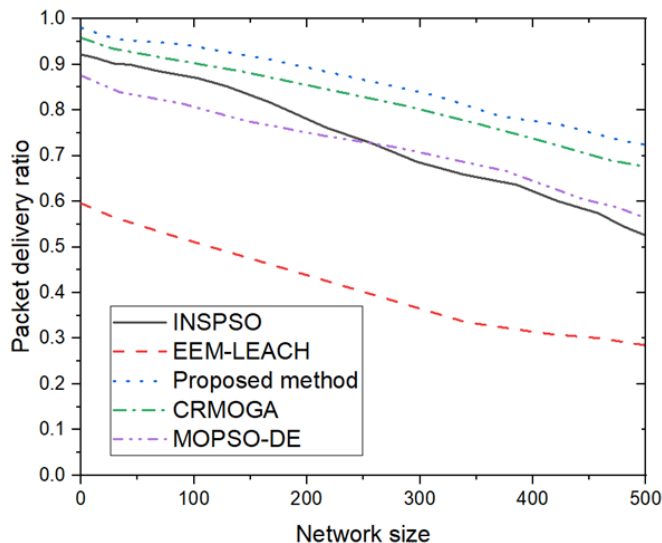

Figure 12 Packet Delivery Ratio versus the Size of Network

6.6. End-to-End Delay

Network size	Proposed method	[47]	[48]	[23]	[21]
100	0.001	0.001	0.001	0.004	0.01
200	0.001	0.002	0.003	0.01	0.03
300	0.002	0.01	0.01	0.015	0.05
400	0.01	0.015	0.03	0.04	0.065
500	0.03	0.05	0.06	0.075	0.08

Table 6 Average End-to-End Delay in Case of Proposed Method, CRMOGA, INSPSO, MOPSO-DE and EEM-LEACH

Delay is defined as the difference between the time taken by the packet to be delivered to the base station and the time taken when sensor nodes send the packet. The lower the value of delay the speedier the network functioning is. In figure 13, the network delay in seconds has been recorded for four protocols and proposed method. The bar graph in figure 13 is taken from table 6 which shows the values of average end-to-end delay for all five schemes. It can be noticed that the proposed method has 0.03 sec as the maximum average delay for 500 nodes capacity network. The delay for the other

approaches increases as the network size increases. The proposed approach investigates 40%, 50%, 60%, and 62.5% decrease in delay when compared with CRMOGA, INSPSO, MOPSO-DE, and EEM-LEACH respectively.
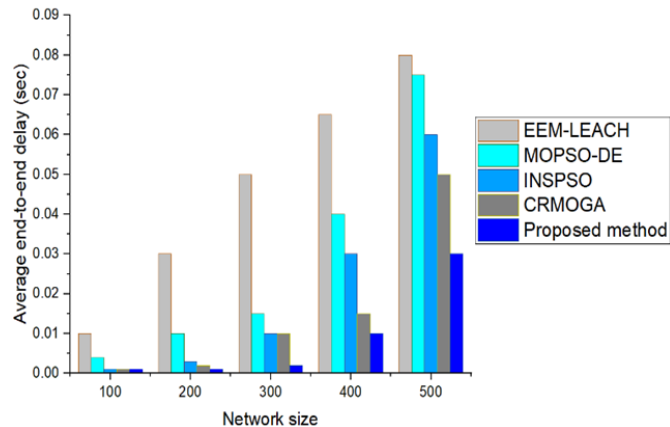

Figure 13 Network Delay (in seconds) versus Number of Nodes in the Network
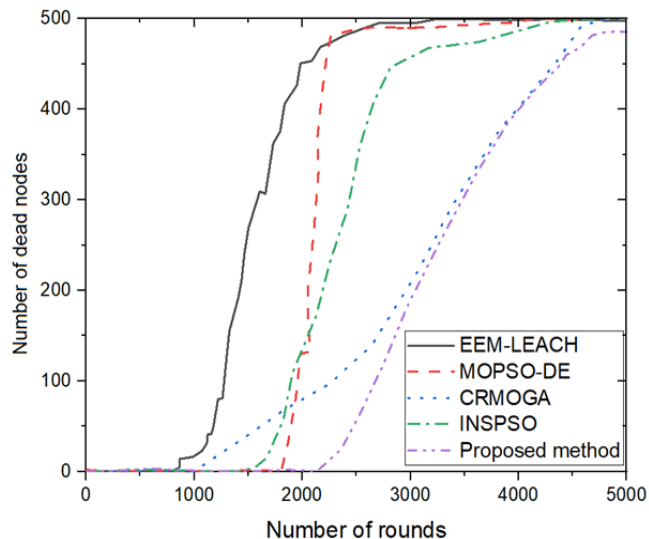
6.7. Dead Nodes

Figure 14 The Rise in Dead Nodes with Increase in Round Count

It is meant by those sensors for which the residual energy value starts reducing and reaches the value which is less than or equal to zero. Figure 14 presents the number of dead nodes increasing with round counts for all five methods. The proposed method has negligible nodes as dead nodes till 2300 rounds and the number of dead nodes attains 500 after 4700 rounds which makes it the best performer among other state-of-the-art approaches shown in the graph. Similarly, for EEM-LEACH the dead nodes start to increase after 1100 rounds only which are the lowest among other methods. The

RESEARCH ARTICLE

performance of CRMOGA is better than INSPSO, MOPSO-DE, and EEM-LEACH algorithms and is very close to the proposed method. The MOPSO-DE records the increase in dead nodes after 1900 rounds and it reaches to maximum at 2300th round. The dead nodes for INSPSO also increase after 1800 rounds but it reaches 500 nodes after it completes 3700 rounds which show it has a longer lifetime than the MOPSO-DE method.

Attributes	EEM-LEACH	MOPSO-DE	INSPSO	CRMOGA	Proposed method
Multi-objective optimization	No	Yes	Yes	Yes	Yes
Evolutionary algorithm	No	Yes	Yes	Yes	No
Swarm intelligence	No	Yes	Yes	No	Yes
Clustering	Yes	Yes	Yes	Yes	Yes
Optimal path selection	No	No	Yes	Yes	Yes
Routing	Yes	Yes	Yes	Yes	Yes
Mobility	No	Yes	No	No	Yes
Alternate path selection	No	No	No	No	Yes

Table 7 Comparison Chart Based on Various Features of Proposed Method and Four Pre-Existing Clustering and Routing Methods Similar to the Proposed Method

7. CONCLUSION

In this article, the novel proposed technique has been designed to solve both the clustering as well as routing issues in an efficient way using the multi-objective paradigm of the optimization approach. The clustering issue has been solved using the multi-objective rider optimization approach in which, among all riders or nodes, a leader rider is selected called the cluster head of the corresponding cluster. Similarly, this process is accomplished for other left-out nodes in the network. Various leader riders (cluster heads) representing their cluster, receive data packets from their cluster members. The communication among all the leader riders to the base station is performed by selecting an optimized path. This task is performed using a highly convergent sailfish optimizer algorithm. The optimizer takes care of the leader node failure when the energy drain occurs for it. For this purpose, it uses a multi-objective approach considering 3 main objectives for choosing the best possible alternate path. Finally, the base station receives all the data packets and the quality-of-service parameters are determined. The proposed method shows remarkable success in terms of end-to-end delay, energy consumption, throughput, and network lifetime. The energy consumption for proposed method is 27.2% less as compared to its competitor CRMOGA and its network lifetime also enhances. Due to efficient route path selection, the throughput and PDR also show a significant increment. The average end-to-end of the network show more than 40% drop which makes the network fast and suitable for applications like surveillance, healthcare, etc. As the future direction, this work can be modified to be used for a greater number of sink nodes or base stations. Moreover, the computational complexity needs to be checked as the expanded work may impart more cost to the system performance.

REFERENCES

[1] B. Pourghebleh, and N. J. Navimipour, "Data aggregation mechanisms in the Internet of things : A systematic review of the literature and recommendations for future research," J. Netw. Comput. Appl., vol. 97, pp. 23–34, Nov. 2017. https://doi.org/10.1016/j.jnca.2017.08.006

[2] M. Shakeri, A. Sadeghi-niaraki, S. Choi, and S. M. R. Islam, "Performance Analysis of IoT-Based Health and Environment WSN Deployment," Sensors, vol. 20, no. 20, pp. 5923, Jan. 2020. https://doi.org/10.3390/s20205923

[3] F. Javed, M. K. Afzal, M. Sharif, and B. Kim, "Internet of Things (IoT) Operating Systems Support , Networking Technologies , Applications , and Challenges : A Comparative Review," IEEE Commun. Surv. Tutorials, vol. 20, no. 3, pp. 2062–2100, Mar. 2018. DOI:10.1109/COMST.2018.2817685

[4] H. V. Chaitra, and G. K. Ravikumar, "Energy efficient clustering

method for wireless sensor network," Indones. J. Electr. Eng. Comput. Sci., vol. 14, no. 2, pp. 1039–1048, May. 2019. DOI: http://doi.org/10.11591/ijeecs.v14.i2.pp1039-1048

[5] W. Asiedu, M. D. Jnr, and S. A. Gyamfi, "Reliable Scheme for Cluster Head Election in Mobile Ad Hoc Networks," International Journal of Computer Trends and Technology (IJCTT), vol. 61, no. 2, pp. 93–99, 2018.doi: 10.14445/22312803/IJCTT-V61P116

[6] S. T. Tayal, "Energy Efficient Clustering In Wireless Sensor Network : A Review," Int J Wired Wireless Comm., 2016.

[7] L. Bhasker, "Genetically derived secure cluster-based data aggregation in wireless sensor networks," IET Inf. Secur., vol. 8, no. 1, pp. 1–7, 2013. doi: 10.1049/iet-ifs.2013.0133

[8] Hasson, S. T., & Abd Al-kadhum, H. (2017, April). Developed clustering approaches to enhance the data transmissions in WSNs. In 2017 International Conference on Current Research in Computer Science and Information Technology (ICCIT) (pp. 99-106). IEEE.

[9] C. Gherbi, Z. Aliouat, and M. Benmohammed, "A survey on clustering routing protocols in wireless sensor networks," Sensor Review. vol. 37, no. 1, Jan. 2017. https://doi.org/10.1108/SR-06-2016-0104

[10] P. Maurya and A. Kaur, "A Survey on Descendants of LEACH Protocol," International Journal of Information Engineering and Electronic Business, vol. 8, no. 2, pp. 46–58, Mar. 2016. DOI: 10.5815/ijieeb.2016.02.06

[11] J. Rejinaparvin and C. Vasanthanayaki, "Particle swarm optimization based clustering by preventing residual nodes in wireless sensor networks, " IEEE Sens. J., vol. 15, no. 8, pp. 4264–4274, Mar. 2015.DOI:10.1109/JSEN.2015.2416208

[12] R. Hamidouche, Z. Aliouat, A. Adamou A. Ari, and M. Gueroui, "An efficient clustering strategy avoiding buffer overflow in IoT sensors : a bio-inspired based approach," IEEE Access, vol. 7, pp. 156733-156751, Sep. 2019. DOI:10.1109/ACCESS.2019.2943546

[13] J. Bhola, S. Soni, and G. K. Cheema, "Genetic algorithm based optimized leach protocol for energy efficient wireless sensor networks," J. Ambient Intell. Humaniz. Comput., vol. 11, no. 3, pp. 1281-1288, Mar. 2020. https://doi.org/10.1007/s12652-019-01382-3

[14] T. Wang, G. Zhang, X. Yang, A. Vajdi, "Genetic algorithm for energy-efficient clustering and routing in wireless sensor networks," J. Syst. Softw.,vol. 146, pp. 196-214, Dec. 2018. https://doi.org/10.1016/j.jss.2018.09.067

[15] G. P. Gupta and S. Jha, "Integrated clustering and routing protocol for wireless sensor networks using Cuckoo and Harmony Search based metaheuristic techniques," Eng. Appl. Artif. Intell., vol. 68, pp. 101–109, Feb. 2018. https://doi.org/10.1016/j.engappai.2017.11.003

[16] W. Osamy, A. A. El-sawy, and A. Salim, "CSOCA : Chicken Swarm Optimization Based Clustering Algorithm for Wireless Sensor Networks," IEEE Access, vol. 8, pp. 60676–60688, Mar. 2020. DOI:10.1109/ACCESS.2020.2983483

[17] G. Yogarajan, and T. Revathi, "Improved Cluster Based Data Gathering Using Ant Lion Optimization in Wireless Sensor Networks," Wirel. Pers. Commun., vol. 98, no. 3, pp. 2711-2731, Feb. 2017. https://doi.org/10.1007/s11277-017-4996-3

[18] N. Sirdeshpande and V. Udupi, "Fractional lion otimization for cluster head-based routing protocol in wireless sensor network," J. Franklin Inst., vol. 354, no. 11, pp. 4457-4480, Jul. 2017. https://doi.org/10.1016/j.jfranklin.2017.04.005

[19] S. B. Sasi and R. Santhosh, "Multiobjective routing protocol for wireless sensor network optimization using ant colony conveyance algorithm," International Journal of Communication Systems, vol. 34, no. 6, pp. 1–13, Apr. 2021. https://doi.org/10.1002/dac.4270

[20] R. Kumar and D. Kumar, "Multi-objective fractional artificial bee colony algorithm to energy aware routing protocol in wireless sensor network," Wirel. Networks, vol. 22, no. 5, pp. 1461-1474, Jul. 2016. https://doi.org/10.1007/s11276-015-1039-4

[21] Antoo, A., & Mohammed, A. R. (2014, July). EEM-LEACH: Energy efficient multi-hop LEACH routing protocol for clustered WSNs. In 2014 international conference on control, instrumentation, communication and computational technologies (ICCICCT) (pp. 812-818). IEEE.

[22] K. Miranda, S. Zapotecas-Martínez, A. López-Jaimes, and A. García-Nájera, "A Comparison of Bio-Inspired Approaches for the Cluster-Head Selection Problem in WSN," In: Shandilya S., Shandilya S., Nagar A. (eds) Advances in Nature-Inspired Computing and Applications, Cham, Germany: EAI/Springer Innovations in Communication and Computing. Springer, 2018, pp.65-187.

[23] D. R. Prasad, P. V Naganjaneyulu, and K. S. Prasad, "Energy Efficient Clustering in Multi-hop Wireless Sensor Networks Using Differential Evolutionary MOPSO," Brazilian Archives of Biology and Technology, vol. 59, pp.1-15, Jan 2017. https://doi.org/10.1590/1678-4324-2016161011

[24] M. Micheletti, L. Mostarda, and A. Navarra, "CER-CH : Combining Election and Routing Amongst Cluster Heads in Heterogeneous WSNs," IEEE Access, vol. 7, pp. 125481–125493, Aug. 2019. DOI:10.1109/ACCESS.2019.2938619

[25] D. Kumar, T. C. Aseri, and R. B. Patel, "EEHC: Energy efficient heterogeneous clustered scheme for wireless sensor networks," Comput. Commun., vol. 32, no. 4, pp. 662–667, Mar. 2009. https://doi.org/10.1016/j.comcom.2008.11.025

[26] M. Alazab, K. Lakshmanna, T. Reddy G, Q. V. Pham, and P. K. R. Maddikunta, "Multi-objective cluster head selection using fitness averaged rider optimization algorithm for IoT networks in smart cities," Sustain. Energy Technol. Assessments, vol. 43, pp. 100973, Feb. 2021. https://doi.org/10.1016/j.seta.2020.100973

[27] T. Han, L. Zhang, S. Pirbhulal, W. Wu, and V. H. C. de Albuquerque, "A novel cluster head selection technique for edge-computing based IoMT systems," Computer Networks, vol. 158, pp. 114–122, Jul. 2019. https://doi.org/10.1016/j.comnet.2019.04.021

[28] V. Jafarizadeh, A. Keshavarzi, and T. Derikvand, "Efficient cluster head selection using Naïve Bayes classifier for wireless sensor networks," Wirel. Networks, vol. 23, no. 3, pp. 779-785, Apr. 2017. https://doi.org/10.1007/s11276-015-1169-8

[29] D. Agrawal and S. Pandey, "FUCA: Fuzzy-based unequal clustering algorithm to prolong the lifetime of wireless sensor networks," Int. J. Commun. Syst., vol. 31, no. 2, pp. 1–18, Jan. 2018. https://doi.org/10.1002/dac.3448

[30] D. Chandirasekaran, and T. Jayabarathi, "Cat swarm algorithm in wireless sensor networks for optimized cluster head selection : a real time approach," Cluster Comput., vol. 22, no. 5, pp. 11351–11361, Sep. 2019. https://doi.org/10.1007/s10586-017-1392-4

[31] T. M. Behera, S. K. Mohapatra, U. C. Samal, M. S. Khan, M. Daneshmand, and A. H. Gandomi, "Residual Energy Based Cluster-head Selection in WSNs for IoT Application," IEEE Internet Things J., vol. 6, no. 3, pp. 5132-5139, Feb. 2019. 10.1109/JIOT.2019.2897119

[32] A. Sarkar and T. S. Murugan, "Cluster head selection for energy efficient and delay-less routing in wireless sensor network," Wirel. Networks, vol. 25, no. 1, pp. 303-320, Jan. 2019. https://doi.org/10.1007/s11276-017-1558-2

[33] N. Lavanya and T. Shankar, "Energy Efficient Cluster Head Selection using Hybrid Squirrel Harmony Search Algorithm in WSN," Energy, vol. 10, no. 12, pp. 477–487, 2019.DOI: 10.14569/IJACSA.2019.0101265

[34] B. Singh and D. K. Lobiyal, "A novel energy-aware cluster head selection based on particle swarm optimization for wireless sensor networks," Human-Centric Computing and Information Sciences, vol. 2, no. 1, pp. 1–18, Dec. 2012. https://doi.org/10.1186/2192-1962-2-13

[35] K. Vijayalakshmi, and P. Anandan, "A multi objective Tabu particle swarm optimization for effective cluster head selection in WSN," Cluster Comput., vol. 22, no. 5, pp. 12275-12282, Sep. 2019. https://doi.org/10.1007/s10586-017-1608-7

[36] P. T. Karthick, and C. Palanisamy, "Optimized cluster head selection using krill herd algorithm for wireless sensor network," Automatika: časopis za automatiku, mjerenje, elektroniku, računarstvo i komunikacije, vol. 60, no. 3, pp. 340–348, Jul. 2019.

RESEARCH ARTICLE

https://doi.org/10.1080/00051144.2019.1637174

[37] S. Hamrioui, C. Adam, M. Hamrioui, J. Lioret, and P. Lorenz, "Smart and self-organised routing algorithm for efficient IoT communications in smart cities," IET Wireless Sensor Systems, vol. 8, no. 6, pp. 305–312, Nov. 2018.doi:10.1049/iet-wss.2018.5022.

[38] Y. Chang, H. Tang, B. Li, and X. Yuan, "Distributed Joint Optimization Routing Algorithm Based on the Analytic Hierarchy Process for Wireless Sensor Networks," IEEE Communications Letters, vol. 21, no. 12, pp. 2718–2721, Sep. 2017. DOI:10.1109/LCOMM.2017.2756035

[39] S. S. Preeth, R. Dhanalakshmi, R. Kumar, and P. M. Shakeel, "An adaptive fuzzy rule based energy efficient clustering and immune-inspired routing protocol for WSN-assisted IoT system," J. Ambient Intell. Humaniz. Comput., pp. 1-13, Dec. 2018. https://doi.org/10.1007/s12652-018-1154-z

[40] H. Salarian, K. W. Chin, and F. Naghdy, "An Energy-Efficient Mobile-Sink Path Selection Strategy for Wireless Sensor Networks," IEEE Trans. Veh. Technol., vol. 63, no. 5, pp. 2407–2419, Nov. 2014.DOI:10.1109/TVT.2013.2291811

[41] A. Kaswan, K. Nitesh, and P. K. Jana, "International Journal of Electronics and Communications (AEÜ) Energy efficient path selection for mobile sink and data gathering in wireless sensor networks," AEUE - Int. J. Electron. Commun., vol. 73, pp. 110–118, Mar. 2017. https://doi.org/10.1016/j.aeue.2016.12.005

[42] T. A. Alghamdi, "Secure and Energy Efficient Path Optimization Technique in Wireless Sensor Networks Using DH Method," IEEE Access, vol. 6, pp. 53576-53582, Aug. 2018. DOI:10.1109/ACCESS.2018.2865909

[43] K. N. Vhatkar and G. P. Bhole, "Improved rider optimization for optimal container resource allocation in cloud with security assurance," International Journal of Pervasive Computing and Communications, vol. 16, no. 3, pp. 235–258, Jun. 2020. https://doi.org/10.1108/IJPCC-12-2019-0094

[44] C. Hua and T. S. P. Yum, "Optimal routing and data aggregation for maximizing lifetime of wireless sensor networks," IEEE/ACM Trans. Netw., vol. 16, no. 4, pp. 892–903, Mar. 2008. DOI:10.1109/TNET.2007.901082

[45] J. Wang, Y. Gao, W. Liu, A. K. Sangaiah, and H. J. Kim, "An Improved Routing Schema with Special Clustering Using PSO Algorithm for heterogeneous wireless sensor network," Sensors, vol. 19, no. 3, pp. 671, Jan. 2019. https://doi.org/10.3390/s19030671

[46] X. Li, B. Keegan, F. Mtenzi, T. Weise, and M. Tan, "Energy-Efficient Load Balancing Ant Based Routing Algorithm for Wireless Sensor Networks," IEEE Access, vol. 7, pp. 113182–113196, Aug. 2019.DOI:10.1109/ACCESS.2019.2934889

[47] M. Fattoum and Z. Jellali, "A Joint Clustering and Routing Algorithm based on GA for Multi Objective Optimization in WSN," In2020 IEEE Eighth International Conference on Communications and Networking (ComNet), Oct. 2020, pp. 1-5.

[48] M. Li, C. Wang, W. Wang, C. Qin, and X. Li. Multi-Objective Clustering and Routing for Maximizing Lifetime of Wireless Sensor Networks. presented at 2017 9th Int. Conf. Adv. Infocomm Technol.(ICAIT), Chengdu, China., Nov. 2017.

[49] L. Xu, R. Collier, and G. M. P. O. Hare, "A Survey of Clustering Techniques in WSNs and Consideration of the Challenges of Applying Such to 5G IoT Scenarios," IEEE Internet of Things Journal, vol. 4, no. 5, pp. 1229–1249, Jul. 2017.DOI: 10.1109/JIOT.2017.2726014

[50] B. Ramakrishnan, R. B. Nishanth, M.M. Joe, M. Selvi, "Cluster based emergency message broadcasting technique for vehicular ad hoc network," Wireless Networks., vol. 23, no. 1, pp. 233-48, Jan. 2017. https://doi.org/10.1007/s11276-015-1134-6

[51] N. Maslekar, M. Boussedjra, and J. Mouzna, L. Houda, "Direction based clustering algorithm for data dissemination in vehicular networks," In2009 IEEE Vehicular Networking Conference (VNC), Oct 2009 (pp. 1-6). IEEE.

[52] D. C. Hoang, P. Yadav, R. Kumar, and S.K Panda, "Real-Time Implementation of a Harmony Search Algorithm-Based Clustering Protocol for Energy-Efficient Wireless Sensor Networks," IEEE transactions on industrial informatics, vol. 10, no. 1, pp. 774–783, Jul. 2013.DOI:10.1109/TII.2013.2273739

[53] M. M. Ahmed, E. H. Houssein, A. E. Hassanien, A. Taha, and E. Hassanien, "Maximizing lifetime of large-scale wireless sensor networks using multi-objective whale optimization algorithm," Telecommun. Syst., vol. 72, no. 2, pp. 243-259, Oct. 2019. https://doi.org/10.1007/s11235-019-00559-7

[54] D. Mehta and S. Saxena, "MCH-EOR: Multi-objective cluster head-based energy-aware optimized routing algorithm in wireless sensor networks," Sustainable Computing: Informatics and Systems, vol. 28,p.100406,Dec.2020.https://doi.org/10.1016/j.suscom.2020.100406.

[55] G. Hacioglu, V. Faryad, A. Kand, and E. Sesli, "Multi objective clustering for wireless sensor networks," Expert Syst. Appl., vol. 59, pp. 86-100, Oct. 2016. https://doi.org/10.1016/j.eswa.2016.04.016

[56] R. Elhabyan, W. Shi, and M. St-hilaire, "A Pareto optimization-based approach to clustering and routing in Wireless Sensor Networks," J. Netw. Comput. Appl., vol. 114, pp. 57-69, Jul. 2018. https://doi.org/10.1016/j.jnca.2018.04.005

[57] S. A. Sert, H. Bagci, and A. Yazici, "MOFCA: Multi-objective fuzzy clustering algorithm for wireless sensor networks," Appl. Soft Comput. J., vol. 30, pp. 151-165, May. 2015. https://doi.org/10.1016/j.asoc.2014.11.063

[58] A. Kaswan, V. Singh, and P. K. Jana, "A novel multi-objective particle swarm optimization based energy efficient path design for mobile sink in wireless sensor networks," Pervasive Mob. Comput., vol. 46, pp. 122-136, Jun. 2018. https://doi.org/10.1016/j.pmcj.2018.02.003

[59] K. Guleria and A. Kumar, "Meta‑heuristic Ant Colony Optimization Based Unequal Clustering for Wireless Sensor Network," Wirel. Pers. Commun.,vol. 105, no. 3, pp. 891-911, Apr. 2019. https://doi.org/10.1007/s11277-019-06127-1

[60] W. R. Heinzelman, A. Chandrakasan, and H. Balakrishnan, "Energy-Efficient Communication Protocol for Wireless Micro-sensor Networks," In Proceedings of the 33rd annual Hawaii international conference on system sciences, Maui, HI, USA, 2000, pp. 10. DOI:10.1109/HICSS.2000.926982

[61] D. Binu and B. S. Kariyappa, "RideNN : A New Rider Optimization Algorithm-Based Neural Network for Fault Diagnosis in Analog Circuits," IEEE Transactions on Instrumentation and Measurement, vol. 68, no. 1, pp. 2-26, May. 2018. DOI:10.1109/TIM.2018.2836058

[62] S. Shadravan, H. R. Naji, and V. K. Bardsiri, "The Sailfish Optimizer: A novel nature-inspired metaheuristic algorithm for solving constrained engineering optimization problems," Eng. Appl. Artif. Intell., vol. 80, pp. 20–34, Apr. 2019. https://doi.org/10.1016/j.engappai.2019.01.001.

Authors

Pallavi Joshi received her bachelor of engineering in Electronics and Communications from Rajiv Gandhi Technical University Bhopal, India in 2011. She pursued MTech in Embedded Systems from VIT University, Vellore, India in 2016. She is currently pursuing PhD in Electronics and Communications from National Institute of Technology, Raipur, India. She has published across 10 research papers in international journals and conferences and has achieved the best paper award in one international conference. Her areas of interest include developing data transmission models for resource constraint WSN and IoT networks, data aggregation in wireless sensor networks. She is an active member of IEEE.

RESEARCH ARTICLE

Dr. Ajay Singh Raghuvanshi received his B.Tech. degree in Electronics and Communication Engineering from the North Eastern Regional Institute of Science and Technology, North-eastern Hill University, India in 1993. He has obtained his Ph.D. degree at the Department of Electronics and Communication Engineering, Motilal Nehru National Institute of Technology, Allahabad, India in 2012. He is currently working as an Assistant professor at NIT Raipur, India. He has published across 20 research articles in various domains. His research interests are in the area of Artificial Intelligence and Machine Learning-based approaches in Data aggregation and Intrusion detection in Wireless Sensor Networks and the Internet of Things.

How to cite this article:

Pallavi Joshi, Ajay Singh Raghuvanshi, "A Multi-Objective Metaheuristic Approach Based Adaptive Clustering and Path Selection in IoT Enabled Wireless Sensor Networks", International Journal of Computer Networks and Applications (IJCNA), 8(5), PP: 566-584, 2021, DOI: 10.22247/ijcna/2021/209988.