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ECR-IoT: Energy-efficient and cluster-based routing method for WSN-based IoT using Harris hawk's and whale optimization algorithms

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Abstract:

Internet of things (IoT) applications from home applications to military applications have been expanding day by day. Energy efficient routing schemes are vital for resource constraint wireless sensor networks (WSNs) and IoT. Clustering based routing scheme is one of the basic methods to extend the lifetime of WSN-based IoT. On the other hand, clustering is NP-hard problem and metaheuristic algorithms are suitable for clustering. In this paper, a new energy-efficient routing scheme is presented for IoT using two metaheuristic algorithms Harris hawk's optimization (HHO) and whale optimization algorithm (WOA). The selection of the cluster header (CH) is based on the WOA using various parameters such as residual energy of nodes, distance to neighbors, distance to sink. After clustering phase, an energy efficient routing scheme was proposed using the HHO algorithm. The simulation results in MATLAB environment justifies that the proposed protocol improves network life by 10%, average energy consumption by 15%, packet delivery rate (PDR) by 12%, throughput by 11% and number of alive nodes by 15%.

1.Introduction

IoT is a technological revolution that connects everything to the Internet. In many applications, the main focus of IoT based on WSNs is to gather data from various applications such as healthcare, intelligent home and transmits it periodically to the sink or base station(BS) (Agarwal et al., 2022, Jaiswal and Anand, 2022). With the evolution of telecommunication technology, especially with the advent of wireless communication, more efforts have been made to integrate sensors with wireless antennas capable of transmitting sensor information over large distances (Subramani et al., 2022, Rajasoundaran et al., 2022). Integrating wireless communication technology with sensors enables humans to obtain useful information from inaccessible areas. In the current era of 5G mobile communications and beyond, and the addition of massive machine-type communications use cases and highly reliable low-latency communications, device connectivity and IoT reliability are increasing. Further, there are many challenges in expanding IoT applications. Among the security challenges, privacy, routing, resource allocation, etc. can still be investigated and require appropriate solutions (Moussa et al., 2022, Dogra et al., 2022).

In WSN based IoT, sensor nodes suffer from energy limitations. Hence, it is essential and important to pay serious attention to the issue of energy in all applications of IoT. The real-time sending of sensitive data through reliable routes plays a vital role in the functioning and performance of the IoT devices and applications (Roberts and Ramasamy, 2023, Jeevanantham and Rebekka, 2022). In various applications of IoT, due to inherent limitations, including frequent network topology changes and extensive energy limitations, routing in this communication technology is different from other wireless networks(Tewari and Tripathi, 2023, Kaur and Chanak, 2022). Due to this importance and considering the very important position of routing in IoT, many researches have been introduced to improve this vital process and improve their service quality(Seyfollahi et al., 2023, Sefati et al., 2023).

In cluster-based schemes, the entire nodes of network are classified and categorized into various clusters for energy-efficient data transmission (Ghaffari, 2014, Jazebi and Ghaffari, 2020). The CH nodes receive data from other nodes (member nodes), then transmit the aggregated data to the sink through hop-by-hop communication. Clustering mechanism is used to increase network lifetime through load balancing and data aggregation(Seyfollahi et al., 2022) .

However, routing algorithm based on clustering schemes suffer from several serious problems such as high communication delay and low throughput (Mottaghinia and Ghaffari, 2018, Seyfollahi et al., 2022). Also, providing a new routing scheme with the ability to be aware of the QoS (quality of service) is one of the basic issues of these networks(Mohammadi et al., 2023). Optimizing end-to-end delay and increasing PDR play a key role in sending sensitive packets. One of the most important solution to improve the QoS in the IoT is to use the clustering method (Lenka et al., 2022). On the other hand, clustering is an NP-hard problem in these networks and meta-heuristic algorithms are suitable for this task.

In this paper, an energy efficient and cluster based routing is presented using the meta-heuristic algorithms of HHO (Heidari et al., 2019) and WOA(Mirjalili and Lewis, 2016). Whale optimization algorithm will be used for the clustering process, and Harris hawk's optimization meta-heuristic algorithm will be used for routing, taking into account different important parameters such as node density, distance and residual energy, and node degree. In the proposed method, two meta-heuristic algorithms, HHO and WOA, are combined to balance the local and global search rates in the search space. With this combination, potential solutions are obtained during the clustering process, the process of choosing the next CHs and choosing the appropriate path from the origin to the destination.

HHO (Heidari et al., 2019) is one of the most important nature-inspired and metaheuristic algorithms that can balance between the rate of exploitation and exploration perfectly, during searching the global optimal solution process. On the other hand, HHO algorithm can optimize the exploration and exploitation phases of WOA. The escaping strategy of WOA resembles the exploitation process which aims the search agent in re-election of CHs when their object function value is below a known threshold value. On the other hand, HHO imitates the natural behaviors of Hawk Harris which utilizes main phases of prey hunting and search for controlling the transitions between the phases of exploration and exploitation for determining optimum solutions. For this purpose, it uses minimum number of operations and fewer parameters. This ability of WOA when combined with HHO algorithms plays an important role in determining more optimal solutions in the search space, and it is identified to boost up the ability of identifying better and optimum solution diversity during the process of exploration phase. This combination can improve and affect the other QoS parameters of network.

In the proposed method, after the clustering process, routing is done step by step between the clusters.

The main contributions of this paper are as follows:

- It combines the two important metaheuristics algorithms (HHO and WOA) to balance the local and global search rates.
- It optimizes the clustering scheme and routing process using appropriate fitness functions with proper parameters.
- It minimizes the clustering process and maximizes the scalability due prevention to local optima problem.

The remainder part of this paper is organized as follows: Section 2 indicates the related works. Section 3 shows the background. Section 4 explains the proposed scheme. Section 5 evaluates the performance of the proposed method. Finally, Section 6 concludes the paper.

2.Related works

Recently, many routing protocols based on the clustering technique have been proposed for IoT. Some of them are reviewed in this paper.

In (Thangaramya et al., 2019), the authors proposed FBCFP (neuro-fuzzy based cluster formation protocol) for WSN-based IoT. FBCFP considers four important parameters such as residual energy of each CH node, distance between the CH and sink, and cluster head degree. So, the convolutional neural network (CNN) was used for training the network for weight adjustment. For this purpose, different fuzzy rules were used in CNN. Hence, for clustering, selecting the appropriate CH nodes, the authors use fuzzy reasoning approach. After CH selection phase, the other nodes apply these parameters for all cluster head nodes using Mamdani Inference System.

In (Gurram et al., 2022), The authors presented SEAMHR (Secure Energy-Aware Meta-Heuristic Routing), an energy-aware and secure protocol for WSNs. To achieve an appropriate training and truth worthy, this scheme uses MEHO (Mutation Elephant Herding Optimization). To achieve the routing decision, this method uses two important parameters such as number of hops, link integrity, and residual energy. To improve the data security and enhancing the authenticates inter-routing, this scheme uses CTR-AEDL (Counter Mode Cryptography scheme) and AEs (Auto encoders). Using five important and essential components such as the size of data packet, secret keys and other important parameters, CTR-AEDL generates the required keys.

In (Vazhuthi et al., 2023), the authors proposed an energy-efficient inter-cluster data transmission and fault prevention method to improve the QoS of IoT-WSNs (IWSN). In this proposed method, for detecting the proper route from origin CH node to sink the Hybrid ANFIS Reptile Optimization Algorithm has been used. In the second phase, to identify the various faults such as sensing, residual energy, and communication in IWSN the Tuned supervision-based fault diagnosis strategy has been used.

In (Altowaijri, 2022), the authors proposed an efficient multi-hop routing protocol (EMRP) for proper data transmission in IoT-WSNs. This scheme is energy-efficient data transmission method and considers a rank-based next-hop selection scheme. This method considers different and important parameters such as the residual energy to select the optimum route for data dissemination. To validate the maximum rank, they extracted the residual energy and evaluated this important and valuable parameter based on the connection degree.

In (Moussa et al., 2022), the authors presented a HDRS (Hierarchical Data Routing Strategy) scheme for fog architecture using WSNs. At first, they clustered the multi-Fog nodes using an energy-efficient method. Then, the authors proposed another new scheme to provide routing process. This new scheme reduces the communication costs and improves the network lifetime. In this method, the data transmission task is based on cluster member nodes and CHs. The routing decision task is taken at the FN level considering various parameters such as storage, energy, and computation capability. In the third phase, the authors proposed an important scheme for removing the faulty nodes.

In (Sharma and Chawla, 2024), a congestion-reducing routing algorithm based on optimized meta-heuristic algorithm of particle swarm optimization (PSO) was proposed for WSN based IoT. The PRESEP (Particle swarm optimized Residual Energy Stable Election Protocol) protocol minimizes CH choosing process because of the advantages of the reactive global search protocol that is easy to optimize congestion for stable routing process in cluster-based and energy-aware WSNs. The CH selectivity enhancement of the residual energy-based model developed by meta-heuristic optimization with incremental round of operation is achieved for varied heterogeneity coefficient. The authors have evaluated the proposed scheme with different scenarios such as network sizes. The simulation results have showed that the proposed scheme outperformed the previous schemes in different parameters such as network lifetime, alive nodes, and average consuming energy.

In (Lahmar et al., 2024), the authors proposed Type-2 Fuzzy Harris Hawks Optimization (T2FHHO) to select the optimum path between the source CH and the BS. To select this optimum route, the authors consider a new fitness function using appropriate terms such as residual energy, distance, data traffic, and buffer size occupation. To determine the optimum CH nodes, they use the T2FHHO scheme again to enhance and improve the node's long-term reward.

In (Gupta et al., 2023), the authors presented an energy efficient data communication scheme (EEDC) with capability of load balancing by utilizing “Region based Hierarchical Clustering for Efficient Routing (RHCER)”—a multi-tier clustering scheme for energy-aware routing process. The sensor nodes deployed for IoT application data collection gather important data and select CH nodes based on a multi-criteria decision function. The authors used a load balanced and hierarchical technique to ensure efficient long-distance communication along all network nodes. The proposed scheme in this paper aims to provide and enhance the load balancing process and network lifetime due to converting the long distances communication into shortest hop-by-hope communications.

In (Arafat et al., 2023), the authors presented a distributed energy-efficient clustering and routing protocol (DECR) using the two-hop-based targeting wearable IoT (WIoT-enabled). DECR is based on two-hop clustering scheme using the modified grey-wolf optimization algorithm (WoA) for choosing the CH nodes among other sensor nodes and enhance the routing scheme. They proposed a fitness function to choose the CH nodes for each cluster using appropriate parameters such as node connectivity and remaining energy of each sensor node. The authors used an analytical process scheme to identify the optimal clusters and cluster head numbers by considering intra- and inter-cluster communication distances. This consideration can reduce the overall transmission distance and number of transmitter nodes in the network. After determination of CH nodes, an energy efficient routing scheme was proposed to enhance the PDR parameter.

3.Background

Table 1 indicates variables and their definition which are used in different equations.

3.1 HHO algorithm

HHO is an important and effective metaheuristic algorithm and can be used for every optimization-based problem such as clustering or routing in IoT devices. HHO is population-based optimization algorithm. In this algorithm, the optimum candidate solutions are Harris' hawks and the intended or nearly the optimum prey (for example rabbit) is the best and optimum candidate solution in each step. In HHO, Harris hawks are distributed in places in random model where they are waiting for hunting using two exploratory methods. The exploration phase of the HHO algorithm mimics the searching behavior of the hawks for the rabbit (prey) if an equal chance *q* for each strategy was considered, they perch based on the locations of other Harris hawks members and the prey, which is indicated in Eq. (1) for the state of *q* <0.5, or perch on random tall trees, which is indicated in Eq. (1) for *q* ≥0.5. The function of HHO algorithm can be modeled as follows:

$$X(t+1)= \begin{cases} X_{rand}(t) - r_1 \left|Xrand(t) - 2r_2X(t)\right| & q \geq 0.5 \\ (X_{rabbit}(t) - Xm(t)) - r_3(L_B + r_4(U_B - L_B)) & q < 0.5 \end{cases} \quad (1)$$

where, in Eq. (1), *X(t)* and *X(t+1)* indicate the location vectors of the hawks in the different iterations, respectively. $x_r(t)$ is a random hawk and this hawk is selected from the Harris hawk's population. $X_{rabbit}(t)$ is the location of the rabbit. *q*, r_1, r_2, r_3 and r_4 are random numbers which are updated in each iteration. L_B and U_B are the lower and upper bounds for creating random positions. The second stage is a transition stage from exploration to exploitation. The random locations inside the group's home range (L_B, U_B) was produced using a simple model. The first rule produces optimum solutions based on a random position and other hawks. In second rule of Eq. (1), the difference of the position of best so far and the average position of the group plus a random component are known. Then, a random scaling coefficient was prepared for the different component to provide more diversification trends and explore various area of the feature space. $x_{mean}(t)$ is the mean position of the Harris hawks and can be estimated as follows:

$$X_{mean}(t)=\frac{1}{N}\sum_{i=1}^{N} Xi(t) \quad (2)$$

$$E=2E_0\left(1-\frac{t}{T}\right) \quad (3)$$

where in Eq. (3), *E* and *T* show the escape energy of the rabbit(prey) and the maximum iterations number respectively. E_0 is the initial energy level of the prey, which is between -1 and +1 (Heidari et al., 2019) Soft blockade can be set as follows (Heidari et al., 2019):

$$X(t+1) = \Delta X(t) - E\left|J \times Xrabbit(t) - X(t)\right| \quad (4)$$

$$\Delta X(t) = X_{rabbit}(t) - X(t) \quad (5)$$

$$J = 2(1 - Rand) \quad (6)$$

In the above equations, the difference position between the hunter and prey is shown as Δx(t). J is a random number which shows the random jumping power of the rabbit. Hard encirclement can be calculated as follows:

$$X(t+1) = X(t) - E\left|\Delta X(t)\right| \quad (7)$$

where in Eq. (7), in case of (|E|≤0.5) and (p <0.5), soft encirclement is performed with fast progressive dive. On the other hand, the next movement of the Harris hawk can be determined using the Eq. (8):

$$k = X_{rabbit}(t) - E\left|J \times X_{rabbit}(t) - X(t)\right| \quad (8)$$

If the last dive of hawks is not useful, the hawk dives using the *L* flight pattern as follows:

$$z = k + s \times L(d) \quad (9)$$

where in Eq. (9), *d* and *S* indicate the problem dimension and a random vector of size *d,* respectively.

$$Levy = \frac{u \times \sigma}{|v|^{\frac{1}{\beta}}} \quad (10)$$

$$\sigma = \left(\frac{\Gamma(1+\beta) x \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) x\, \beta\, x\, 2^{\left(\frac{\beta-1}{2}\right)}}\right)^{\frac{1}{\beta}} \quad (11)$$

where in Eq. (11), *u* and *v* belong to [0, 1]. β is equal to 1.5. The last rapid gradual dive of the soft enclosure is determined using Eq. (12):

$$X(t+1) = \begin{cases} Y & , \text{ if } F(Y) < F(X(t)) \\ Z & , \text{ if } F(Z) < F(X(t)) \end{cases} \quad (12)$$

Hard encirclement with rapid progressive dive occurs when (| E | ≥ 0.5) and (p < 0.5) because the prey does not have sufficient energy to ran out using Eq. k can be calculated using Eq.(13).

$$k = X_{rabbit}(t) - E\left|J \times X_{rabbit}(t) - X_{mean}(t)\right| \quad (13)$$

Fig. 1 indicates the flowchart of the HHO algorithm (Heidari et al., 2019).

3.2 Whale optimization algorithm

Another optimization and population-based algorithm used in this paper is WOA (Mirjalili and Lewis, 2016) . In this algorithm, at first humpback whales must detect the location of prey for hunting purpose. After identifying the prey position, they can be encircling the preys. After definition of the optimum search agent, the other search agents will try to update their location towards this optimum state and solution. The behavior of whales in WOA for exploration and exploitation phases is expressed through Eq. (14) and (15) of the article:

$$\vec{D} = \left|\vec{C}.\overrightarrow{X^{*}(t)} - \vec{X}(t)\right| \quad (14)$$

$$\vec{X}(t+1) = \overrightarrow{X^{*}}(t) - \vec{A}.\vec{D} \quad (15)$$

In Eq. (14) and Eq. (15), t, $\vec{A}$, and $\vec{C}$ indicate the current iteration and coefficient vectors, respectively. $\overrightarrow{X^{*}}$ and $\vec{X}$ are the location vector of the best solution and the location vector respectively. *A* and *C* are vectors and can be obtained as follows:

$$\vec{A}=2\vec{a}.\vec{r} - \vec{a} \quad (16)$$

where in Eq. (16), $\vec{a}$ is linearly reduced from 2 to 0 and $\vec{r}$ is a random vector in [0,1].

$$\vec{C} = 2.\vec{r} \quad (17)$$

In Eq. (16) and Eq. (17), the value of *r* is between 0 and 1 and we have:

$$\vec{X}(t+1) = \overrightarrow{D'}.e^{bl}.\cos(2\pi l) + \overrightarrow{X^{*}}(t) \quad (18)$$

where in Eq. (18), '*D*' and *b* are the distance between the first whale.

Humpback whales create a spiral-shaped path with swim around the prey within a shrinking circle. To model the behavior of this type of whales, it is assumed that there is a probability of 50% to select between either the shrinking encircling model or the scheme to update the position of whales during optimization. The mathematical model for this behavior of whales, we can use Eq. (19) as follows:

$$\vec{X}(t+1) = \begin{cases} X^{*}(t) - \vec{A}.\vec{X}, & if\ p < 0.5 \\ \overrightarrow{D'}.e^{bl}.\cos(2\pi l) + \overrightarrow{X^{*}}(t), & if\ p\ \ x \geq 0.5 \end{cases} \quad (19)$$

where in Eq. (19), the value of *P* is between 0 and 1.

Fig.2 indicates the flowchart of the WOA.

4.Proposed scheme

This section indicates the proposed scheme, where an energy-efficient cluster-based routing scheme was proposed in WSN based IoT. The proposed method has two stages: clustering stage and step-by-step routing stage between the source and destination cluster head nodes in Internet of Things. In the first stage of the proposed method, the optimal CH nodes can be identified using WoA and various optimum parameters. After clustering phase (identifying the CH nodes and cluster members for each CH nodes), the HHO is also used to choose the appropriate path between the CH nodes (from source CH node to the base station). In the next step, the routing phase between CH nodes is done.

The architecture of CR-IoT was shown in Fig.3. In this figure, the aggregated data will be transferred to the base station in hope-by-hope scheme. In CR-IoT, after the clustering stage and determining the members of each cluster and CH node, the source CH node sends its data to the destination through intermediate cluster head.

4.1. CH selection using WOA

Considering that clustering is an NP-hard problem, in CR-IoT for clustering, the WOA is used. In CR-IoT, the number of cluster heads is equal to 5 percent of all nodes. Using appropriate clustering scheme balances the loads in each cluster and nodes and increases the network lifetime. For clustering, the heads of the clusters are determined first, and then each CH advertises itself as the head of the cluster and selects its members based on appropriate parameters. The amount of available energy of the nodes, the centrality of the node, the distance between the sensor nodes and the degree of the nodes are considered parameters for choosing the appropriate cluster head for each created cluster. The description of the important and appropriate parameters considered for CH nodes selection is given below:

- *Residual energy*

Energy is an important parameter in resource constraint WSNs and the operation of these devices directly depends on this important parameter. Energy of WSN based IoT device was prepared using battery. Although all the nodes have equal energy at the beginning, in the later stages, a node with more available energy will be selected as the CH nodes.

$$Max\ f_1 = \sum_{i=1}^{m} ECH_i \quad (20)$$

where in Eq. (20), ECH_i is the residual energy of the *i*th cluster head and *m* is the number of created clusters. In this equation, we want to maximize the value of f_1 function.

- *Distance between source and next CH nodes and base station*

This distance is a suitable parameter for selecting the appropriate CH nodes. The required consuming energy for transmission and receiving data directly depends on the distance between the source and destination nodes. To improve the end-to-end delay in transmission packets, if this distance is minimal, that node will be suitable to be the CH nodes. The Euclidean distance (*dis(i,j)*) between two nodes *i* and *j* with characteristics (x_i,y_i) and (x_j,y_j) is obtained from the Eq. (23).

$$\boldsymbol{dis}(\boldsymbol{i},\boldsymbol{j}) = \sqrt{(\boldsymbol{x_i}-\boldsymbol{x_j})^2+(\boldsymbol{y_i}-\boldsymbol{y_j})^2} \qquad (21)$$

Due to the fact that the distance plays an essential role in determining the cluster head node, nodes will be selected as the cluster head whose sum of the average distance between them with the next cluster head and the base station is minimum. On the other hand, for the maximum value of Eq. (22), the value of function f_2 can be determined from Eq. (22).

$$Max\ f_2 = \frac{1}{\sum_{i=1}^{m} dis(CH_i,NH)+dis(NH,BS)} \qquad (22)$$

where in Eq. (22), $\boldsymbol{dis}(\boldsymbol{CH_i},\ \boldsymbol{NH})$ and $\boldsymbol{dis}(\boldsymbol{NH},\ \boldsymbol{BS})$are the distance between CH and next CH and distance between next CH and base station.

- **Nodes degree**

In Eq. (23), function $f_3$is equal to the degree of neighboring nodes. If the degree of a node means the number of its neighboring nodes is more, that node is suitable for becoming a cluster head. Because the cluster head can reduce the congestion of data packets by aggregating the data of the neighboring nodes, and the more the cluster head's neighboring nodes are, the aggregation will be appropriate.

$$Max\ f_3 = \sum_{j=1}^{m} deg_{CHj} \qquad (23)$$

- **Node centrality**

The centrality of the sensor node is actually a value that indicates how central the node is among its neighbor nodes in the network. If this value is low, the other nodes need low energy to transmit data through that node to the CH node. Therefore, the centrality of the node is calculated using the Eq. (24):

$$Max\ f_4 = \frac{1}{NC} = \frac{NZ}{\sqrt{M}} \qquad (24)$$

$$M = \sum_{j\epsilon s(s)} \frac{d^2(i,j)}{|s_i|} \qquad (25)$$

where in the above equations, *d,* |Si| and *NZ* are the distance, neighbor nodes number and the size of the sensory field area.

- **Fitness function**

The objective function of the proposed method for selecting the cluster head is Eq. (26) and the objective is to maximize the value of this function. Therefore, all the components of this function must also have their maximum value:

$$\boldsymbol{Max\ F} = \boldsymbol{\alpha}\times\boldsymbol{f_1}+\boldsymbol{\beta}\times\boldsymbol{f_2}+\boldsymbol{\gamma}\times\boldsymbol{f_3}+\boldsymbol{\delta}\times\boldsymbol{f_4} \qquad (26)$$

In E q. (26), parameters α, β and γ are weight parameters and their sum is equal to 1. Function $\boldsymbol{f_1}$shows the expiration time of the communication link between two cars, $\boldsymbol{f_2}$ shows the average distance between nodes and the cluster head, and $\boldsymbol{f_3}$ shows the degree of neighboring nodes. On the other hand, normalization causes the values of each parameter to be between 0 and 1 and the units of each parameter are removed so that they can be added together. For normalization, the following relationship is used, which is called the Min-Max function.

$$F(x) = \frac{f-f_{min}}{f_{max}-f_{min}} \qquad (27)$$

In Eq. (27), f_{min}, f_{max}, and *f* are the minimum, maximum, and normal value, respectively.

Algorithm 1 indicates the pseudocode of CH selection phase.

Algorithm 1: Clustering phase

1: Start
2: Input information related to CH selection
3: Initializes the maximum number of iterations (Max-Iter) and size of population of FF (n)
4: Initializes the location of FFs and assess the objective function
5: **For** (t = 1: Max-Iter)
6:   **For** (t = 1: n)
7:   Determine status of *F* by using Equations (26) and WOA
8:   Update *F* by using Equation (26)
9:   **End for**
10:   Save the best determined CH nodes
11: **End for**
12: Return the best solution
13: **End**

4.2. Selecting cluster members

To select the members of each cluster, a fitness function is considered with the parameters of the Euclidean distance of each node to the CH and the available energy. To determine the members of each cluster, Wall's algorithm with the following fitness function is used.

$$Minf_2 = \omega \times \left(\sum_{i=1}^{m} \frac{1}{E_{CHi}}\right) + (1-\omega) \times \left(\sum_{i=1}^{m} \sum_{j=1}^{k} dist(s_j, CH_i)\right) \quad (28)$$

Again, the min-max function is used for normalization. The ω parameter is the weight that shows the priority and importance of each parameter. Nodes choose their cluster head based on the above fitness function and send the membership request to it. The cluster head schedules its member nodes to receive data.

4.3. Routing using HHO algorithm

Routing is finding the right and proper path from the sender to the receiver to send the collected data. The suitable route is a short route with the ability to reduce energy consumption and increase the package delivery rate. After clustering the Internet of Things equipment and determining the appropriate cluster heads by WOA, the information packets must be sent to the destination in a hierarchical manner through these cluster heads. Determining the cluster head or the next step is necessary and necessary to increase the lifetime of the network. For this purpose, the brown falcon meta-heuristic algorithm will be used. The fitness function f_3 of this algorithm is based on the distance and energy parameters of the nodes as follows.

$$Min\ f_3 = \theta \times \left(\sum_{j=1}^{m} d(CH_i, CH_j)\right) + (1-\theta) \times \left(\sum_{j=1}^{m} \frac{1}{E_{CHj}}\right) \quad (29)$$

In the above relationship, the goal is to minimize the fitness function of the brown hawk algorithm. The minimum value of the object function means choosing the optimal cluster head as the next step for sending the message. In Eq. (29), θ is the weight parameter and its value is between 0 and 1. Step-by-step forwarding through the appropriate cluster head nodes can be done as a next step.

In fact, in the proposed method, each falcon is a problem solution, and its structure will be an n-dimensional array. For routing from the origin cluster head to the base station by sending a route request packet, a suitable route will be obtained . Fig. 4 indicates the flowchart of the proposed scheme.

4.4. Energy consumption model

Fig.5 indicates the model of consuming energy for WSNs. In this model the consuming energy directly related to the distance and packet size. In the proposed method, consuming energy model of the proposed scheme according to the previous methods is obtained from the following relationship.

$$E_{tr}(l, d_0) = \begin{cases} l(E_{elec} + \varepsilon_{fs} d^2), & d_{ij} < d_0 \\ l(E_{elec} + \varepsilon_{mp} d^4), & d_{ij} \geq d_0 \end{cases}$$

In Eq. (30), E_{elec} indicates the consumed energy; ε_{fs} and ε_{mp} shows the consumed energy of the amplifier in different spaces such as free space and multipath fading channel, respectively. In addition, the consuming energy required to receive l-bit is obtained from the following equation.

$$E_{re}(l) = l.E_{elec} \quad (31)$$

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{amp}}}$$

In Eq. (31), d_0 is the threshold distance, which is 78 meters.

1. Performance evaluation

The proposed method should be evaluated for efficiency and compared with one of the previous works. Using MATLAB software, ECR-IoT scheme is simulated and compared with the basic article MCH-EOR [Jaiswal: 2022] based on service quality parameters. MATLAB software is used for simulation.

For simulation the proposed scheme, many nodes are distributed in an environment in random manner with an area of 200 meters × 200 meters. Evaluable parameters in the simulation of packet delivery rate, throughput, network lifetime, and the number of live nodes, which can be evaluated based on the number of sensor nodes. In the proposed method, the number of network nodes varies from 100 nodes to 500 nodes and the initial energy of each node is equal to 2 joules. The size of the sent packets is equal to 1000 bits and the network bandwidth is 2 megabits per second. The transmission radio range of nodes is 40 meters, and the position of the base station is (0, 0). In the proposed method, the cluster heads receive the data from the members and send it step by step to the base station. Table 2 indicates the parameters and values which were used in simulation phase of ECR-IoT scheme. These parameters belong to the basic article method. In the following sections, the evaluable parameters related to MCH-EOR (Mehta and Saxena, 2020), their definitions and graphs are shown.

4.1. PDR

Eq. (32) shows the package delivery rate. In this regard, M_i and N_i show the number of received and sent packets, respectively.

$$PDR = \frac{\sum_{i=1}^{n} M_i}{\sum_{i=1}^{n} N_i} \times 100\% \qquad (32)$$

Fig. 6 shows the average packet delivery rate based on the number of network nodes. Package delivery rate is a very important parameter for service quality. According to Fig.6, as the number of nodes in the network increases, the packet delivery rate decreases. The reason for this is that with the increase of the node, the congestion level of packet production will increase, and the packets will be deleted due to congestion and buffer filling. The proposed method has a better packet delivery rate compared to other methods. Because ECR-IoT scheme for clustering and routing uses suitable meta-heuristic algorithms such as Wall and Brown Hawk algorithm and suitable parameters. Choosing the right cluster heads using the Wall algorithm and the next step node using the brown hawk to send data can play a good role in improving this parameter. The increase in the data transmission rate in the proposed method indicates an increase in reliability and shows that the proposed method chooses appropriate routes for sending its data. This parameter indicates that the selected next step is also appropriate due to the amount of empty buffer that packets cannot be deleted due to congestion.

4.2. Throughput

Network throughput is the number of successfully transmitted bits per second of network simulation. Eq. (33) shows the throughput, where *k* is the number of necessary tests, S_P and S_T are the start and end times of the simulation.

$$\text{Throughput} = \frac{1}{K}\frac{\sum_{i=1}^{n} X_i \times P_s}{S_P - S_T} \times \frac{8}{100} \qquad (33)$$

Also, in Eq. (33), P_s is the size of the sent packet in terms of bits and X_i is equal to the number of sent packets.

Fig.7 shows the throughput based on the number of network nodes. In this form, with the increase in the number of network nodes, the operational capacity decreases due to congestion in the network. According to the shape of the proposed method, it has a better throughput than the comparable method. The reason for that is choosing the right nodes for the cluster head and choosing the right path for routing considering better parameters.

4.3. Lifetime of the network

According to the definition, the network lifetime is equal to the time when the energy of the first node of the network runs out and the so-called node dies. Fig. 8 shows the graph of network lifetime by number of nodes. In this way, with the increase in the number of nodes, the lifetime of the network also increases. Also, according to the diagram, the proposed method has a longer lifespan compared to the other MCH-EOR method (Mehta and Saxena, 2020). The reason is loading balancing in the proposed method, which increases the length of the network. Load balancing makes the balance of energy consumption in the nodes to be observed and as a result, the energy discharge time of the nodes increases.

4.4. Energy consumption

Energy is a vital parameter for Internet of Things networks based on WSNs. According to energy consumption model in WSNs, the distance between the sender and receiver and packet size has direct effect on more energy consumption. According to the results of Fig.9, with the increase in the number of nodes in the network, the energy consumption also increases. The results of Fig. 9 show that ECR-IoT consumes less energy than MCH-EOR. Proper clustering balances the load in the network and consumes energy optimally. Aggregation of data by the CH nodes also has a significant impact on energy consumption. Hence, in the proposed scheme due to using HHO and WOA with different important parameters for clustering and routing process, the energy consumption is improved in comparing with MCH-EOR method.

4.5. Number of alive nodes

In wireless networks, if the nodes run out of energy, those nodes will not be able to collect information. Therefore, the number of live nodes will play an essential role in the survival of the network. Fig. 10 shows the graph of the number of alive nodes in the network based on the number of execution steps. In this figure, by increasing the number of simulation steps, the number of alive nodes decreases in both methods. The reason for this reduction is the number of packets sent in each execution stage and energy consumption. When the number of sent packets increases with the increase of simulation steps, the energy consumption will also increase. By draining the node's energy, that node will not be able to cover the environment and will not be able to report the events related to that area. Therefore, premature energy depletion of nodes through load balancing and clustering should be avoided. The proposed method improves this parameter to some extent compared to the MCH-EOR method. This improvement is the result of proper application of Wall and Brown Hawk meta-heuristic algorithms for clustering and routing.

4.6. Number of generated clusters

Selecting the optimum number of clusters in cluster-based routing algorithm can affect the quality-of-service (QoS) parameters such as PDR, network lifetime, and number of alive nodes in IoT. Fig. 11 indicates the number of created clusters or CH node number based on the number of different sensor nodes under the impact of transmission radio range of 40 meters and area size of 200m x 200m in the proposed scheme and MCH-EOR method. From the result of Fig.11, we can realize that the proposed method and MCH-EOR reduced the number of generated clusters with proportional increase in the number of sensor nodes or IoT devices. From this figure, the proposed scheme has even better result than MCH-EOR, since it balances the degree of local and global search by expanding or contracting the search space. This can improve and minimize the number of generated clusters and stabilizes the consuming energy to a remarkable level. Under the transmission radio range of 40 meters, the proposed work reduced the number of created clusters to the expected level of 7.27%, better than the MCH-EOR. This important achievement can affect the abovementioned QoS parameters.

5. Conclusion and future works

IoT has many sensor nodes in its primary layer to collect data from an area of interest. These sensor nodes are powered by a battery, which is a significant limitation in IoT networks due to its limited capacity (battery). Since these sensor nodes are deployed in large numbers and form a network, the lifetime of the network must be extended to serve the purpose of deploying sensor nodes. If the sensor nodes consume their energy at par, the lifetime of the network can be easily increased. Due to the inherent limitations of IoT devices, choosing the optimal cluster head and finding the right path is one of the challenging problems of IoT based on WSNs. Clustering by aggregating information and load balancing is one of the appropriate solutions to overcome these limitations. Clustering is considered one of the NP-hard problems and algorithms based on collective intelligence are suitable for clustering. In this paper, a combination of HHO and WOA algorithms are used for routing to improve overall energy consumption, PDR and throughput. Choosing the proper CH nodes is based on the HHO algorithm using various parameters such as the residual energy and distance. This fitness function is used to select the appropriate CH nodes. HHO algorithm used with various parameters of distance and residual energy for energy efficient route selection. Simulation results in the MATLAB environment indicate that the ECR--IoT improves the network lifetime parameters, energy consumption, packet delivery rate and the number of dead nodes compared to the basic paper. The performance criteria of the ECR-IoT scheme are simulated in terms of alive nodes, throughput, network lifetime and energy consumption, PDR and throughput.

As future works, new meta-heuristic algorithms with new parameters can be used for clustering and routing. The use of machine learning techniques can also help to improve routing parameters.

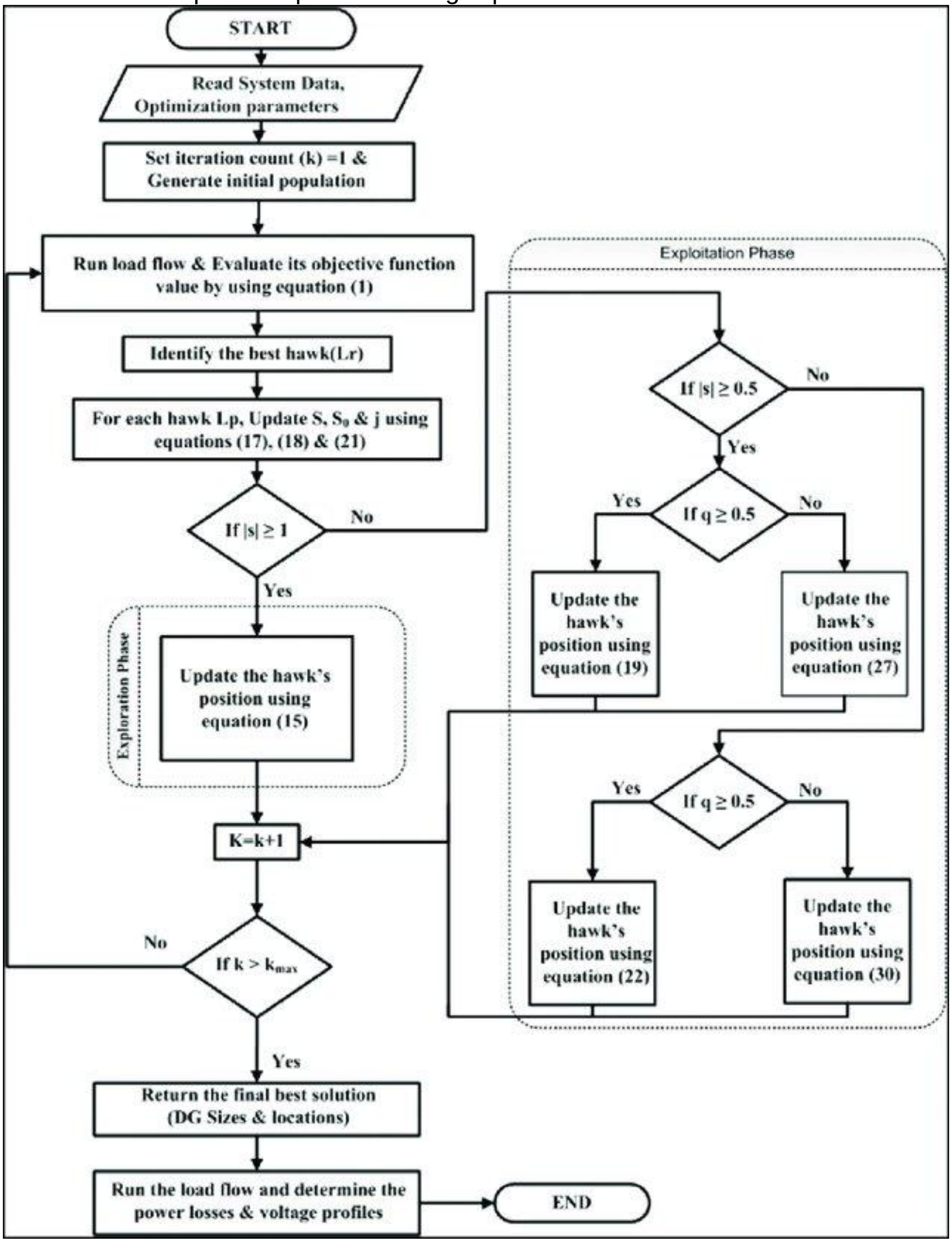

Fig. 1. Flowchart of the HHO algorithm

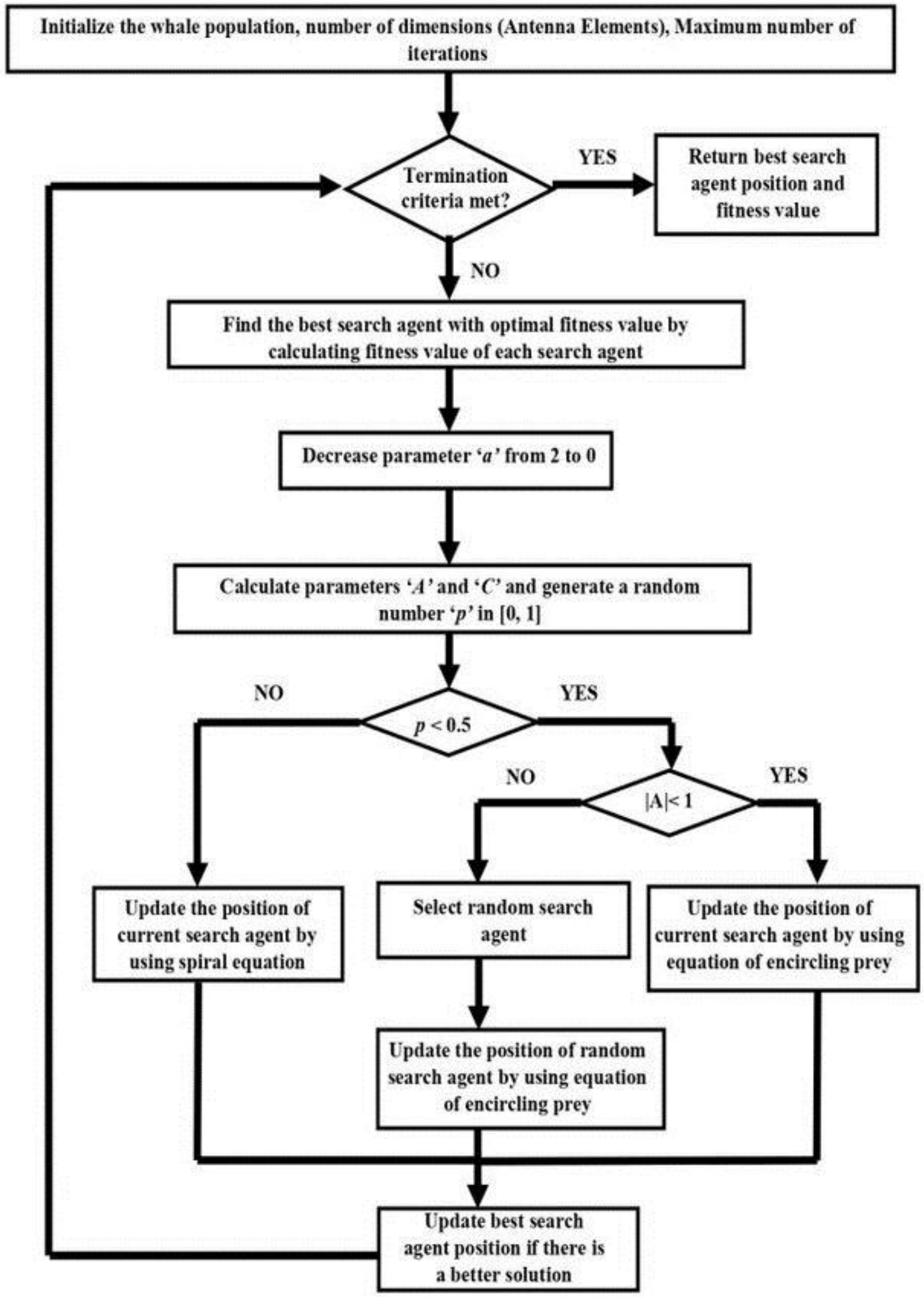

Fig.2. Flowchart of the WOA

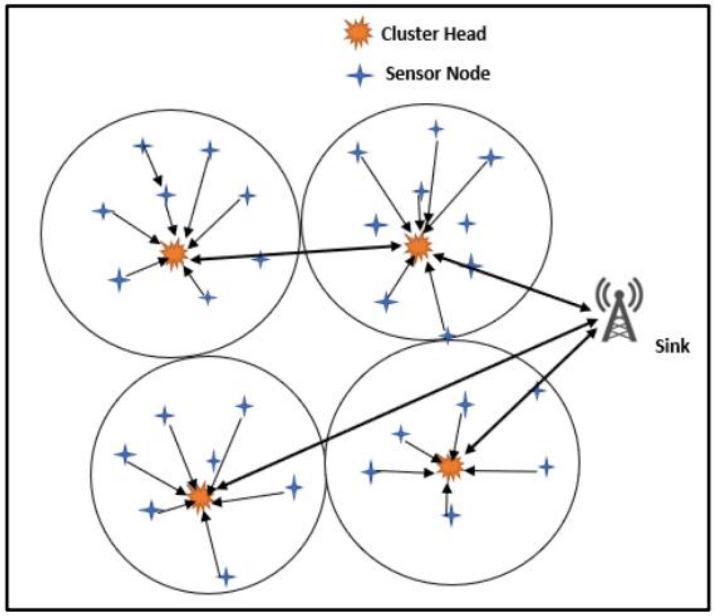

Fig.3. Architecture of CR-IoT

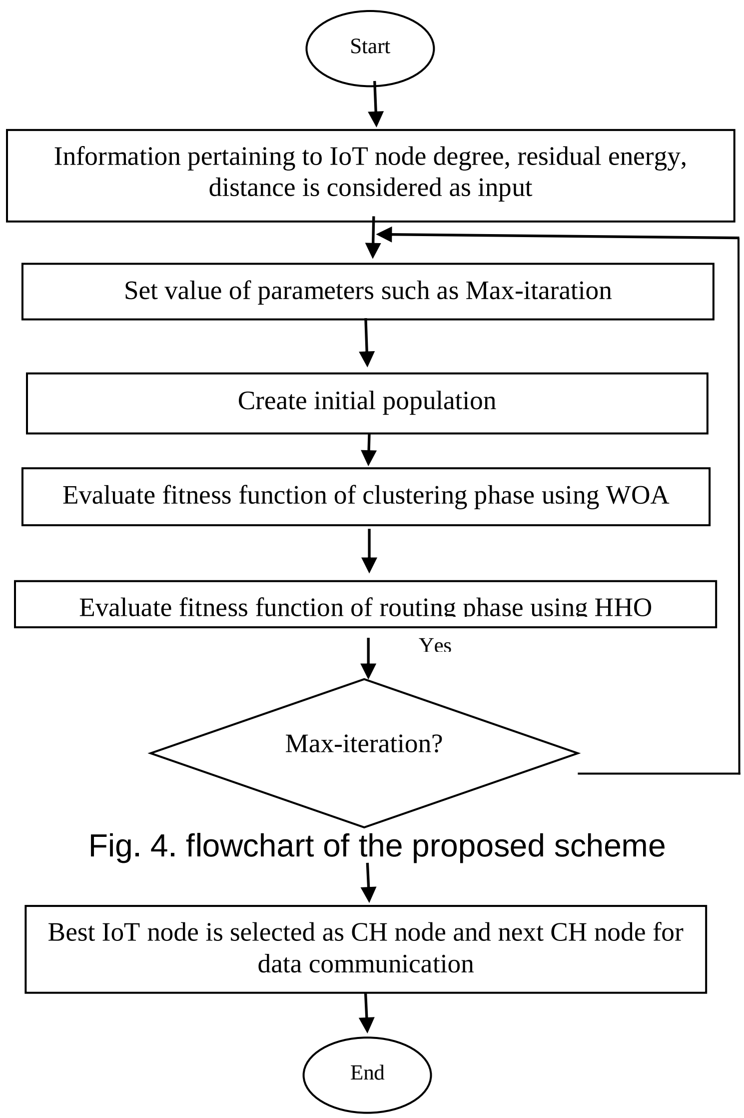

Fig. 4. flowchart of the proposed scheme

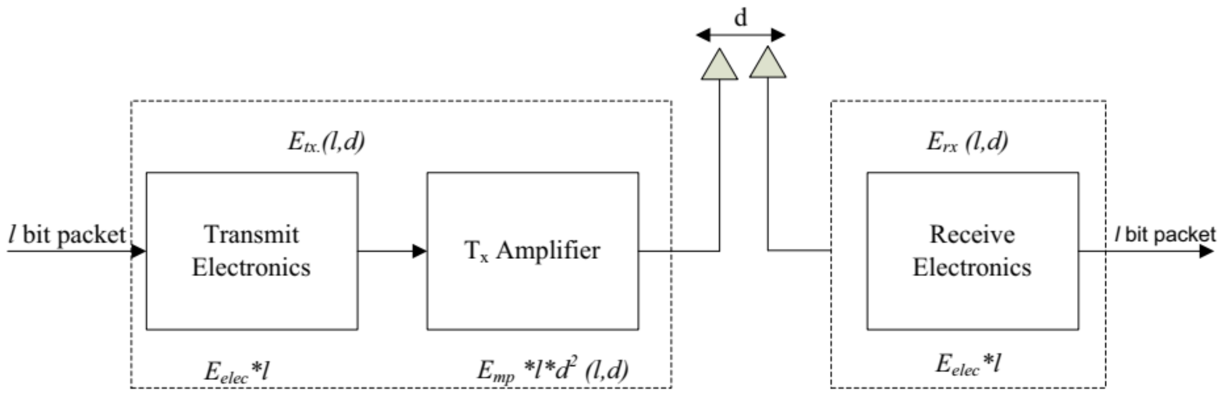

Fig. 5. Consuming energy model

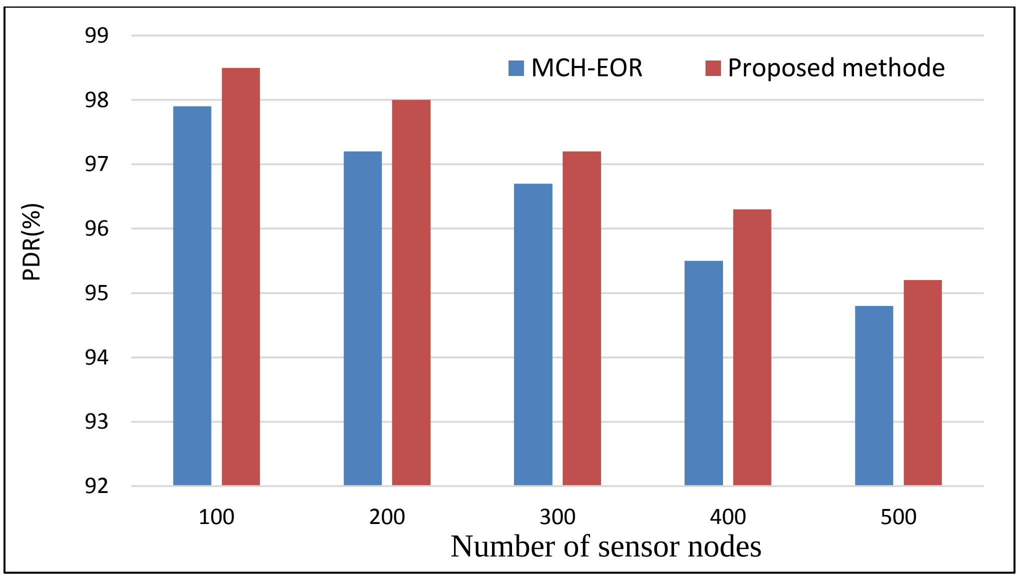

Fig.6. PDR

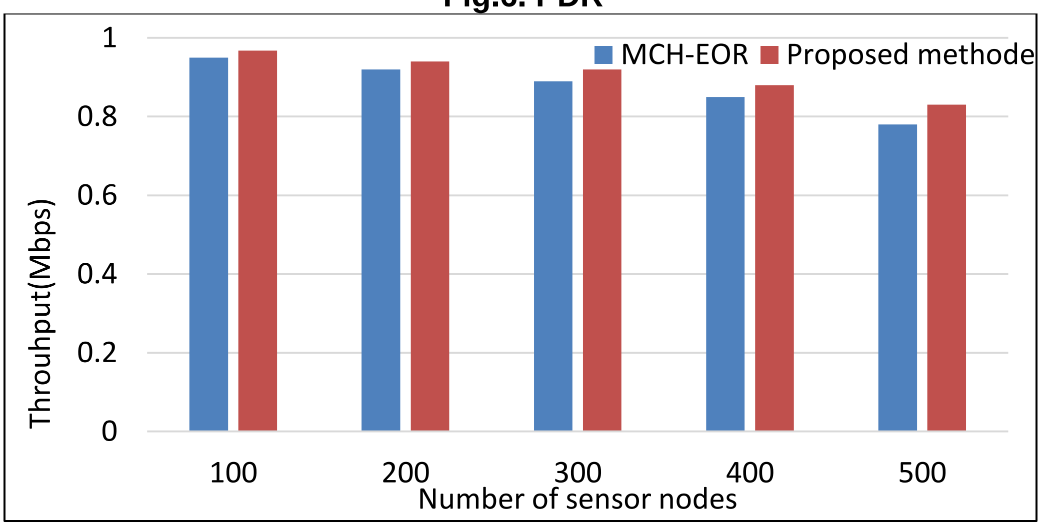

Fig.7. Throughput

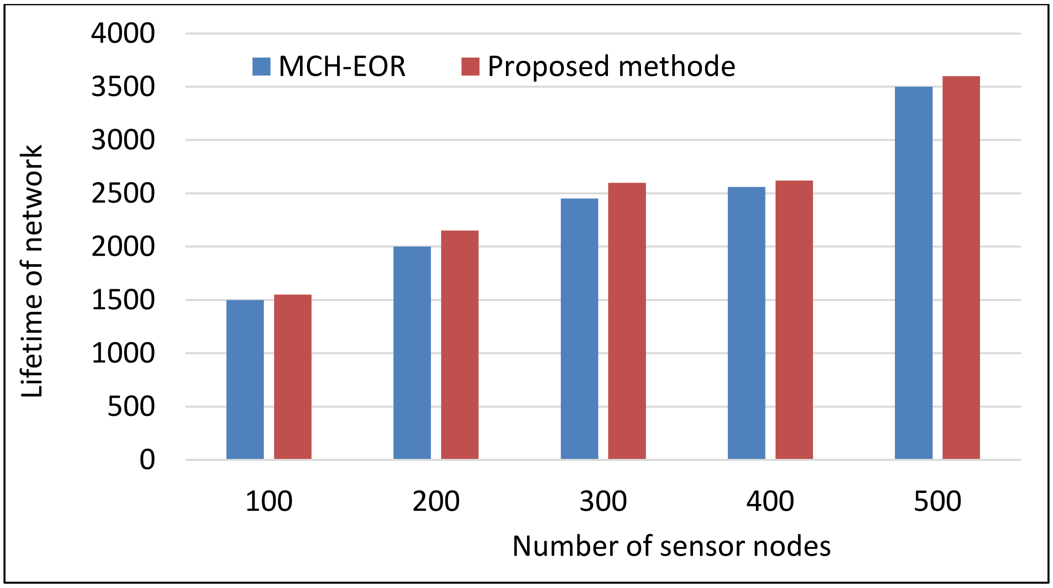

Fig.8. Network lifetime

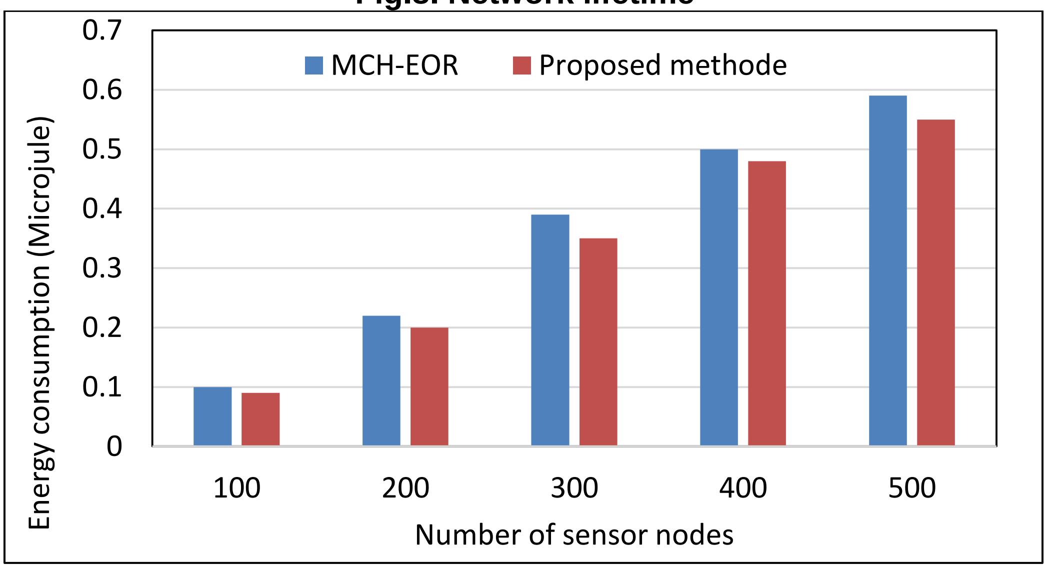

Fig. 9. Energy consumption

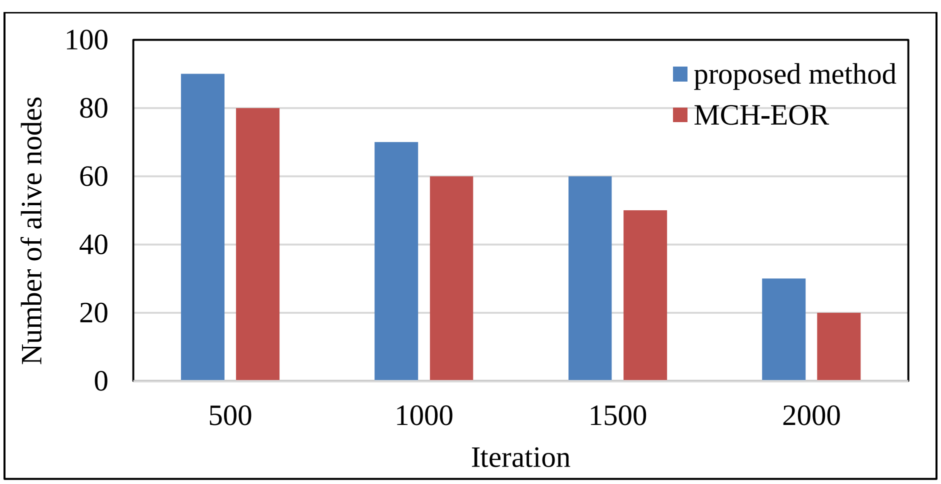

Fig.10. Number of Alive nodes

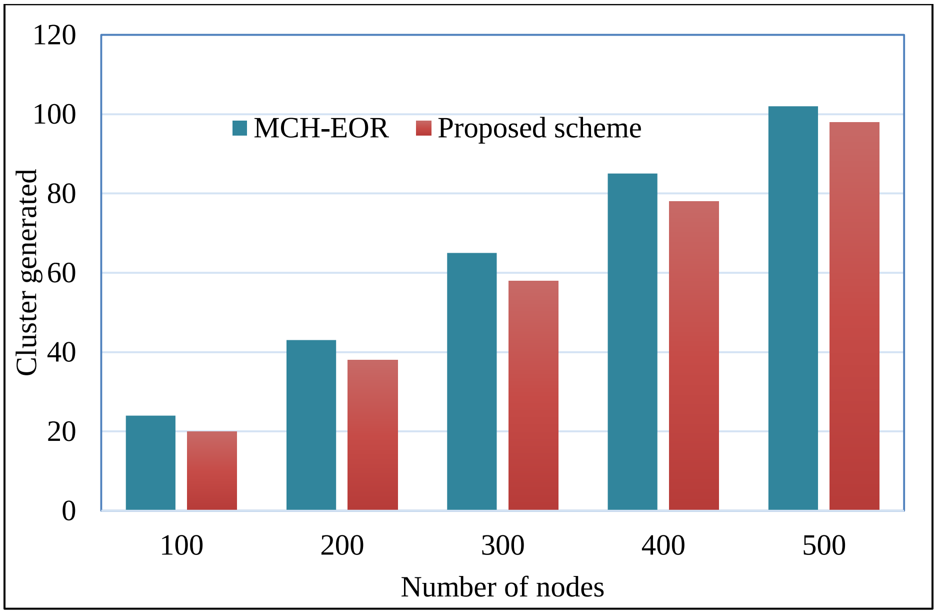

Fig.11. Number of constructed clusters

Table 1. Definition of different variables

Variable	Definition
X(t+1)	The next state position vector for Harris hawks
$X_{rabbit}(t)$	Prey position
X(t)	Hawks current position vetor
r_1, r_2, r_3, r_4, r_5, u, v and q	Random numbers (0, 1)
X_m	average position
$X_m(t)$	Position in iteration *t*
N	Total hawks' number
E	escaping energy of the prey
T	maximum iterations number
E_0	initial state of its energy
$\Delta X(t)$	difference between the position vectors
J	The rabbit random jump strength
D	Problem dimention
S	random vector
LF	levy flight function
β	default constant set to 1.5
$\vec{A}$, $\vec{C}$	coefficient vectors
X*	Location vector of the best solution
r	random vector in [0,1]
$\overrightarrow{D'}$	Distance of the *i*th whale to the prey
p	random number in [0,1]
$\boldsymbol{dis(CH_i, \quad NH)}$	distance between CH and next CH
$dis(NH, BS)$	distance between next CH and base station
ECH_i	Residual energy of *i*th CH
deg_{CHj}	Node degree of jth CH
|Si|	Number of neighbor nodes
NZ	Area
f_{min},	Minimum value of each parameter
f_{max},	Maximum value of each parameter

f	normal value of each parameter
E_{elec}	indicates the consumed energy
ε_{fs}	consumed energy of the amplifier in free space
ε_{amp}	Amplifier constant
E_{re}	Receiver consumed energy
ε_{mp}	multipath fading channel
l	Packet length
α, β, θ, δ	Weight parameter inside (0, 1)
d_0	threshold distance
Mi	number of received packets
Ni	Number of sent packets
PDR	Packet delivery rate
k	number of necessary tests
S_P , S_T	start and end times of the simulation
P_s	size of the sent packet in terms of bits
X_i	number of sent packets

Table 2. Parameters and values for simulation

Parameter	Value
Area	200m×200m
Number of nodes	100-50
Initial energy	2 j
Packet size	1000 bit
Bandwidth	2 Mbps
Sink position	(0, 0)
E_{elec}	50nj/bit
ε_{amp}	30pj/bit/m^4
Radio range	40 m
Round	3500

Table 3. HHO and WOA initial parameters value

Algorithm	Parameter	Value
HHO	Interval of E0	[-1, 1]
	B	1.5
	Generation number	1000
	Harris' Hawks number	100,..., 5000
WOA	Whales number	100,..., 5000
	A	(2, 0)
	α2	(-1 , -2)
	Probability of encircling mechanism	0.5
	spiral factor	1

References

AGARWAL, V., TAPASWI, S. & CHANAK, P. 2022. Intelligent fault-tolerance data routing scheme for IoT-enabled WSNs. *IEEE Internet of Things Journal,* 9**,** 16332-16342.

ALTOWAIJRI, S. M. 2022. Efficient next-hop selection in multi-hop routing for IoT enabled wireless sensor networks. *Future Internet,* 14**,** 35.

ARAFAT, M. Y., PAN, S. & BAK, E. 2023. Distributed energy-efficient clustering and routing for wearable IoT enabled wireless body area networks. *IEEE Access,* 11**,** 5047-5061.

DOGRA, R., RANI, S., KAVITA, SHAFI, J., KIM, S. & IJAZ, M. F. 2022. ESEERP: Enhanced smart energy efficient routing protocol for internet of things in wireless sensor nodes. *Sensors,* 22**,** 6109.

GHAFFARI, A. 2014. Designing a wireless sensor network for ocean status notification system. *Indian Journal of Science and Technology***,** 809-814.

GUPTA, D., WADHWA, S., RANI, S., KHAN, Z. & BOULILA, W. 2023. EEDC: An Energy Efficient Data Communication Scheme Based on New Routing Approach in Wireless Sensor Networks for Future IoT Applications. *Sensors,* 23**,** 8839.

GURRAM, G. V., SHARIFF, N. C. & BIRADAR, R. L. 2022. A secure energy aware meta-heuristic routing protocol (SEAMHR) for sustainable IoT-wireless sensor network (WSN). *Theoretical Computer Science,* 930**,** 63-76.

HEIDARI, A. A., MIRJALILI, S., FARIS, H., ALJARAH, I., MAFARJA, M. & CHEN, H. 2019. Harris hawks optimization: Algorithm and applications. *Future generation computer systems,* 97**,** 849-872.

JAISWAL, K. & ANAND, V. 2022. FAGWO-H: A hybrid method towards fault-tolerant cluster-based routing in wireless sensor network for IoT applications. *The Journal of Supercomputing,* 78**,** 11195-11227.

JAZEBI, S. J. & GHAFFARI, A. 2020. RISA: routing scheme for Internet of Things using shuffled frog leaping optimization algorithm. *Journal of Ambient Intelligence and Humanized Computing,* 11**,** 4273-4283.

JEEVANANTHAM, S. & REBEKKA, B. 2022. Energy-aware neuro-fuzzy routing model for WSN based-IoT. *Telecommunication Systems,* 81**,** 441-459.

KAUR, G. & CHANAK, P. 2022. An Intelligent Fault Tolerant Data Routing Scheme for Wireless Sensor Network-assisted Industrial Internet of Things. *IEEE Transactions on Industrial Informatics,* 19**,** 5543-5553.

LAHMAR, I., ZAIER, A., YAHIA, M., LLORET, J. & BOUALLEGUE, R. 2024. Optimal data transmission for decentralized IoT and WSN based on Type-2 Fuzzy Harris Hawks Optimization. *Internet of Things,* 25**,** 101028.

LENKA, R. K., KOLHAR, M., MOHAPATRA, H., AL-TURJMAN, F. & ALTRJMAN, C. 2022. Cluster-based routing protocol with static hub (CRPSH) for WSN-assisted IoT networks. *Sustainability,* 14**,** 7304.

MEHTA, D. & SAXENA, S. 2020. MCH-EOR: Multi-objective cluster head based energy-aware optimized routing algorithm in wireless sensor networks. *Sustainable Computing: Informatics and Systems,* 28**,** 100406.

MIRJALILI, S. & LEWIS, A. 2016. The whale optimization algorithm. *Advances in engineering software,* 95**,** 51-67.

MOHAMMADI, R., AKLEYLEK, S. & GHAFFARI, A. 2023. SDN-IoT: SDN-based efficient clustering scheme for IoT using improved Sailfish optimization algorithm. *PeerJ Computer Science,* 9**,** e.1424

MOTTAGHINIA, Z. & GHAFFARI, A. 2018. Fuzzy logic based distance and energy-aware routing protocol in delay-tolerant mobile sensor networks. *Wireless Personal Communications,* 100**,** 957-976.

MOUSSA, N., KHEMIRI-KALLEL, S. & EL BELRHITI EL ALAOUI, A. 20 .22Fog-assisted hierarchical data routing strategy for IoT-enabled WSN: Forest fire detection. *Peer-to-Peer Networking and Applications,* 15**,** 2307-2325.

RAJASOUNDARAN, S., PRABU, A., ROUTRAY, S., MALLA, P. P., KUMAR, G. S., MUKHERJEE, A. & QI, Y. 2022. Secure routing with multi-watchdog construction using deep particle convolutional model for IoT based 5G wireless sensor networks. *Computer Communications,* 187**,** 71-82.

ROBERTS, M. K. & RAMASAMY, P. 2023. An improved high performance clustering based routing protocol for wireless sensor networks in IoT. *Telecommunication Systems,* 82**,** 45-59.

SEFATI, S. S., ABDI, M. & GHAFFARI, A. 2023. QoS-based routing protocol and load balancing in wireless sensor networks using the markov model and the artificial bee colony algorithm. *Peer-to-Peer Networking and Applications,* 16**,** 1499-1512.

SEYFOLLAHI, A., MOODI, M. & GHAFFARI, A. 2022. MFO-RPL: A secure RPL-based routing protocol utilizing moth-flame optimizer for the IoT applications. *Computer Standards & Interfaces,* 82.103622 ,

SEYFOLLAHI, A., TAAMI, T. & GHAFFARI, A. 2023. Towards developing a machine learning-metaheuristic-enhanced energy-sensitive routing framework for the internet of things. *Microprocessors and Microsystems,* 96**,** 104747.

SHARMA, S. K. & CHAWLA, M. 20 .24PRESEP: Cluster Based Metaheuristic Algorithm for Energy-Efficient Wireless Sensor Network Application in Internet of Things. *Wireless Personal Communications***,** 1-21.

SUBRAMANI, N., PERUMAL, S. K., KALLIMANI, J. S., ULAGANATHAN, S., BHARGAVA, S. & MECKANIZI, S. 2022. Controlling energy aware clustering and multihop routing protocol for IoT assisted wireless sensor networks. *concurrency and computation: practice and experience,* 34**,** e7106.

TEWARI, P. & TRIPATHI, S. 2023. An energy efficient routing scheme in internet of things enabled WSN: neuro-fuzzy approach. *The Journal of Supercomputing***,** 1-25.

THANGARAMYA, K., KULOTHUNGAN, K., LOGAMBIGAI, R., SELVI, M., GANAPATHY, S. & KANNAN, A. 2019. Energy aware cluster and neuro-fuzzy based routing algorithm for wireless sensor networks in IoT. *Computer Networks,* 151**,** 211-223.

VAZHUTHI, P. P. I., PRASANTH, A., MANIKANDAN, S. & SOWNDARYA, K. D. 2023. A hybrid ANFIS reptile optimization algorithm for energy-efficient inter-cluster routing in internet of things-enabled wireless sensor networks. *Peer-to-Peer Networking and Applications,* 16**,** 1049-1068.