TSINGHUA SCIENCE AND TECHNOLOGY
ISSN 1007-0214 05/21 pp985–1001
DOI: 10.26599/TST.2023.9010056
Volume 29, Number 4, August 2024

Efficient Communication in Wireless Sensor Networks Using Optimized Energy Efficient Engroove Leach Clustering Protocol

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Abstract: The Wireless Sensor Network (WSN) is a network that is constructed in regions that are inaccessible to human beings. The widespread deployment of wireless micro sensors will make it possible to conduct accurate environmental monitoring for a use in both civil and military environments. They make use of these data to monitor and keep track of the physical data of the surrounding environment in order to ensure the sustainability of the area. The data have to be picked up by the sensor, and then sent to the sink node where they may be processed. The nodes of the WSNs are powered by batteries, therefore they eventually run out of power. This energy restriction has an effect on the network life span and environmental sustainability. The objective of this study is to further improve the Engroove Leach (EL) protocol's energy efficiency so that the network can operate for a very long time while consuming the least amount of energy. The lifespan of WSNs is being extended often using clustering and routing strategies. The Meta Inspired Hawks Fragment Optimization (MIHFO) system, which is based on passive clustering, is used in this study to do clustering. The cluster head is chosen based on the nodes' residual energy, distance to neighbors, distance to base station, node degree, and node centrality. Based on distance, residual energy, and node degree, an algorithm known as Heuristic Wing Antfly Optimization (HWAFO) selects the optimum path between the cluster head and Base Station (BS). They examine the number of nodes that are active, their energy consumption, and the number of data packets that the BS receives. The overall experimentation is carried out under the MATLAB environment. From the analysis, it has been discovered that the suggested approach yields noticeably superior outcomes in terms of throughput, packet delivery and drop ratio, and average energy consumption.

Key words: wireless sensor networks; energy efficient engroove leach protocol; meta inspired Hawks fragment optimization; heuristic wing antfly optimization

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Manuscript received: 2023-04-22; revised: 2023-05-28; accepted: 2023-06-06

1 Introduction

There are a number of sensor nodes in the environment that are utilized to collect, process, and transmit data in a Wireless Sensor Network (WSN). Despite their low cost, these sensor nodes are able to detect, analyze, and transmit much more data. Weather forecasting, the military, medicine, and a wide range of commercial and industrial uses all make use of WSN, as do many other things. A single battery powers all of WSN's sensors, which are very small and run on a single power source. An Analog to Digital Converter (ADC) is used by the sensor to get data and send it to the main location, which is called the "Base Station" (BS). To make decisions for different applications, BS looks at the data it gets. A WSN sensor node acts as a repeater, sending data to neighboring nodes and to the sink. Consequently, the WSN's power source must be utilized correctly since it cannot be swapped or refilled because the sensor is situated in a hostile and non-human environment. Scalability, fault tolerance, energy efficiency, and other characteristics influence the design of WSNs. Environmental factors and data transfer to BS via the nodes are two ways in which WSN sensors use up their energy. When compared to data sensing and processing from the environment, WSN data transmission uses more energy than the latter. WSNs are plagued by a lack of power sources for sensor nodes. Therefore, network failure is caused by a node failing. As a result, the node's lifespan will be reduced. As a result, the primary distinction between WSNs and other types of wireless networks is their heightened sensitivity to external energy sources. Data sent from each sensor to BS make the sensor nodes run out of power quickly. In addition, a longer lifespan and improved performance of WSN are only possible with effective energy utilization in WSN. Thus, clustering sensors into groups is used to reduce network energy consumption and boost network scalability. In a network, the Cluster Head (CH) serves as the point of contact for all other CHs in the network. In clustered WSNs, a routing protocol is utilized to find the most energy-efficient path between the CHs and the BS since transmitting data directly to the BS use more energy. Routing protocols include many desirable properties, including fault tolerance, reliability, data accumulation, and scalability. The study's goal is to reduce the nodes' data transmission energy usage. Increased packet transfer to BS may be achieved by reducing sensor node energy consumption. Because of its ability to search, resilience, and self-adaptability, the optimization algorithm is heavily relied upon in this study.

In the following, we list the study's most significant contributions:

• Because of their great stability and low computational cost, Meta Inspired Hawks Fragment Optimizations (MIHFOs) are often used in WSN clustering. For this purpose, MIHFO uses many objective metrics, including residual energy, distance from the BS, degree of connection to nearby nodes, and centrality of neighboring nodes, in order to pick a CH that is optimal for the network.

• Heuristic Wing Antfly Optimization (HWAFO) is used to identify the fastest route from CH to BS because of its ability to swiftly locate solutions in WSN. The HWAFO uses a combination of residual energy, distance, and node degree to address the problem of an uncertain convergence time.

• Effective CH selection and proper creation of data transmission channels help to improve the network's life expectancy. Additionally, the BS receives more packets since the nodes use less energy when delivering data packets.

The following is the structure of the remainder of the manuscript. Section 2 presents a literature review of current research on clustering and routing algorithms. Section 3 discusses the problems and solutions gleaned from previous studies. The MIHFO and HWAFO algorithms are discussed in detail in Section 4 of this article. Comparing the suggested technique against existing algorithms is the focus of Section 5. In Section 6, the conclusion is reached.

2 Related Work

Protocol optimization may extend the life of a network. Consider, for example, the following examples: It is the main purpose of Ref. [1] to gather information about data packet clusters. Network efficiency is increased by using a passive clustering technique[2] with the optimization of gateways. Using a multi-objective fractional algorithm, the Internet of Things (IoT) network cluster heads in Ref. [3] are chosen. The IoT-network design includes a Fractional Gravitational Search Algorithm (FGSA) in order to improve the Node's distance. Factors like distance and time are taken into consideration when evaluating cluster head node health as part of Ref. [4] and FGSA[5]. The Fuzzy dependent Secured Authentication and Clustering (FSAC) Algorithm evaluates the various types of data packets transferred inside the sensors to avoid an attack. In order to make advantage of the qualifying path[6], FSAC was established. Fuzzy logic is employed in the following stage to choose the optimum route for data packets. The network wireless sensor frame (E2SDRSNF) in Ref. [7] is made up of three parts. Data flows between virtual backbone nodes and base stations connected by CH may be recognized using the approach given. For the time being, the present signature approach is sufficient for WSN contact efficiency. The clustering of the WSN's energy efficient fuzzy and gravitational search algorithms was demonstrated in their work[8]. Gravitational Search Algorithms (GSAs) are now being used in the selection process since Sensor Nodes (SN) and CH form a cluster. A Fuzzy Inference Search (FIS) method is used to choose Sensor Cluster Head (SCH) from the previously selected network CHs. The recommended SCH is used as a middleman to deliver and receive data packets from the sink to the base station. Based on the number of hops in the signal network, transmission pathways are prioritized. New WSN routing methods in Ref. [9] ensure that all nodes have a stable supply of power, resulting in longer network lifespans. The suggested technique creates virtual regions, each with a cluster head node. It is explained in Ref. [10] that how to improve clustering techniques. Multiple levels of clustering are used in Multi-Scale Controlled Clustering (MSoC), which is a new approach to clustering. The use of a Radio Frequency (RF) transceiver idea makes it easier to gather massive amounts of WSN data. For Ref. [11] this inquiry, Quality of Service (QoS) in sensor systems, energy management, data security, and software maintenance are the major objectives. For efficient data transmission and maintenance, Secured Energy Efficient Framework (SEEF) includes a cross-layer for controlling power and traffic, a node-and-path inquiry for network security, and an upgraded dynamic routing algorithm to promote QoS. A smart service cycle planning protocol tries to extend the lifespan of a network by reducing the need for data synchronization, transfer disputes, traffic conflicts, and the depletion of network resources. CH is a recent natural optimization method that uses a gravity search algorithm named CH[12]. For the GSA mass evaluation, they propose a ranking mechanism. Additionally, a Fuzzy Logic Controller (FLC) is used to help us determine the purpose of the procedure. Alternatively, the algorithm may run on its own without any outside help. Clustering algorithms for WSNs are needed in order to get a more energy-efficient result. As a general rule, the algorithm relies on a collection of frequently used search characteristics. For greater energy efficiency and load balancing in heterogonal sensor networks, the energy and transit aware sleep galaxy technique offers a hybrid solution[13]. An overly high or low amount of energy or traffic might cause a node to cycle between resting and notifying the other nodes (Efficient Trust Assessment Scheme (ETAS)). It is out of the ordinary. It was assessed whether or not a slot was available for the series of pairings using SEED Time Division Multiple Access (TDMA) technology. As a result of resolving the passive listening issues, stress levels will be lowered. Neuro-Fuzzy Basic Regulation (NFBR) was used to develop a novel cluster development FBCFP routing protocol for efficient routing in WSNs based on the Internet of Things[14]. In order to reduce energy consumption in cluster nodes and across the system, the LEACH protocol improves by positioning the cluster head as near as feasible to the base station[15]. According to these findings, LEACH might both increase the network's lifespan and reduce its energy use. It is claimed that a novel and effective technique for SN clustering has been developed using Eigen Values[16]. The Laplacian matrix is used in this work to better understand spectral clustering. To organize WSN nodes and their autonomous values, a Laplacian matrix and a related function are utilized. Logical reasoning as well as energy and distance constraints lead to a conclusion that CH is the clear winner in this race. Comparing the findings to LEACH and Hybrid Energy Efficient and Distributed model (HEED) is a part of this study's methodology[17]. Invest in the WSN's energy-intensive algorithms and lengthy network life in order to develop new applications. Routing protocols for CH utilize a variety of methods to choose the proper CH and to determine cluster memberships using fuzzy logic classification parameters, and we have employed neural network learning to do this. Reference [18] outlined an approach that uses less energy. Currently, cluster development relies heavily on the Fuzzy Logic based Clusters Formation Protocol (FLCFP) protocol since that is where the emphasis is. Models for low-energy adaptive hierarchical clusters are compared to the proposed model. The new protocol will prolong the life of your network as a consequence of the evaluation. Resources Control Protocols (RCPs), Traffic Control Protocols (TCPs), Priority-Aware protocols (PAs), and Queue Assistance Protocols (QAPs) were all included in Ref. [19]'s comprehensive examination of WSN congestion management solutions. Reliable Data Dissemination for the Internet of Things (RDDI) optimization scheme by Harris Hawks was suggested in Ref. [20] as a technique for safe data distribution in order to assist WSNs. RDDI, which detects threats and records node activity, monitors information replacement. Lightweight Load Balancing and Route Minimizing (L2RMR) in Ref. [21] enabled load balancing and route optimization for Routing Protocol for Low Power and Lossy Networks (RPL). To avoid the Herd Decampment Phenomenon (HDP) problem from becoming prevalent, the HDP was included as an extra probability function. As a novel method for intelligent transportation systems, Quantum Particle Swarm Optimization (QPSO) was used to anticipate traffic flow based on the energy of remaining nodes in Ref. [22] (Intelligent Transportation System (ITS)). In Ref. [23], the Butterfly Optimization Algorithm (BOA) is used to choose cluster leaders. The cluster head is determined by the remaining energy, the distance to neighbors, the distance to the base station, and the number of nodes in the network. Using Ant Colony Optimization (ACO), the shortest path between a node' s central node and its base station may be found. For the BS, nodes that are still alive or dead, together with the amount of energy used and data packets received, are considered performance metrics. There are two unconnected ways to alleviate unbalanced load around a Sink Connection Area (SCA) and reduce energy consumption in WSNs. All intra-layer congestion may be eliminated by using the best route transmission cycle to discover two uncorrelated shortest pathways for each node toward the sink[24]. As illustrated in Ref. [25], T2MFLS and ACO were utilized in conjunction for WSN optimization. The remaining energy, the closeness of surrounding nodes, and the distance from the BS were all taken into account while selecting the CHs. Using ACO, an overall routing path for all CHs was established. In addition to delivering data to the BS, each CH interacted with its neighbors. Nodes' remaining energy was taken into account in order to prevent network disconnection. Fuzzy logic was used to create clustering and ACO routing between nodes, and this had a significant impact on network performance[26]. Fuzzy logic was used to choose the CHs based on residual energy, proximity to the BS and its neighbors, and the CH's node degree/centrality. From CHs to BS, ACO-routed pathways may be found. The WSN's cluster maintenance program maintained that all CHs were using the same amount of energy at any one time. As a result, the WSN will have a longer lifetime. Transmissions may be cut in half when proactive and reactive measures are used in concert. Transmission of data from one point to another necessitates energy saving. Since the battery life of the sensor nodes is limited, an energy efficient WSN is required. The limited energy supply of sensors makes it difficult to boost the performance of WSN networks. This work has resulted in the development of a self-configuration method for energy-aware routing. Data transmission and routing to the BS are major challenges for the WSN. A routing system is thus designed to identify the best way from the source node to BS, with the best route selection and energy usage, optimal. It is the focus of Ref. [27] to select the cluster head in a non-uniform sensor node distribution. Each band includes a base station, which increases the likelihood of a node becoming a cluster head and the network's overall energy efficiency. To minimize route loss and enhance energy efficiency, base station location is optimized[28]. Authors focus on cluster-based localization to boost transmission efficiency and to limit collisions[29]. In order to determine the best CH for the given power and coverage area, it will be determined by these factors[30]. This technique (the proximity-based approach, triangulation and trilateration, and scene analysis) may be used to identify a node if one follows the instructions carefully. A weighted clustering approach and a triangulation strategy are going to be used in the construction of the cluster that will be presented in their research. In this study, the innovative Dijkstra's routing management technique[31] and the distance-based Dijkstra's routing strategy[32] are contrasted with regard to the number of lost packets and the number of packets that were successfully sent. There have been a number of different suggestions made for node localisation with non-uniformly dispersed nodes, all of which are geared towards balancing the amount of energy that is used and enhancing the lifespan of the network[33, 34]. One of the primary issues in recent times is the length of time it takes for a packet to be sent, and over the years, there have been extensive research efforts to expand and enhance the length of time it takes for a packet to be delivered from a variety of research works[35]. In recent time, the time it takes for a packet to be delivered has become one of the major worries. Both particle swarm optimization[36] and ant colony optimization were utilized as algorithms in the process of selecting CH and conducting the gravitational search. They were put into place so that data could be sent from the CH to the washbasin[37]. Because of the employment of these methods, the system was able to achieve optimum clustering and hop route selection, which led to improved system performance[38].

It is clear from the existing body of literature that the currently used research approaches have a number of drawbacks, which can be summarized as shown in Table 1.

3 Problem Statement

The current WSN is now grappling with the following issues: It is possible to increase the energy efficiency of WSNs by considering the network's goals. Energy consumption can only be reduced if the appropriate approach considers both energy and distance. Small- and large-scale WSN installations may both benefit from the energy-efficient WSN. When CH incorporated non-CH nodes in its cluster, clustering and routing based on HSA had a detrimental influence on WSN performance. The number of nodes in a network affects its performance, much as the number of nodes in a network affects its performance. It takes a lot more energy to transport data directly between CH and BS in WSNs than to use a more efficient transmission mechanism. A hot spot between two networks might cause packet loss. The mix of proactive and reactive algorithms employed in HWAFO routing results in additional packet losses. The hostile and unregulated environment in which the sensor node is installed makes it unreliable and prone to malfunction. The power consumption of the nodes is also a critical issue while sending data packets to their final destination. Due to the lack of energy in the nodes, data transmission is plagued by packet loss.

Table 1 Proposed method's advantage against existing methods' problems.

Existing methods' problem/drawback	Proposed method's solution
Slow	Facilitates clustering operations
Convergence	Performs well in live nodes
Non-uniform CH	Improved lifetime
Not stable	High and better speed clustering
Not mobile CH	High density in cluster

4 Proposed Work

WSN paradigm in which all nodes and certain gateways are randomly distributed and remain in place after they are utilized is examined. If a sensor node is within range of a gateway, that gateway will be assigned to that node. Many distinct types of gates are currently available for sensor nodes. As a result, no more than one gateway may be assigned to any two sensor nodes at the same time[39].

Rounds are used to separate the data collecting process. Each cycle, the SN and CH collect data from the surrounding area and transmit it to the relevant CH (i.e., the gateway). Duplicate and unrelated data may be eliminated by using an additional CH as a relay node to transmit to the base station. Multiple nodes simultaneously switch off their power-saving radios in two waves. Wireless internet access is available to everyone. Even if two nodes are very near to one another, a wireless link may be established between them. When it comes to network life spans, literature provides examples of how long a network will endure before its first node dies, how long it will last before its final node dies, and how long it will continue until its last nodes die. There is another term for being present in some network configurations: the time till the whole space is occupied[40]. The N-of-1, K-of-1, and M-of-1 lifespans of the network have all been calculated. N-of-N refers to the maximum duration of the portal's lifespan. According to K-of-N and M-in-K, there are a total of K active gates and M gates in K, which indicates the network's range. The method's step-by-step flow is shown in Fig. 1.

4.1 System model

Depending on the transmitter-to-receiver distance, a declining power law function may be used to depict the wireless channel in use today.

Several ground propagation models were investigated, including the free space model and the two-ray model, which included ground reflected signals. Using the free space model when the distance is smaller than the crossover point is the preferred method. When the distance between the two points is

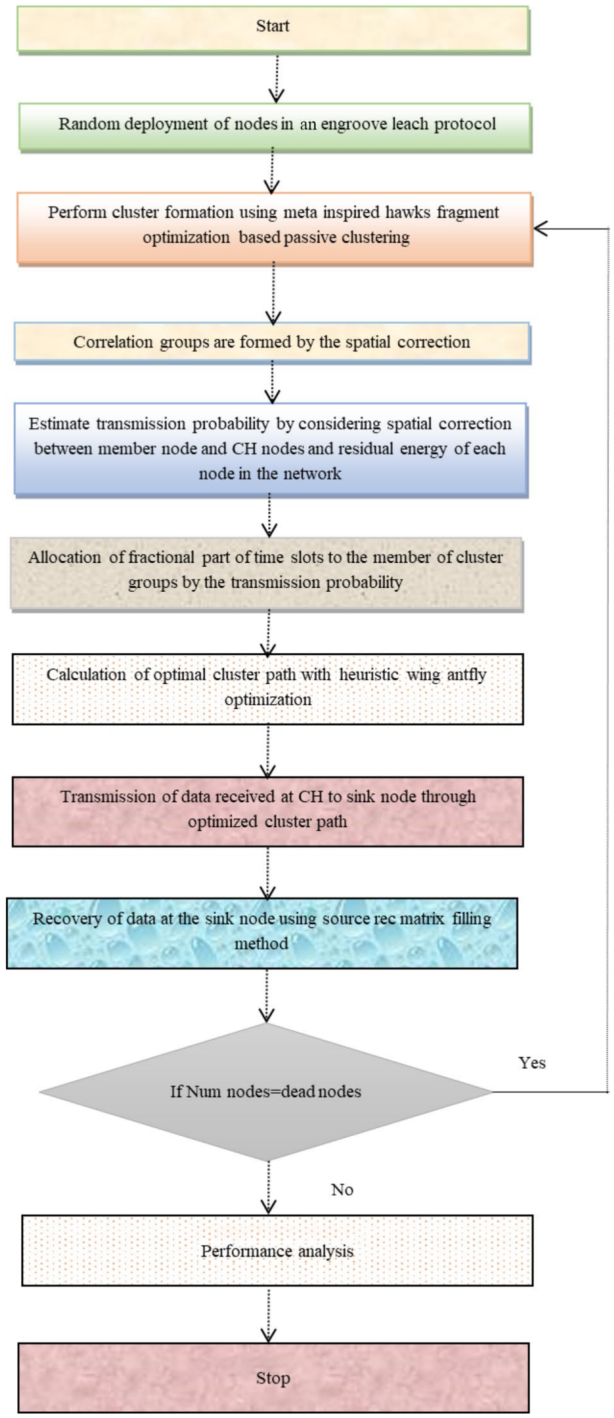

Fig. 1 Schematic representation of the suggested methodology.

larger than the crossover point, this model employs two rays for ground propagation. An example of how a crossover is characterized may be found in Eq. (1):

$$S_{\text{crossover}}=\frac{4\pi\times\sqrt{k}\times g_e\times g_r}{\lambda}\tag{1}$$

where the system loss factor is k, and λ is wavelength. The wavelength of the carrier signal is denoted by g_r, and its wavelength is denoted by g_e. On the basis of the following, the transmitted power is reduced as follows:

$$O_e=\begin{cases}\dfrac{o_r\times f_r\times f_e\times\lambda^2}{(4\pi s)^2\times k}, \text{ if } s<s_{\text{crossover}};\\ \dfrac{o_r\times f_r\times f_e\times g_r^2\times g_e^2}{(4\pi s)^2\times k}, \text{ if } s\geqslant s_{\text{crossover}}\end{cases}\tag{2}$$

Antenna gain f_r and antenna gain f_e are used to determine how much power is received at a distance of s between a transmitter and a receiver. Models for transmitting and receiving power dissipation have been suggested in this study. The radio electronics, power amplifier, and receiver all need energy to operate, and this energy is dissipated by the transmitter. To send a j-bit message across a distance of d, the following model may be used:

$$W_{\text{Rz}}(j,s)=W_{\text{Rz}-\text{elec}}(j)+W_{\text{Rz}-\text{emp}}(j,s)\tag{3}$$

$$W_{\text{Rz}}(j,s)=\begin{cases}W_{\text{elec}}\times j+\varepsilon_{\text{da}}\times j\times s^2, \text{ if } s<s_0;\\ W_{\text{elec}}\times j+\varepsilon_{\text{no}}\times j\times s^4, \text{ if } s\geqslant s_0\end{cases}\tag{4}$$

where $W_{\text{Rz}}(j,s)$ is energy dissipated due to transmission of bit size packets up to distance from transmitting node to the receiving CH per round. It is being estimated. $W_{\text{Rz}-\text{elec}}(j)$ is energy consumed by the transmission circuit. $W_{\text{Rz}-\text{emp}}(j,s)$ is energy consumed by amplifier. W_{elec} is energy dissipated by electrons. ε_{da} is free-spacetransmission. ε_{no} is multi-path loss which represents attenuated transmission.

And to receive this message,

$$W_{\text{Ez}}(j)=W_{\text{Ez}-\text{elec}}(j)\tag{5}$$

$$W_{\text{Ez}}(j)=W_{\text{elec}}\times j\tag{6}$$

where $W_{\text{Ez}}(j)$ is energy dissipation while receiving signal. $W_{\text{Ez}-\text{elec}}(j)$ is energy consumed by the transmission circuit.

Assumptions are made in the simulation work that each sensor node is sufficient to serve as a cluster head and to carry out data fusion operations. In other words, enough power is available to all sensor nodes to reach the sink. In addition, the algorithm checks to see whether nodes have data to broadcast at regular intervals. Each of the nodes in the simulated network has an equal amount of energy capacity at the beginning of a round. As a result, algorithms that have been developed have node homogeneity.

4.2 Engroove leach protocol

Engroove leach's cluster-head selection method is modified to minimize energy consumption, where an optimum cluster-head selection approach extends the lifespan of wireless sensor networks based on the LEACH architecture. LEACH's key drawback is that the route selection algorithm fails to take into account the residual energy and placement of nodes. In other words, this method of path selection cannot be relied upon to avoid selecting nodes that are too far apart or have too little remaining energy as a viable route. Remaining energy and its distance from base station must be taken into account while selecting nodes. We have got some ideas about how to solve the disadvantages of LEACH mentioned above while still using Engroove Low Energy Adaptive Clustering Hierarchical routing protocol (E-LEACH). Node with greater residual energy should have a higher likelihood of selecting the appropriate route in order to enhance network longevity. The distance between the transmitter and receiver affects the amount of energy required to transfer data. A sensor node's residual energy and distance from the BS are taken into account while determining threshold criteria in E-LEACH. From Eq. (7):

$$R_{\text{new}}(b) = \frac{O_{\text{new}}}{1 - O_{\text{new}} \times \left(e \cdot \operatorname{mod} \frac{1}{O_{\text{new}}}\right)} \left(\frac{W_{\text{current}}}{W_{\text{initial}}} \times O_{\text{new}}\right), \quad \text{if } b \in F_0 \tag{7}$$

$$\text{Otherwise}, O_{\text{new}} = \sqrt{\frac{b}{2\pi}} \times \sqrt{\frac{\varepsilon_{\text{da}}}{\varepsilon_{\text{no}}}} \times \frac{Z_n}{s_{\text{bVA}}^2} \tag{8}$$

where s_{bVA} is the distance between the sensor node and the BS, e is round of operations, W_{current} is the sensor node's current power source, and W_{initial} is the sensor node's initial energy. Z_n is the network length. At any given moment, sensor nodes might choose to lead their respective clusters.

4.3 MIHFO-based passive clustering

There are two steps to the MIHFO algorithm: To begin with, it is important to get to know the prey (i.e., the rabbits). After scouting for food, Harris Hawks use a variety of striking and batting methods to startle their victim. The MIHFO procedure may be used to any optimization issue since it analyses the behavior of the bird population. In this case, it is used to estimate the data transmission probability parameters. An in-depth look at the MIHFO implementation is shown in Fig. 2. The MIHFO's actions during the exploration stage may be predicted by simulating the real-world behaviour of Harris Hawks. Harris Hawks are used as possible solutions in this method, and the best one that first tracks and takes prey is chosen as the best one. When the MIHFO algorithm is used, Harris Hawks sit in random places and looks for prey. This can be done in one of two ways. To start, Harris Hawks sit near other members of their family. This gives them a better chance to attack and catch their prey. In this method, a factor called p is used to figure out how far apart the hawks in a family are. It has a value of 0.5.

Second, the Harris Hawks stand in a variety of places, like high trees, but they are still in a certain range. In this case, the q factor has a value of 0.5:

$$Z(r+1) = \begin{cases} Z_{\text{rand}}(r) - e_1 \left|Z_{\text{rand}}(r) - 2e_2 Z(r)\right|, & p \geqslant 0.5; \\ (Z_{\text{rabbit}}(r) - Z_n(r)) - \\ e_3(KV + e_4(YV - KV)), & p < 0.5 \end{cases} \tag{9}$$

where $Z(r+1)$ represents the Harris Hawks' future location, $Z_{\text{rabbit}}(r)$ represents their current location, and $Z(r)$ represents their current location, with e_1, e_2, e_3, and e_4 paring random integers between 0 and 1 to replicate the Hawks' random allocations, which are updated on each iteration. All of the related variables have been divided into lower and higher bands. $Z_{\text{rand}}(r)$ is a randomly picked Hawks from the population, and $Z_n(r)$ represents the middle position of the Hawks. An MIHFO-based passive clustering technique is used to determine how to divide the network into two distinct sections. An evaluation of the intermediate partition may be made using,

$$Z_n(r) = \frac{1}{B} \sum_{u=1}^{B} Z_u(r) \tag{10}$$

where $Z_u(r)$ represents the Hawks' current location in iteration r, and B is the total number of partitions. With the passage of time, the prey's ability to flee is reduced. The rabbit's energy may be measured in order to replicate this motion:

$$W = 2W_i\left(1 - \frac{1}{R}\right) \tag{11}$$

where W is the rabbit's escape energy, R is the maximum number of repetitions that can be done, and W_i is the amount of energy that the rabbit had at the start of a match. The W_i of the MIHFO algorithm goes

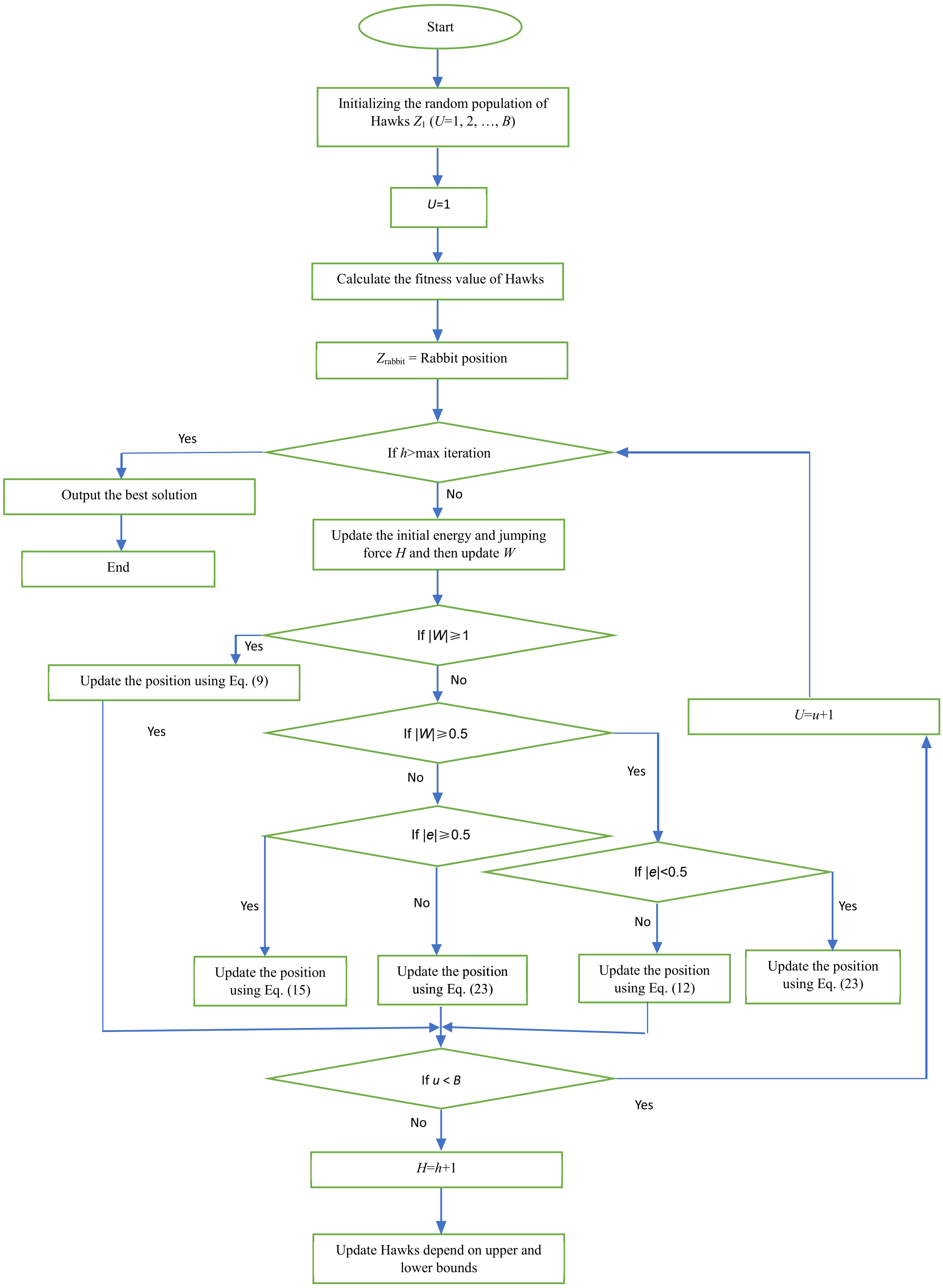

Fig. 2 Steps of MIHFO.

from −1 to 1 each time it is run. It is possible to model the sudden attack action with one of four different methods. Due to the fact that prey often attempt to flee, it is reasonable to assume that the probability of successful escape for a prey is equal to the probability of the prey failing to flee, or $e \geqslant 0.5$ before an unexpected assault occurs. Whatever the prey does, the Hawks will use a powerful or weak assault to bring it in. The parameter W is used to numerically depict the change from exploration to exploitation. Since the exerted force is lesser when $|W| \geqslant 0.5$, and if $|W|<0.5$ then the powerful assault occurs, therefore this is the case. When $|W| \geqslant 0.5$ and $e \geqslant 0.5$, the prey still has enough energy to escape by doing random leaping motions, but it ultimately fails to escape. Before they strike, Hawks swirl slowly and gently about their target to wear them down so they can flee faster. It may be formally represented using the following equations:

$$Z(r+1) = \Delta Z(r) - W|HZ_{\text{rabbit}}(r) - Z(r)| \quad (12)$$

$$\Delta Z(r) = Z_{\text{rabbit}}(r) - Z(r) \quad (13)$$

A random number between zero and one, e_5 is used to indicate the prey's ability to leap at random inside the escape area, and $H = 2(1-e_5)$ is used to express the prey's random jumping power within the escaping region. Prey leaping movements are mimicked by randomizing the H value for each repetition. Association groups are formed when MIHFO spatial modification is applied to hawk positions. Decisions may be made and new views gained via spatial analysis. For each spatial adjustment, we should compensate for each cluster N individually.

$$\text{spatial\_radius } S_{\text{rad}} = \min/\max(Z_n(r)_c(i),\ Z_n(r)_c(j)) \quad (14)$$

When $|W| < 0.5$ and $e < 0.5$ as the prey's stored energy begins to deplete, its movement slows and the Hawks begin to circulate. After that, a quick assault is made to grab the prey, and consequently, the Hawks' current locations are updated as follows:

$$Z(r+1) = Z_{\text{rabbit}}(r) - W|\Delta Z(r)| \quad (15)$$

When $|W| \geqslant 0.5$ and $e < 0.5$, the prey is still able to utilize its remaining energy to flee while the feeble onslaught continues. It is thus necessary to represent it using the Levy Flight (LF) concept, which is more complex than the preceding state. Rabbits' zigzag movements may be replicated using the LF principle (preys). Hawks are supposed to be able to tell when the next time they move toward the prey by using this expression. This will help them avoid having a weak strike with the energy that the prey has saved.

$$T = Z_{\text{rabbit}}(r) - W|HZ_{\text{rabbit}}(r) - Z(r)| \quad (16)$$

A node's total distance from all other nodes may be calculated by adding the distances between the node and each subsequent node. If we look at how far away each neighboring node is from CH, we may infer its location. However, the CH is closer to the nearby node than the neighboring node is to the surrounding node. The failure of nodes and connections will alter the node area. In a steady state process, the next round is duplicated once all previous rounds have been finished. As more nodes die, the cluster improves more often, which leads to more community observations. As neighbors are a potential source of information for every node, this means that all nodes have the same amount of information available to them. It is simple to go to the closest node. Each component is added to the list based on its likely location. The following equation is used by Hawks after a few seconds of dive to determine the probability of a new path:

$$M = T + A \times \text{LF}(S) \quad (17)$$

where A is a vector with size $1 \times S$, optimization issue dimension S is equal to the Levy flight pattern function LF which has the following value:

$$\text{LF}(z) = 0.01 \times \frac{y \times \sigma}{|c|^{\frac{1}{\beta}}},$$
$$\text{where } \sigma = \left(\frac{\Gamma(1+\beta) \times \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}} \right)^{\frac{1}{\beta}} \quad (18)$$

where c is the random number between 0 and 1, y is the number between 0 and 1, Γ is variable constant, and β is a constant with value of 1.5.

This can be rewritten as follows:

$$M\sigma\left(\frac{p}{\partial}, \mu\right) = \left[\frac{\varphi(\partial+\mu)}{\varphi(\partial)\varphi(\mu)}\right] p^{(\partial+\mu)(\mu-1)} \quad (19)$$

where ∂, p, and μ represent node common features, and φ indicates the variation in the geographic distribution. As a consequence, it leads to the formation of connected groupings.

Sensor node transmission speeds are influenced by the consistency of the links, and quality measures are used to assess the link's quality.

$$\text{dest\_nodecon}_{\text{node}} = \text{dest}_{\text{node}}\text{dest\_idel}_{\text{node}} \quad (20)$$

When it comes to the chance of transmission, let us take a closer look at μ. Use spatial adaptation, effective interactions between nodes, CH, and residual energy to figure out how far each node can spread. The formula may be used to determine the probability of transformations,

$$P\left(\frac{\theta}{z}\right) = \left(P\frac{\left(\frac{z}{\theta}\right)}{p(z)}\right) P(\theta) \quad (21)$$

where $P(\theta)$ is the probable function, $P\left(\frac{z}{\theta}\right)$ is the degree of likelihood, and $P\left(\frac{\theta}{z}\right)$ is the overall predicted evidence. This means that a mathematical formula may be devised to calculate the Hawks' location during the weak assault phase.

$$Z(r+1)=\left\{P\left(\frac{\theta}{z}\right)\begin{array}{l}T, \text{ if } D(T)<D(Z(r));\\ M, \text{ if } D(M)<D(Z(r))\end{array}\right. \tag{22}$$

where T and M are obtained using Eqs. (22) and (23).

They are at this point when their stores of power have been used up, but the Hawks keep pounce until the rabbits get caught. $|W|<0.5$ and $e<0.5$. A mathematical representation of this activity may be found in the form of an equation:

$$Z(r+1)=\left\{\begin{array}{l}T, \text{ if } D(T)<D(Z(r));\\ M, \text{ if } D(M)<D(Z(r))\end{array}\right. \tag{23}$$

where T and M under this case are calculated by

$$T=Z_{\text{rabbit}}(r)-W\left|HZ_{\text{rabbit}}(r)-Z_n(r)\right| \tag{24}$$

$$M=T+A\times\text{LF}(S) \tag{25}$$

According to the flowchart shown in Fig. 2, MIHFO implementation may be summarized.

Finally, a fitness probability solution may be found. The likelihood of K transmission is calculated after getting the notification. Randomly distributed parameters were used. As long as the positions of the nodes are known, F values may be calculated. A comparison of the most basic fitness benefits is necessary. This is it! Finally, the lowest feasible value has been identified. This could be seen as giving the relevant particles too much overall value. A single molecule, like the smallest amount of value, needs the smallest amount of value. Afterwards, the fitness factor F is changed to account for the new variables that were added to the model. After area segmentation, there will still be two sub-regions. Before the final M cluster is made, they will still be there. In the next step, we will choose where the cluster will be.

Following this, the possibility of transmission to the CH is determined for a fraction of the time slots. All cluster nodes, including the cluster head, will collect energy in one-time slot "t" equal to the expected amount. Estimates of the transmission energy (E) may be made,

$$E=E_{\text{ch}}+1 \tag{26}$$

where E_{ch} illustrates the energy required for the cluster head.

After that, it will be possible to estimate the data's mass. The weights indicate the quantity of data that each cluster member represents.

$$\text{weight\_val }\vartheta=1/(x(\text{clu}(jj),i)+e) \tag{27}$$

4.4 Path selection

The Hybrid Whale Archimedes Optimization (HWAO) technique was employed here to choose the pathways, as shown in Algorithm 1. To find the best routes between their colony and food sources, ants collaborate. They use pheromones, which they spread on the ground, to indicate the best routes for travel. Pheromone-rich trails are more likely to be followed by subsequent ants. In this manner, ants are able to effectively search for the quickest route. In order to overcome optimization challenges, HWAO employs a similar strategy. Nodes and edges are used to represent the solution components and alternative movement directions in a HWAO method, which uses an artificial ant army to seek for solutions. The structure of the issue is expressed in the linked graph, which is the construction graph. A route on a graph may represent any of the possible solutions. A colony's collective exploration history is recorded in pheromone trails, whereas problem-specific knowledge is derived from

Algorithm 1 HWAO algorithm

Input: Path probability features
Output: Fitness_path solution
Initianlize_Graphical_Nodes();
Initialize_Node_Phermone();
While (total num_of_iterations>0) do
For total number of ants
η_h ← search space of the objective function
Rules of transition[h] = $o_h^n(r)=\dfrac{\zeta_{u,h}\cdot\eta_{x_h}^{\beta}}{\sum_{j=1}^{N}h\left(\zeta_{u,j},\eta_{x_j}^{\beta}\right)}$
Node of selection with the highest $o_h^n(r)$
Pheromone level of update $\tau_{uh}(r+1)=(1-\rho)\cdot\tau_{uh}(r)+\Delta\tau_{uh}(r)$
Total number_of_path;
While end
$\zeta_{u,h}=(1-\rho)\cdot\zeta_{u,h}+\rho\cdot R_j, \forall \underline{x_u x_h}\in O_j$
Fitness_sol← with the best solution η_h
(Fitness_sol)
$\zeta_{u,h}=(1-\rho)\cdot\zeta_{u,h}+\rho\cdot R_{\text{best}}, \forall \underline{x_u x_h}\in O_j$
While
End
End

heuristic information. The movement of the sink is guided by three elements.

(1) **Total residual energy:** Remaining residual energy of ABs at a potential sink site is evaluated using the average residual energy. ABs with higher residual energy are utilized as a guidance for the sink. This collection of ABs, $B(x_u)$ represents the range of potential sink sites. We may write this down as follows:

$$Y_{x_u} = \frac{\sum_{m_h \in B(x_u)}^{B} W_h}{|B(x_u)|} \tag{28}$$

where W_h represents the energy drop, and Y_{x_u} is total residual energy.

(2) **Average communication hop:** It is preferable to locate the sink in areas with fewer communication hops in order to decrease energy usage. Consider the distance between two points on the graph, x_u, m_h, and the range of communication between those two points, m_h, as $s(x_u,m_h)$. Data transmission from m_h to x_u may be figured out by determining the lowest number of communication hops.

$$j_{uh} = \left\lceil \frac{s(x_u,m_h)}{E} \right\rceil \tag{29}$$

As a result, the average number of hops in a communication is x_u that can be approximated by

$$C_{x_u} = \frac{\sum_{h=1}^{b} B\left\lceil \frac{s(x_u,m_h)}{E} \right\rceil}{b} \tag{30}$$

(3) **Maximum step distance:** In order to minimize lengthy delay, the sink's step distance must be lower than or equal to the maximum step distance E_c. In order to explain this, we use the term "factor".

$$S_{x_u} = \begin{cases} 1, \text{ if } s(x_u,m_0) \leqslant E_c; \\ 0, \text{ otherwise} \end{cases} \tag{31}$$

where m_0 is the position of the sink node.

It is based on these considerations that the heuristic information to direct the sink's movement is defined as

$$\eta_{x_u} = Y_{x_u} C_{x_u}^{-\alpha} S_{x_u} \tag{32}$$

where α is a predefined constant.

The route issue may be solved in two sections using HWAO. Here, the sink sites are identified in Eq. (31), and the preferred route is determined in Eq. (33).

$$\left\{ \begin{array}{c} [z_1 t_1], [z_2 t_2], \ldots, [z_n t_n], \\ \left[y_{0,0}^1 \cdots y_{0,b}^1 \cdots y_{b,0}^1 \cdots y_{b,b}^1\right], \\ , \ldots, \\ \left[y_{0,0}^2 \cdots y_{0,b}^2 \cdots y_{b,0}^2 \cdots y_{b,b}^2\right], \\ \left[y_{0,0}^n \cdots y_{0,b}^n \cdots y_{b,0}^n \cdots y_{b,b}^n\right] \end{array} \right\} \tag{33}$$

where $[z_u t_u]$ represents the positions of m_h and $y_{u,h}^j$ represents the data rate from m_u to m_h when the sink is at a_j. It lists the locations and visiting order of sink sites, as well as the flow routing for each sink site.

The whole monitoring area is divided into $Q \times G$ separate grids in order to make sure that the sink sites do not end up in places that are not allowed. Because infeasible grids have their center points in the forbidden zones, they are not the center points of feasible grids. At the intersections of all grids, there may be places where water could be stored. There is a network made up of nodes that show where possible sinks might be, and edges that show possible routes. The three main parts of HWAO's algorithmic architecture are starting, making solutions, and updating the global pheromone. The following sections show how HWAO works in the real world.

Step 1: Initialization

An initial grid is used to find a best-so-far solution for a sink that is still being set up, so it can be found. Soon after that, it starts to go around and around in circles. At the sink's highest heuristic value, it starts each round at the sink's most likely place each time. A routing strategy is used to figure out how the flow will get to the specified sink location. Data from the spot where the sink was before are gathered during a time called r. Sink: As soon as the timer runs out, it starts looking for a new place to get data from. Before the next phase can start, the method above must be used again until at least one SN has run out of energy. After O_{best} is achieved by the greedy method, the pheromones at the graph's edges are initialized.

$$\zeta_{u,h} = R_0, \forall u \in [1,\ b] \tag{34}$$

where $\zeta_{u,h}$ is the pheromone on the edge connecting x_u and x_h, and R_0 is the network lifetime of O_{best}.

Step 2: Solutions construction

These steps are used by the ants to build a solution at this point. This is where the artificial ant is put in its first place, like the one in the middle. The ant then picks a new place for the sin a_j by

$$a_j = \begin{cases} o_{x_h}, \text{ if } \operatorname{rand}(0,\ 1) < p_0; \\ \text{proportion} - \text{selection, otherwise} \end{cases} \tag{35}$$

where o_{x_h} is the selection probability of x_h. The value of o_{x_h} is computed by

$$o_{x_h} = \frac{\zeta_{u,h} \cdot \eta_{x_h}^{\beta}}{\sum_{j=1}^{N} h\left(\zeta_{u,j}, \eta_{x_j}^{\beta}\right)} \tag{36}$$

Since we know that there are a finite number of potential sink locations, we can use u to represent the index of the sink's current location on the list of potential sinks. The proportion-selection approach uses the roulette wheel selection method to pick a sink site based on the selection probability of the candidate sink sites. As soon as it is known where the next sink site will be, the ant goes to a_j, where it uses the Fuzzy Attribute (FA) technique to update the flow routing (i.e., $y^j_{u,h}, \forall u \in [0,b], \forall h \in [0,b]$) while maintaining data collection at a_j for an amount of time (Δr). All prospective sink sites are updated when the specified working time is reached and the ant proceeds to choose new sink sites. This is a fourth step in the process. A solution is said to have been created when all of the SNs in the system have run out of energy for a period of time measured in r.

The pheromone values are updated once an ant completes the solution-creation procedure.

$$\zeta_{u,h} = (1-\rho)\cdot\zeta_{u,h} + \rho\cdot R_j, \forall \underline{x_u x_h} \in O_j \tag{37}$$

where O_j is the artificial ant's solution and R_j is the lifespan of O_j in the network. Ants with greater social status would have higher levels of pheromone concentration on their travel routes, while those with weaker social status would have lower levels.

Step 3: Pheromone updation

After all ants have finished their answers, the global pheromone is updated. Following ants will be able to more thoroughly investigate possible solutions if the pheromone concentration is increased. The global pheromone update action may be expressed as

$$\zeta_{u,h} = (1-\rho)\cdot\zeta_{u,h} + \rho\cdot R_{\text{best}}, \forall \underline{x_u x_h} \in O_j \tag{38}$$

where R_{best} is the ant's lifespan that has been discovered to be the finest so far.

Once a termination condition has been fulfilled, the process repeats itself until the second phase is completed.

5 Performance Analysis

Simulations have been run using the new optimization approach here under MATLAB environment. More tests would be conducted, which would lead to a greater degree of reliability in the results. It is thus important to evaluate how the recommended strategy in this section performs overall. Results and feasibility of the proposed solution are computed and compared to the parameters of the calculation. Table 2 shows the proposed system's simulation parameters.

Figure 3 depicts a WSN network model that may be used to begin the procedure. Many unique approaches to current work are discussed in this section.

It is shown in Fig. 4 that the recommended technique has a greater number of live nodes than LEACH, BOA ACO, and Distribute Energy-Efficient Clustering (DEEC) when the BS is located in the center of the sensing area when it comes to the LEACH, a single-hop data transmission in the WSN is to fault. Determining a cluster head in DEEC is based only on

Table 2 Simulation parameters.

Parameter	Value
Number of nodes	150
Number of round cycles	9000
Initial energy	0.1
Energy transmission	70.0×0.000 000 001 W
Energy sampling	40.0×0.000 000 001 W
Energy amplitude	0.0018×0.000 000 000 004 W
Energy aggregate	5.0×0.000 000 001 m^2
Size of the packet	512 bytes
Position of the sink	Random

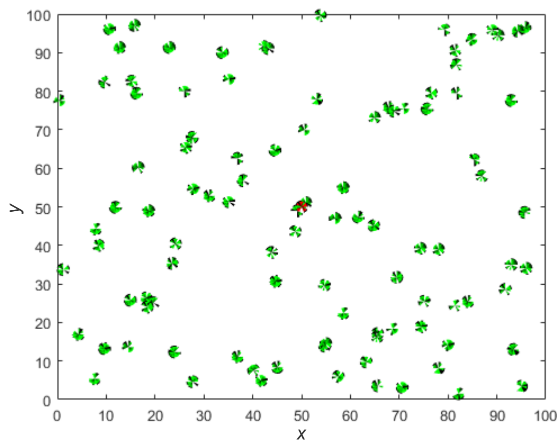

Fig. 3 Implemented system model.

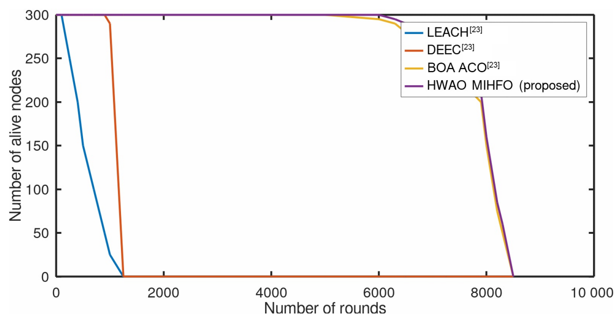

Fig. 4 Number of nodes vs. alive nodes.

the amount of energy remaining in each node. LEACH, BOA ACO, and DEEC methods were studied and determined to have worse performance than the alive node approach. Because of the recommended methodology's balanced use of energy, a higher number of sensor nodes are still active. Nodes' energy consumption is equally divided via the shortest path between the source node and the BS.

As seen in Fig. 5, LEACH, BOA ACO and DEEC are used to calculate average energy consumption. It displays the typical energy use for BS situated in the heart of the sensing area and farther out from the region.

The amount of packets transmitted to BS is counted in a variety of scenarios and nodes. Figure 6 depicts the algorithms used to evaluate packets sent to the BS, including LEACH, BOA ACO, and DEEC. In all Scenarios 1 and 2, the proposed technique gets more packets at the BS than LEACH, BOA ACO, and DEEC. Increases in data packets at BS may be attributed to E-LEACH, the recommended methodology's effective fitness function. Fitness functions state that the most efficient way to increase WSN node count and, by extension, BS message volume is to retain the nodes' remaining energy. The HWAO MIHFO fitness function is used to guarantee that only nodes with adequate energy are picked. Transmission to the BS is therefore protected against packet loss.

This section compares the throughput of the proposed approach with that of current methods. Figure 7 shows the results of a throughput test using the suggested methods of LEACH, BOA ACO, and DEEC. Two potential situations are explored in this study, one of which being the location of BS in the center. It demonstrates that the suggested technique outperforms the other two methods in terms of throughput. The sensors on the LEACH, BOA ACO, and DEEC have lower throughput since they lose energy more quickly than the suggested technique. Higher energy usage is mostly caused by the incorrect CH selection of LEACH, BOA ACO, and DEEC. Due to the energy-efficient CH selection and optimum route design, the suggested approach transfers more data bits than the current methods. Successful transmission of packets to the BS is the first step in achieving the high throughput technique.

This method, as illustrated in Fig. 8, seems to have enhanced the network's lifetime by choosing and creating energy-efficient pathways. CH and route generation optimization guarantees that WSN sensor nodes have sufficient energy to transmit data for a

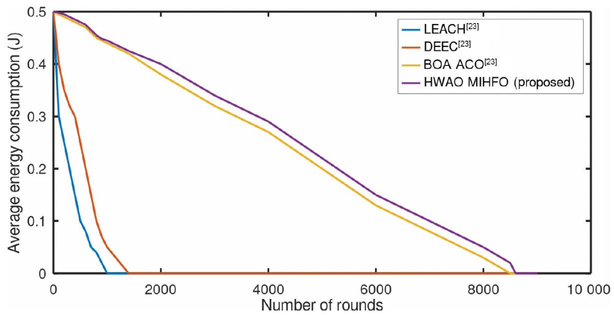

Fig. 5 Number of nodes vs. average energy consumption.

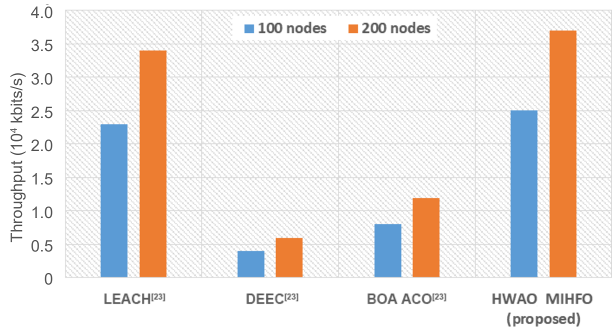

Fig. 7 Number of nodes vs. throughput.

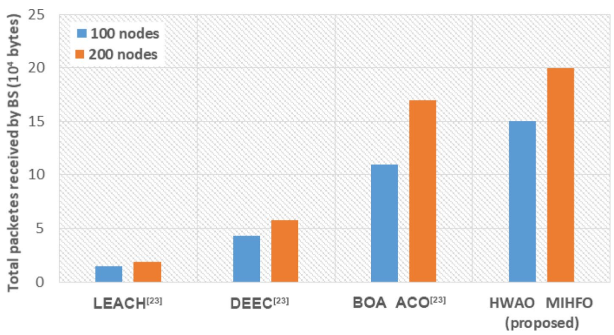

Fig. 6 Number of nodes vs. packet delivery ratio.

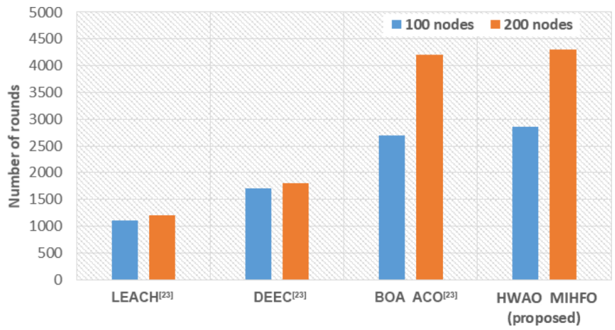

Fig. 8 Number of nodes vs. number of rounds.

longer length of time.

Here, the proposed solution is compared to existing practices in terms of packet loss rates and routing overhead. Various numbers of nodes were tested to see what the packet drop ratio was. Figure 9 shows that when the number of nodes rises, the amount of routing overhead increases. The findings are shown in Fig. 10. Figures 9 and 10 show that the proposed method has a lower packet loss ratio and a lower routing overhead than the present solutions. To reduce transmission losses, a fitness function is proposed as part of the solution. More data packets are received by the BS when node failure is prevented during route establishment. In the LEACH, BOA ACO, and DEEC, poor CH selection and a short network lifetime lead to high packet loss ratio and routing cost.

6 Conclusion

For sensor networks that are reliant on WSNs, the researchers turned to an optimization-based cluster-based routing approach. Here, a passive clustering technique is used. In WSNs, the sensitivity threshold, packet retransmission methods, channel-dependent packet size reframing, and other functional aspects are given additional attention. The HWAO MIHFO optimization was used in WSNs to efficiently transmit packets. Sensor nodes and the CH's area were taken into account as well as how much energy was wasted in the CH. Use the largest possible packet size, allocate the maximum data and hardware transmission capacity, and prevent route blunders that need transceivers to go deep into the transitional zone. MATLAB simulations were used to test the proposed technique. Clustering is an adaptable and scalable strategy that can be deployed in a large number of nodes with a variety of base station locations and node deployment styles thanks to optimization algorithms. The results of the simulation shown that the suggested protocol is superior than LEACH, DEEP, and BOA ACO in terms of energy efficiency as well as reliability in the clustering process. The study's results suggest that this strategy is superior to other well-established ways for reducing energy usage and extending the lifespan of the WSN system.

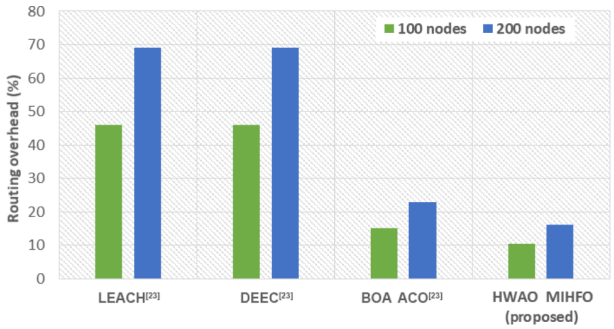

Fig. 9 Number of nodes vs. routing overhead.

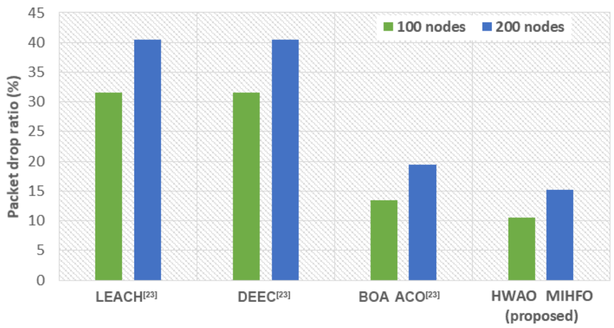

Fig. 10 Number of nodes vs. packet drop ratio.

Acknowledgment

This work was supported via funding from Prince Sattam Bin Abdulaziz University (No. PSAU/2023/R/1444).

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