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Article *in* Peer-to-Peer Networking and Applications · May 2023

DOI: 10.1007/s12083-023-01502-z

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Peer-to-Peer Networking and Applications
https://doi.org/10.1007/s12083-023-01502-z

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QoS-based routing protocol and load balancing in wireless sensor networks using the markov model and the artificial bee colony algorithm

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Received: 1 June 2021 / Accepted: 4 May 2023

Abstract
Due to resource constraints in wireless sensor networks (WSNs), energy consumption and networks' lifetime are considered significant challenges. Because sensors have a tiny battery and cannot be charged again. In WSN, collected data is usually transferred to the Base station (BS) directly or hop-by-hop. Therefore, load balancing and routing are one of the main issues in the WSN. This paper proposes a new routing scheme with load-balancing capability using the Markov Model (MM) and the Artificial Bee Colony (ABC) algorithm. LEACH algorithm is used to maintain load balancing between Cluster Heads (CHs). Then the Markov Model and the Artificial Bee Colony (MMABC) algorithm were used to find the best candidate nodes of each cluster to be turned into a CH. The simulation results in MATLAB software demonstrated that the proposed method surpasses the compared methods in terms of energy efficiency, number of alive nodes, and the number of delivered packets to BS and CH.

Keywords Wireless sensor network · Routing · Clustering · Energy balancing · Markov model · Artificial bee colony

1 Introduction

In WSNs gathered data are transmitted from source sensor nodes to the base station in a single-hop or multi-hop manner [1, 2]. However, sensor nodes in WSNs have resource limitations such as energy, radio range, processing power, and memory [3, 4]. Various routing algorithms are proposed to transmit data from source sensor nodes to BS in many applications [5, 6]. These algorithms must be scalable and efficient due to the large size of a network and the significant number of sensor nodes. The WSNs have many applications such as healthcare, target tracking, battlefield, environment monitoring, and air pollution [7, 8]. Based on the WSN structure, the routing protocols are divided into two types single-hop and multi-hop [9]. The first method transmits data directly to the BS by the sensor nodes. In the second method, the sensor nodes forward the data hop-by-hop by applying appropriate clustering and aggregating the data by the CH.

Routing schemes with load balancing capability improve the lifetime of WSNs and energy consumption of each sensor nodes [10]. Hence, energy efficient routing schemes are one of the most important and crucial issues in WSNs [11]. Since load balancing and clustering are also considered a Nondeterministic Polynomial time (NP-hard problem) [12], the metaheuristic algorithms are appropriate solutions for this problem.

This paper proposes a new cluster-based routing method to balancing load and improve the Quality of Service (QoS) in WSNs using the Markov Model (MM) [13] and the Artificial Bee Colony (ABC) algorithm [14]. In the proposed method, the residual energy of each sensor is predicted by MM based on the location; then, the ABC algorithm performs a local search and is responsible for assessing the quality of the options proposed by the MM. The proposed method determines the number of CH candidate nodes by the MM. Then, the ABC algorithm selects one of them as the CH node based on the parameters given by the MM.

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These parameters can include residual energy, the location of nodes, and the central location of the environment. The proposed method first applies the Low-energy Adaptive Clustering Hierarchy (LEACH) algorithm [15], where the CH is selected using the thresholding method. From the second iteration onward, the MM is applied and proposes qualified nodes according to specified parameters to turn them into CHs. It should be noted that the LEACH algorithm cannot select a CH after the second iteration, and the CHs are chosen by the MM and the ABC algorithm for the network. The main contributions of the proposed scheme are as follow:

- This paper proposed the MMABC algorithm to select the new CH and load balancing between them. This algorithm can bring low cluster-building time in comparison with other algorithms.
- This paper uses MM for load balancing between the CH and the ABC algorithm for routing. This proposed method can decrease the energy consumption of the WSNs.
- The proposed method improves various QoS parameters such as live node, number of total packets sent to CH and BS, and average residual energy. According to using MM and Artificial Bee Colony ABC algorithm, the MM predicts the energy of CH using the location and then tries to evaluate this process using the ABC. This process increases the QoS of the WSN.

The rest of the paper is organized as follows: Sect. 2 deals with the related works, while the proposed method has been introduced in Sect. 3. In addition, Sect. 4 presents experimental data and the simulation results. Finally, the discussion and future studies have been presented in Sect. 5.

2 Related works

This section explains the related works.

Zuhairy and Al Zamil [16] proposed a new method called Multinomial Logistic Regression (MLR). In this method cloud server sends tasks to the BS. After the second round, each cloud server tries to analyze and categorize the tasks and determine whether the task is similar to the previous ones or not. Each BS has 6 types of sensor nodes, which are different from each other in terms of energy consumption and applications. This method improves dependability, accessibility, and energy consumption.

In De Schepper, et al. [17], tasks have to be performed based on the radio range of networks. In this study, the load balancing problem has been discussed by taking into account various dimensions of loads in networks (e.g., the number of stations, the manner of making decisions on load balancing, the records of load balancing in a network, etc.) with the title of Mixed Integer Quadratic Program (MIQP). On the other hand, the re-routing strategy is used to control load balancing. In the case of large network, re-routing can cause additional load.

Sampathkumar, et al. [18] proposed a method called load balancing and routing strategies using the Glowworm swarm optimization approach (LBR-GSO). This method proposed a solution for load balancing based on energy efficiency through an advanced global update strategy and enhancing the local exploration scheme. Through indirect vector diagrams, this study illustrated a situation where nodes are made based on a BS and are determined by integers. If the sensor nodes are below the communication area, they may be accompanied by an edge. The source node sometimes may collect the assessment data from the surrounding areas and transmit them to the next hop to deliver them to the BS.

In Touati [19], the fuzzy logic was applied in WSNs to maintain load balancing. In this study, a parameter called the Fuzzy Induction Estimator (FIE) was defined by applying the heredity concept. The routing decisions to select optimal routes are taken according to the results obtained by the FIE. The concept of child and parent heredity in FIE provided an adaptation, resulting in estimating the fuzzy social bonds index to improve the decision-making process by selecting an optimal route to transmit data to the destination. For this purpose, the FIE design mechanism by considering such limitations as the residual energy, network depth, and the distance between nodes. Due to mathematical calculations, this scheme is not scalable.

Chen, et al. [20] proposed a method based on the imbalanced distribution of loads among the nodes that facilitates the premature death of nodes in a sensor node. They studied the relationship between neighbors' energy, transmission power, and loading. Thus, they proposed the distributed topology control algorithm based on the Load Balancing Evaluation Model (LBEM). In this method, based on the energy of the neighboring nodes, the adaptation performance of nodes can regulate their transmission power to improve node adaptability.

Edla, et al. [21] proposed a method called Shuffled Complex Evolution of Particle Swarm Optimization (SCE-PSO). They set a new fitness function by considering a network's average cluster distance and threshold loading. In the SCE-PSO method (the combined form of SCE and PSO approaches), a population of points is sampled randomly from the accessible space. After the initial values and the location of particles are set, the population is divided into pre-specified sets with N members. The division of the groups is conducted based on the fitness function of the particles.

Li, et al. [22] proposed an algorithm called the Energy-efficient load balancing ant-based routing algorithm

(EBAR). This algorithm is a pseudo-random route discovery and an improved scheme of the pheromone trail to balance energy consumption in sensor nodes. It uses an efficient exploratory update algorithm based on the criterion of the expected energy costs to optimize route communication. If two sensor nodes are located within the communication area, they are connected through crests. A source node periodically collects evaluation results from the surrounding environment and sends them to the next hop to deliver to the BS node. The goal is to find an adequate energy route and the ant colony system was used for routing.

Kim and Choi [23] proposed an approach regarding load balancing called Cloud Radio Access Network (C-RAN) using IoT-enabled devices. In CRANs, Remote Radio Heads (RRHs) are installed at small distances and concentrated short ranges to provide coverage, and the control messages are repeatedly produced. This scheme is based on the establishment of a balancing relationship between RRHs and IoT-enabled devices. The researchers of that study evaluated and compared the performance of their proposed algorithm with the common methods of load balancing using network simulation. They attempted to balance the traffic between RRHs.

We can distinguish the many fairly balancing characteristics in the state-of-the-art discussion presented above, so we tried to identify the areas covered by the pre-existing papers. This paper used the MM for estimating the new CH selection and it can bring a new novelty for load balancing in WSN. This paper utilized a systematic approach to locate, propose, and evaluate algorithms for any given scenario based on a set of predetermined criteria.

3 The proposed scheme

In the proposed method, the nodes are clustered using the LEACH algorithm, and from the second iteration, the network implements the MMABC algorithm. First, MM techniques nominate several nodes as candidates for becoming CHs based on the history of network nodes. Then, the ABC is applied to approve one of the selected options. As illustrated in Fig. 1, some CHs can establish direct connections with the BS. At the same time, some other CHs are forced to use multiple hops to transmit data to the BS. The CHs are responsible for collecting the received data and preparing them for sending to their destination. Then, CHs have to transmit such data to the BS using single hops (direct) or, in case of being far from the BS, multiple hops (indirect) through other cluster heads of a network.

3.1 Energy consumption model

The energy consumption of the proposed model was calculated using the LEACH algorithm. The energy required

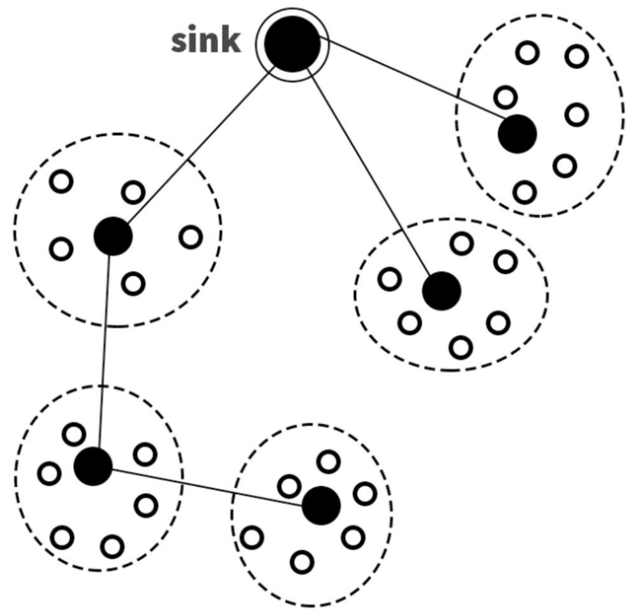


Fig. 1 The network model

to transmit a data packet with the size of k bits through the distance of d (the distance between the sending and receiving nodes) can be calculated using the following formula [24]:

$$E_{tx}(i) = k(E_{elec} + E_{amp} * d^2) \tag{1}$$

where E_{elec} indicates energy consumption in the electrical circuit, and E_{amp} is the energy required to boost the signals transmitted to send a bit of data. Furthermore, the energy required to receive a packet of data with the size of k bits can be calculated using the following equation:

$$E_{rx}(i) = k * E_{elec} \tag{2}$$

In addition, for the nodes located on a pint between the sending and receiving nodes, the consumed energy will be equal to the sum of the energy required for sending and receiving the data:

$$E_{cons}(i) = \sum_{i=1}^{n} [E_{tx}(i) + E_{rx}(i)] \tag{3}$$

Thus, the energy consumed by any nodes, either sending or receiving, in such networks can be calculated using the above formulae. Figure 2 shows the transmission of energy.

3.2 LEACH algorithm

When establishing network nodes in domains, the LEACH algorithm is applied in addition to the MM and the ABC

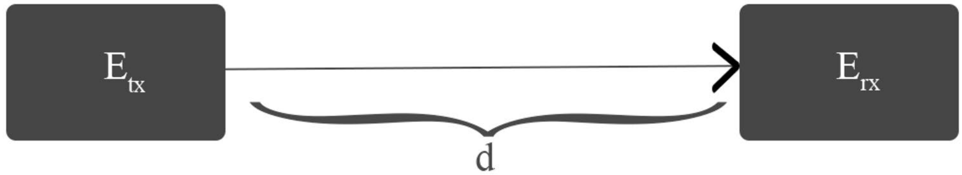


Fig. 2 The transmission of energy

algorithm to select the best CH based on the network condition in each iteration. In other words, from the second iteration onward, the MM declares the best candidates for becoming cluster heads in each domain. The ABC algorithm approves one of them as the best qualities concerning location and energy [25]. Energy transmission is performed in single hops for near destinations and multiple hops, using the most immediate neighbor method, to distant destinations [26]. Nodes work as CHs cannot attain the same role until the p_{th} iteration (P is an arbitrary percentage of clusters). Thus, in each iteration, a node has the possibility of 1/p becoming a CH. Cluster members can only communicate with the CH using the Time-division multiple access (TDMA) schemes [27] and perform it according to the schedule created by CH. The LEACH algorithm always uses single hops to transmit data from all CHs to the BS (Fig. 3).

3.3 Markov model

On transitory data, the MM is a technique that is frequently applied [28].

The MM is a statistical model with a wide application area. The MM is used extensively for performance modeling and performance-prediction analysis, where the MM can predict the future state of a target system based on its current state. We assume a discrete observation in each state from the set as follows:

$$\{v_1, v_2, ...v_m\} : bj(m) = P_r(o_t = v_m | q_t = s_j) \quad (4)$$

where $bj(m)$is the observation or emission probability, also assume a homogeneous model for which the probabilities do not depend on t. The values thus observed constitute an observation sequence O. The state sequence Q is not observed directly (being "hidden"), but it should be possible to infer it from the observation sequence O. An example of an observable model for an MM is shown in Fig. 4, where $M = N$ and $b(m) = 1$ if $j = m$ and $bj(m) = 0$ otherwise. To summarize and formalize, an MM has the following elements, N shows the number of states in the model.

$$S = \{S_1, S_2, S_3, ..., N\} \quad (5)$$

M: the number of distinct observation symbols in the alphabet

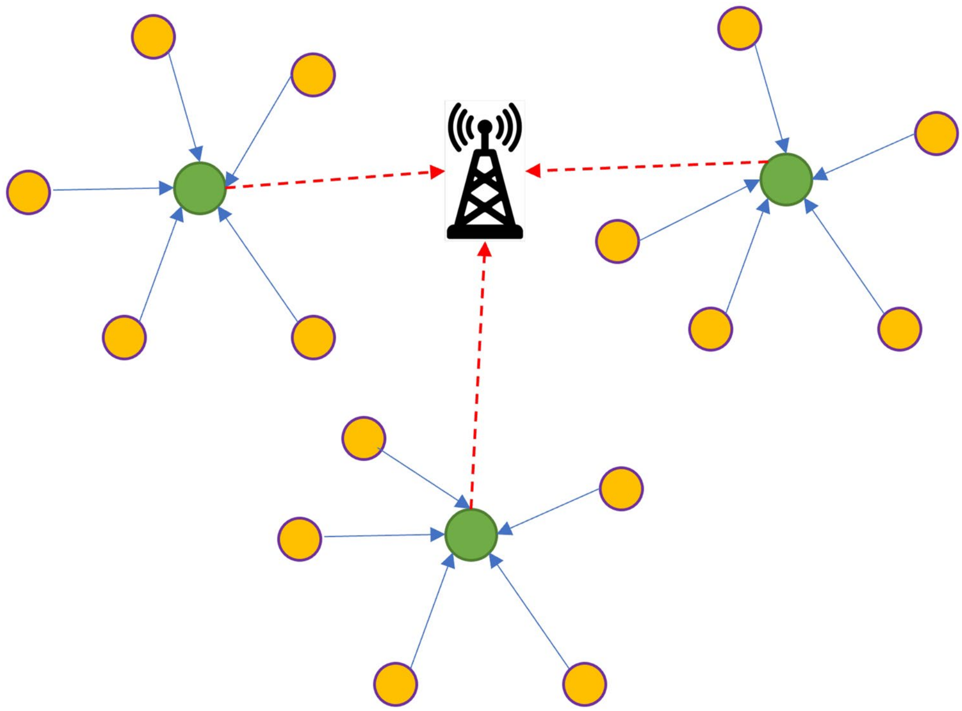


Fig. 3 The LEACH algorithm

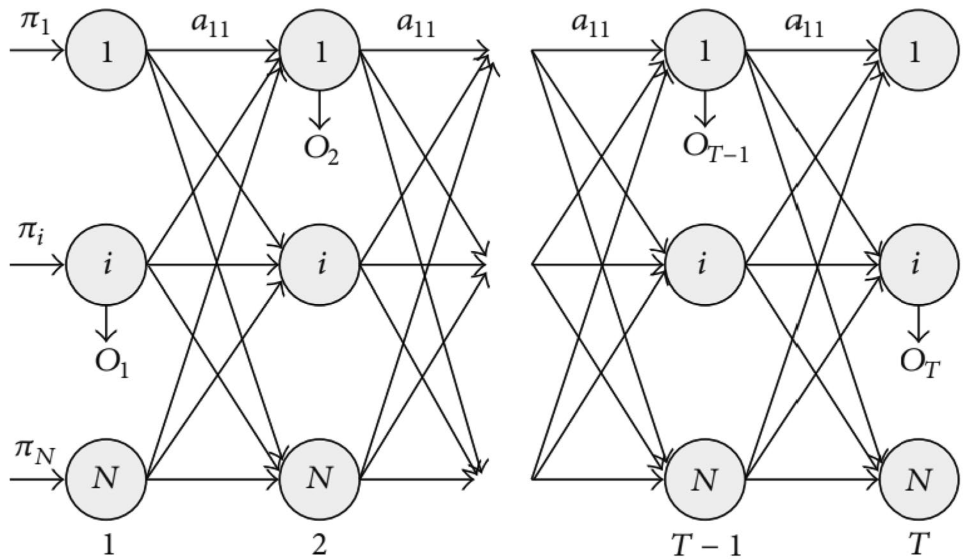


Fig. 4 The Markov Model

$$V = \{V_1, V_2, \dots, V_m\} \tag{6}$$

State transition probabilities:

$$A = [a_{ij}], where\ a_{ij} = P_r(q_t + 1 = S_j | q_t = S_i) \tag{7}$$

Observation probabilities:

$$B = [b_j(m)], where\ b_j(m) = P_r(o_t = v_m | q_t = S_j) \tag{8}$$

Initial state probabilities:

$$\Pi = [\pi_i], where\ \pi_i = P_r(q_1 = S_i) \tag{9}$$

N and *M* are implicitly defined by the other parameters, leaving $\lambda = (A, B, \Pi)$ as the parameter set for an MM. Given λ, the model can be used to generate an arbitrary number of observation sequences of arbitrary length, but we are usually interested in the other direction, namely, that of estimating the parameters of the model given a training set of sequences.

3.4 Artificial bee colony algorithm

The ABC includes a group based on the search algorithm and simulates the behavior of bee colonies while searching for food. This algorithm conducted a local search and can be applied to optimization problems [29]. The process of food search by a colony starts with the scout bees being sent to search for good flower patches. The scout bees move randomly from one patch to the next. During the harvest (i.e., bloom) season, the colony continues the search process by keeping a colony's population as scout bees. When searching all flower patches was completed, each scout bee danced a patch with a definite quantity of nectar and pollen. Figure 5 shows the ABC algorithm.

3.5 MMABC algorithm

In the proposed method, MM is used to select nodes with maximum residual energy. Then, ABC algorithm is used to select the CH nodes among the nodes proposed by MM. The least active central node is selected as the CH in each round. The sequence of symbols produced by a Markov model gives information about the sequence of states. In general, the learning problem deals with how to estimate the parameters of the MM model. MM uses linear mathematical equations to calculate probabilities. As a result, in terms of time cost, it is a very suitable option for use in WSNs. The detailed stages of the proposed method are as follows:

Step1. First, sensor nodes are distributed randomly in a particular environment.

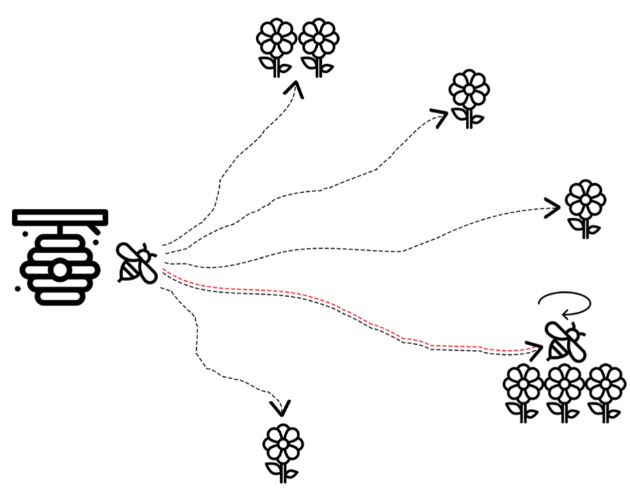


Fig. 5 The ABC algorithm

Step2. LEACH algorithm selects a number of the nodes as CHs.

Step3. The CH nodes broadcast advertisement packets to select cluster members (CMs).

Step4. The other nodes become members of a CH based on the received signal strength (RSS).

The LEACH algorithm uses Eq. (10) to calculate *T(n)* as a threshold value:

$$T(n) = \begin{cases} \frac{p}{1-p\times(r mod \frac{1}{p})}, n\epsilon G \\ 0, otherwise \end{cases} \tag{10}$$

where in Eq. (10), G indicates a set of nodes that have not been selected as CH within the $\frac{1}{p}$ rounds, r is the current round, and p is the percentage used for the selection of nodes as CHs. The proposed scheme uses the MM and the ABC schemes to select CH nodes and hence, Eq. (10) is not applied from the second iteration onward.

Step5. Data transmission is performed using the LEACH algorithm.

Step6. From the second iteration onward, the MM is applied. One of the functions of this model is to make explorations to find the best ones based on their fitness functions and the history of data transmission (which indicates their energy in a network). Another part of the MM is to propose nodes distinguished in terms of the above criteria to become CHs in the next iteration.

Step7. Equation (11) shows the fitness function.

$$Fitness(i) = a\left(\frac{E_{res}(i)}{E_{init}}\right) + \beta(1 - \frac{D_{cen}(i)}{D_{\max}}) + \gamma(\frac{B_{res}(i)}{B_{init}}) \tag{11}$$

$$a + \beta + \gamma = 1 \tag{12}$$

where α, β, and γ are the weight parameters, whose values equal 0.33. In addition, E_{init} is the initial energy of all nodes when the network starts its operation. In Eq. (11), D_{cen} indicates the distance of a node from the middle point of the domain plane, E_{cons} is the energy consumed by a node, D_{max} is the longest distance produced in the domains, and B is the buffer size of each node.

$$E_{res}(i) = E_{init}(i) - E_{cons}(i) \tag{13}$$

$$D_{cen}(i) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{14}$$

$$D_{\max} = \sqrt{(x_0 - x_1)^2 + (y_0 - y_1)^2} \tag{15}$$

$$B_{res(i)} = B_{init}(i) - B_{cons}(i) \tag{16}$$

where x_i and y_i indicate the coordinates of the center of the domain. x_0 and y_0 against x_1 and y_1 are two points in the domain that have the highest distance from each other.

Step8. After MM proposes several nodes to become the CHs during the next iteration, the ABC algorithm investigates the candidate nodes. It approves the best one to become the CH.

Step9. Data transmission is performed using the nearest neighbor to communicate between the sensor and CHs and between CHs and the BS.

Step10. After the transmission of data from sensor nodes to the BS, step 8 is repeated.

Step11. The algorithm ends if the number of iterations is over or the energy level of all nodes is equal to zero.

The pseudo-code of the above stages has been presented below:

Algorithm 1. The pseudo-code of the proposed scheme

```
Input: n sensor node, the energy and buffer size of nodes
Output: Finding appropriate route to BS
    //initializing the network by distribute sensor nodes in the environment
Step1: first round
    Each nod selects a number between 0 and 1 randomly nodes = random (0,1);
    CHs = Nodes that select a number less than the threshold
    CHs broadcast a signal to attract other nodes
    Based on received signal strength (RSS) nodes become members of the CH
    Sending data ();
Step2: Second round onwards
    while (Residual energy of nodes =0 or the number of rounds=Max-round) {
    for each zone {
            Calculate fitness (all of the nodes);
            Candidate nodes = MM ();
            Approved nodes = ABC (candidate nodes); // set approved nodes as new CHs
            Sending data ();
                }
```

The algorithm receives *n* nodes and information related to the energy and buffer size of the nodes as input. While the network is being initialized, all the nodes have initial energy equal to 1 J and buffer size equal to 65 bytes. Finally, after CHs were determined at each iteration using the MM and the ABC, the data were transmitted to the BS using the nearest neighbor method.

4 Performance evaluation

The proposed method was compared with the Ant Colony Optimization (ACO) [30], the Glowworm Swarm Algorithm (GSO) [18], and Greedy Meta-heuristic Algorithm [31], Meta-Heuristic Ant Colony Optimization based Unequal Clustering (MHACO-UC) [32], and Chaotic Discrete Artificial Bee Colony (CDABC) [33] using a similar dataset. In addition, the simulation factors and results were investigated.

Table 1 The simulated parameters [35]

Network parameter	Values
Number of base stations	1
Number of nodes	100
Data size of packet	200 Bits
Control packet size	25 bits
The initial energy of the node	1 j
Initial buffer size of the node	65 byte
Number of rounds	2000
E_{elec}	50 nj/bit
E_{amp}	0.0013 pj/bit/m^4

4.1 Simulation environment

The proposed scheme has simulated in MATLAB R2016b. The hardware involved in the simulation was an Intel Core i7 3.2 GHz processor with a 16-gigabytes RAM using Windows 10. MATLAB has numerous mathematical superiorities compared to other software and allows its users to share its source codes [34]. Considering such advantages, MATLAB was applied to perform simulation and evaluation of the proposed method. Table 1 and Table 2 show the parameters utilized in the simulation.

5 The obtained results

The results of comparing the performance of networks using different algorithms in two scenarios have been reported in terms of the number of alive nodes, average residual energy, the overall number of packets received by the BS, and the overall number of packets sent to CHs. The simultaneous use of the LEACH algorithm, MM, and the ABC algorithm leads to more favorable results in establishing a network.

Comparative analysis of the proposed scheme for the number of alive nodes and number of rounds as shown in Fig. 6. In the first rounds, the CDABC method has a good performance compared with other algorithms. After 1500 rounds, the proposed method obtained the highest network lifespan by having a more significant number of alive nodes.

According to Fig. 7, the proposed method showed superior performance compared to other methods in terms of the energy consumption in different iterations. Also, from the first rounds, the proposed method has an efficient implementation compared with other algorithms. MHACO-UC and CDABC also have good performance in these results. A greedy algorithm is a complex algorithm because of that, most of the time, the simulation in the energy is not suitable. As illustrated in Fig. 7, it can be inferred that the proposed method can save overall energy and prolongs the network's lifetime.

Table 2 Network size

# of scenario	Network size	BS
1	100×100	50×50
2	150×150	75×75

According to Fig. 8, the proposed method showed the best performance regarding the total number of packets received by the CH. The proposed method received the most significant amount of data in CH. İn this experimental result, the proposed method performs well in compering with other algorithms. In the second algorithm, the CDABC has good performance, but according to the complexity, the GSO algorithm does not have good results.

Figure 9 demonstrates the total packets received by BS in the different rounds. According to simulation results, the proposed method and CDABC have good performance compared with other algorithms. The greedy algorithm loses the energy earlier than other algorithms; it can not send the data to BS better than GSO or ACO algorithm. In the first rounds, the proposed method and CDABC algorithm are approximately the same.

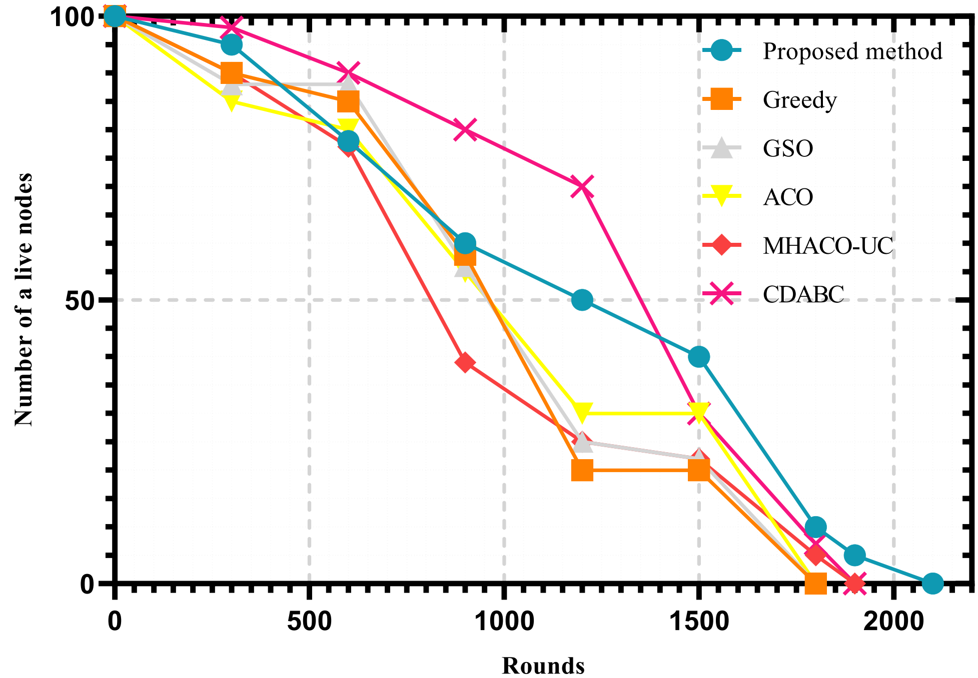
In Fig. 10, different algorithms have been compared with each other regarding the number of alive nodes in various iterations of the second scenario. As mentioned in the current study, the number of active nodes can provide us with an understanding of the network lifetime and, particularly, the load balancing issue. That is because higher load balancing rates increase the nodes' average energy and reduce their wastage during the network's lifetime. İn addition, when the number of dead nodes decreases, it means that the number of alive nodes has increased in a network.

Suitable average residual energy in all a network can indicate sufficient load balancing among all CHs. Because the main rule of load balancing is to distribute energy and data among the nodes fairly. As shown in Fig. 11, the proposed method outperformed and is better than other methods in different iterations.

In Fig. 12, different algorithms have compared in terms of the total number of packets received in the CH within the framework of the second scenario. As Fig. 12 shows the CH received the most significant number of accurate packets in the proposed method. But ACO algorithm is not scalable, and the CH can not receive the data very well.

As seen in Fig. 13, the proposed method has performed better than other methods regarding the number of data sent to the BS. The reason for this is load balancing and increasing the network lifetime, obtained by the ABC algorithm and the Markov model. As seen from the results, the proposed method has obtained almost the same results for networks with small and large sizes. But in general, in the ways that rely on the CH selection scenario, networks with larger sizes show better results than networks with small dimensions. The amount of initial energy affects the average performance of the network, so the higher the initial energy, the higher the efficiency of the network.

Fig. 6 The number of alive nodes in different iterations of the first scenario

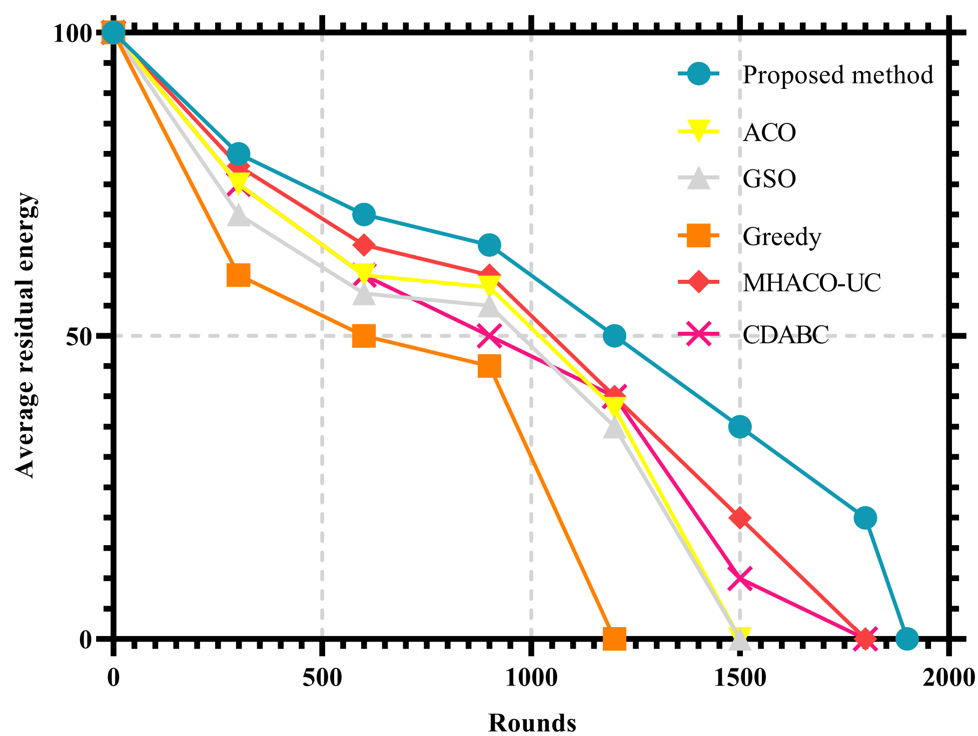


By increasing the initial energy of the nodes, due to load balancing, the network life will be increased.

Figure 14 shows that the suggested technique converged more quickly than all the other methods included in our analysis, which plots the algorithms' convergence with the number of requests. Moreover, after around 40 cycles, the convergence reached its minimal value. Therefore, only 100 repetitions of the findings have been displayed. An iterative algorithm is said to converge when, as the iterations proceed, the output gets closer and closer to some specific value. More precisely, no matter how small an error range you choose, if you continue long enough the function will eventually stay within that error range around the final value.

How well an algorithm can solve issues to the feasible precision specified by its conditioning is measured by its stability. When choosing key features, stability is

Fig. 7 The average energy consumption



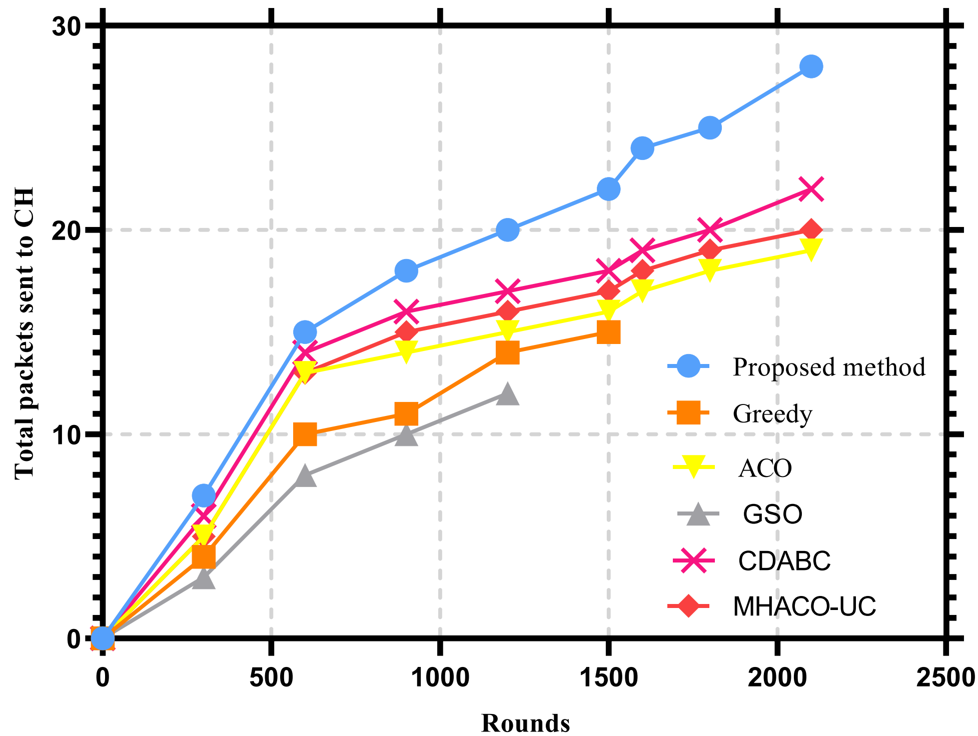


Fig. 8 The total number of packets received by the CH in the first scenario

frequently defined as a sensitivity to the interruption of input data. Due to the unexpected and uncertain nature of metaheuristic algorithms, stability testing is a crucial additional test for these algorithms. Figure 15 contrasts the proposed method's stability with alternative methods for various jobs and iterations. There were three categories for the stability index's strength of agreement: weak, medium, and excellent.

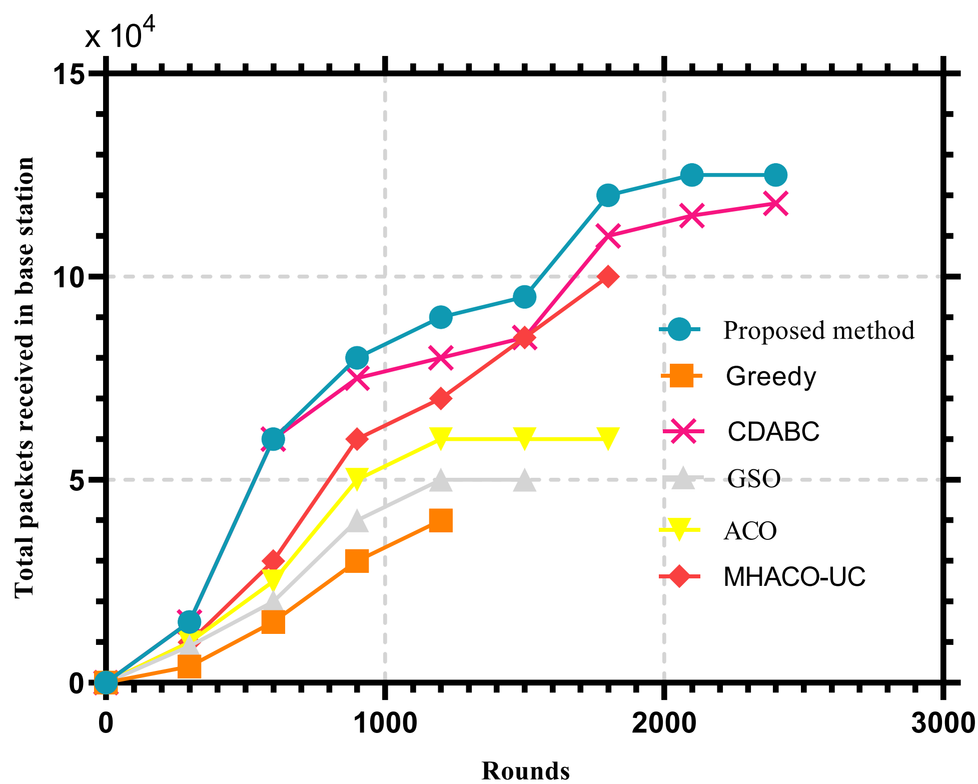


Fig. 9 The total number of packets received by the BS in the first scenario

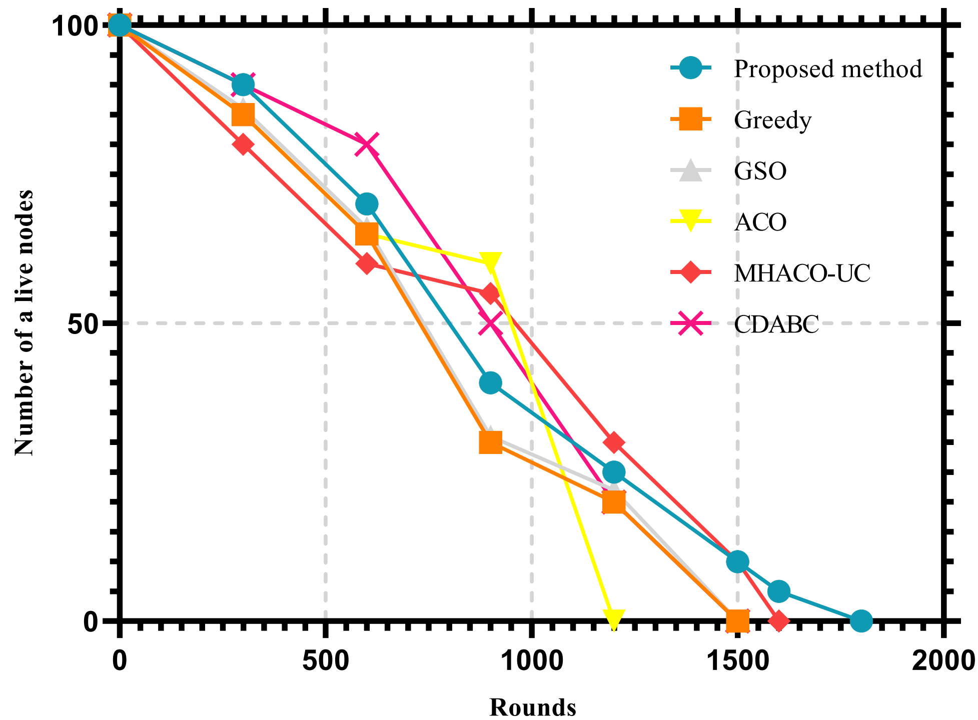


Fig. 10 The number of alive nodes in different iterations of the second round

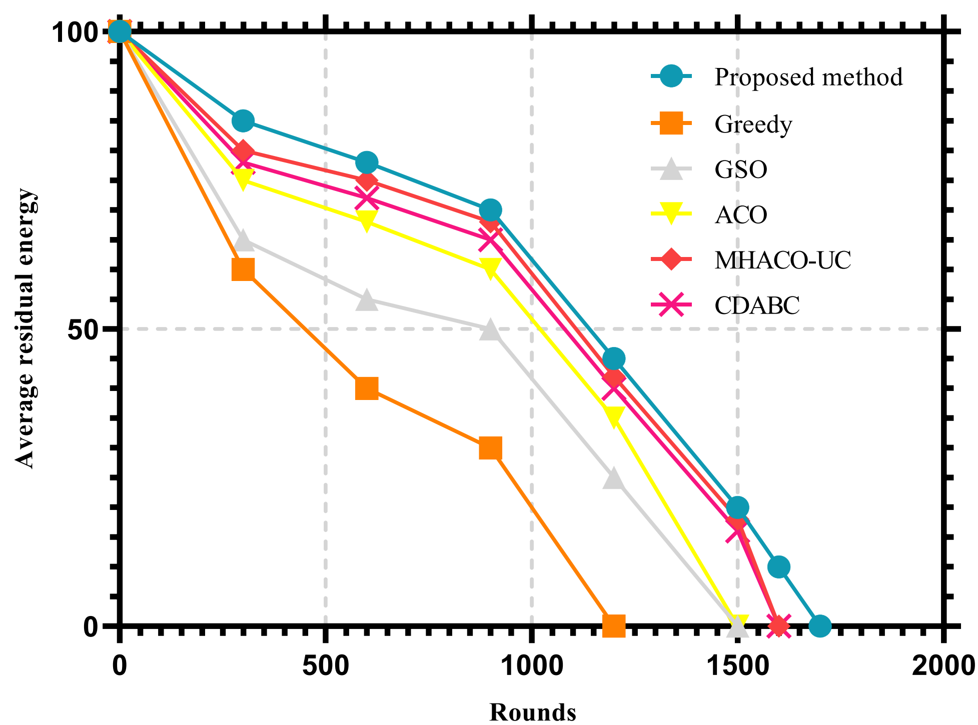


Fig. 11 The average energy left in the network nodes in different iterations of the second scenario

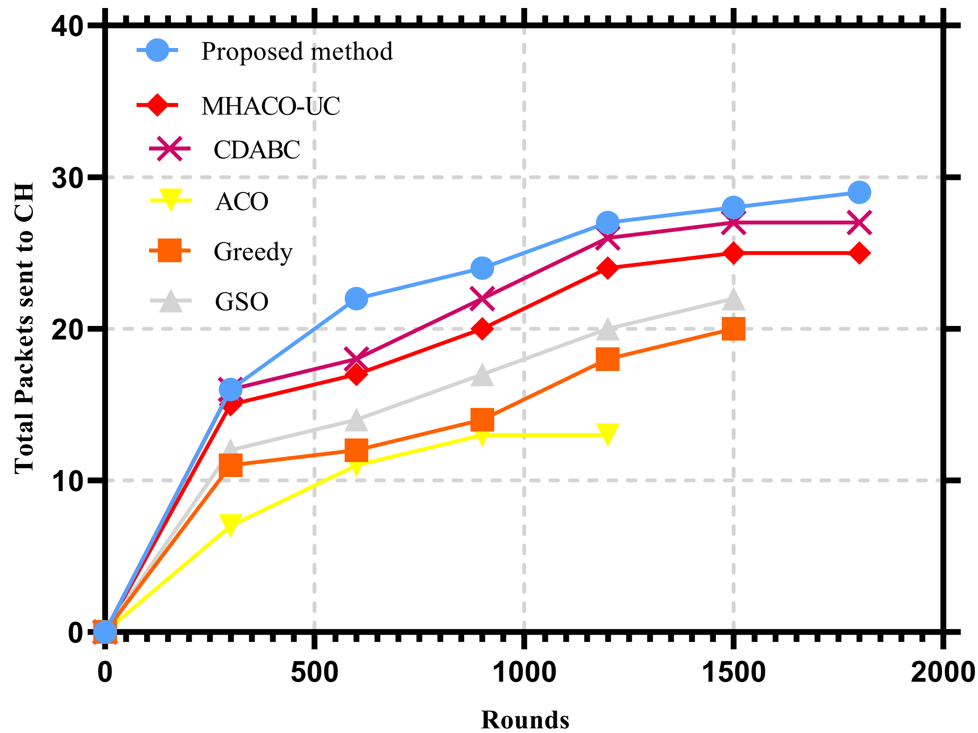


Fig. 12 The total number of packets received in the CH in the second scenario

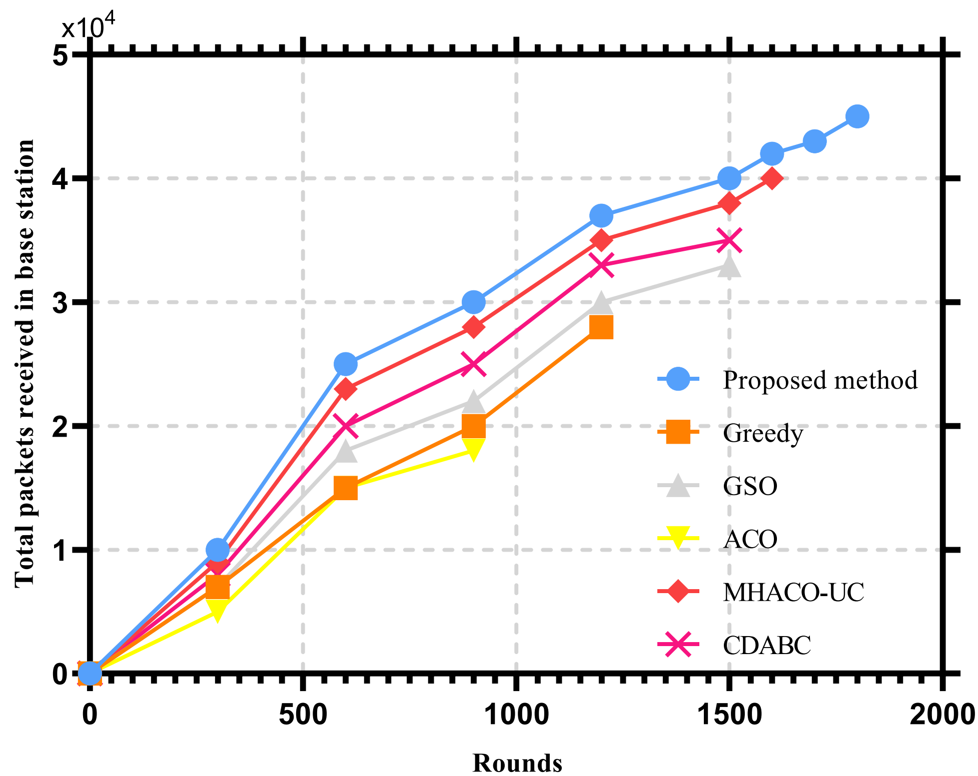


Fig. 13 The total number of packets received in the BS in the second scenario

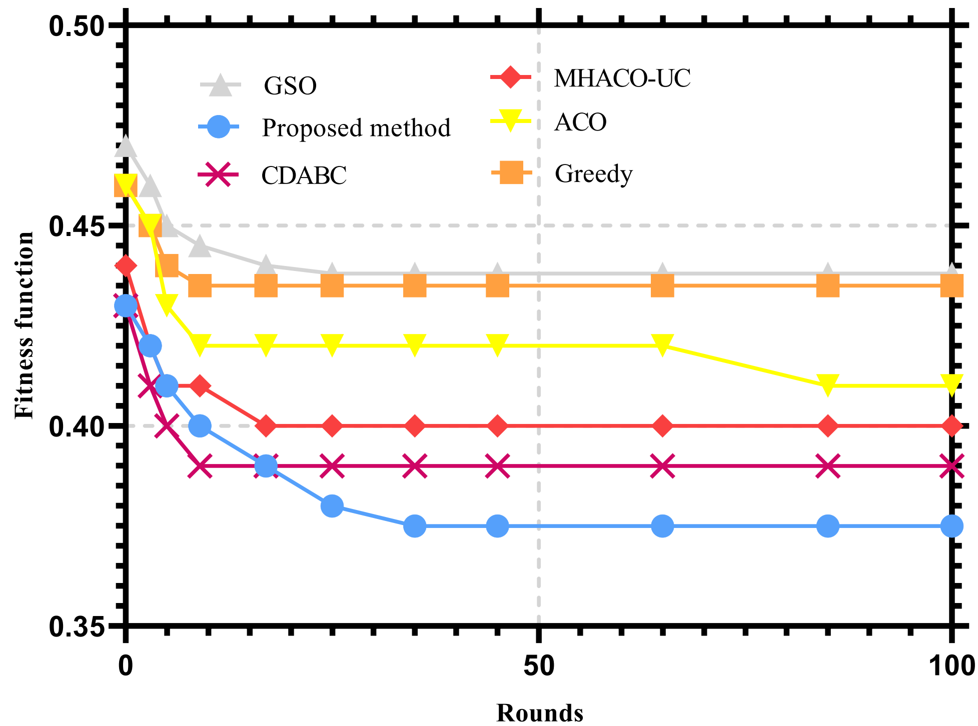


Fig. 14 Convergence in 100 rounds

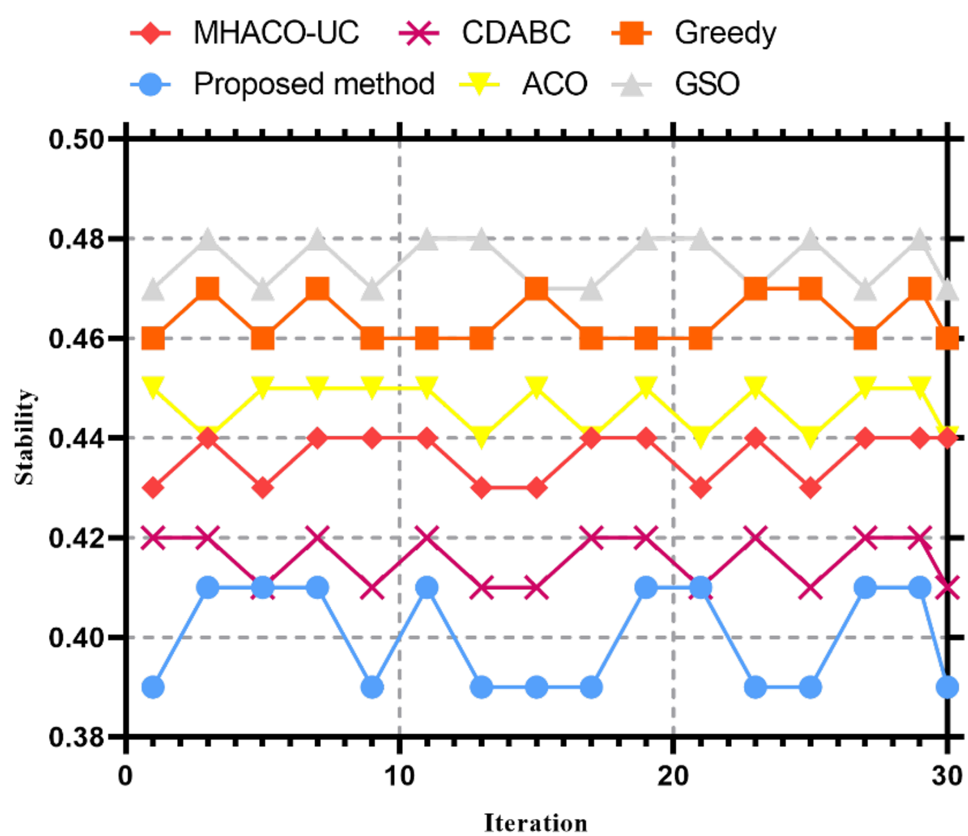


Fig. 15 Stability in 30 times the implementation of the algorithm

6 Conclusion and future work

The proposed scheme combines MM and ABC methods to select the best CH nodes and fairly balances the load between CHs. Thus, the proposed method improves energy consumption and network lifetime. One of the significant challenges in WSNs is balancing energy consumption. Appropriate CH node selection can affect the energy consumption of nodes and improves the network lifetime. Thus, reducing energy consumption is a primary issue and challenge in WSNs. When the pattern of energy consumption in a WSN is optimized, the network can be expected to have more productivity and efficiency. In this paper, after distributing the sensors randomly in the area, the LEACH algorithm selects the CH. But after the second round, the MMABC algorithm starts to work. The Markov model selects the suitable CH according to energy consumption and location in this proposed method. Then ABC algorithm qualifies this CH, whether this CH is appropriate or not. The simulation results show that the energy consumption of the proposed method is better than the other algorithms, and also, data received by CH and BS is higher than other methods. For future work, the researchers can use machine learning techniques for load balancing between the CH and the Software Defined Network (SDN) for routing in the WSN system.

Acknowledgements This study has been conducted under the project 'Mobility and Training for beyond 5G ecosystems (MOTOR5G)'. The project has received funding from the European Union's Horizon 2020 program under the Marie Skłodowska Curie Actions (MSCA) Innovative Training Network (ITN) having grant agreement No. 861219.

Data availability Not applicable.

Declarations

Institutional review board statement Not applicable.

Informed consent statement Not applicable.

Conflicts of interest The authors confirm that there is no conflict of interest in this research paper.

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