

Remote Health Monitoring Using IoT-Based Smart Wireless Body Area Network

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Abstract: A wireless body area network (WBAN) consists of tiny health-monitoring sensors implanted in or placed on the human body. These sensors are used to collect and communicate human medical and physiological data and represent a subset of the Internet of Things (IoT) systems. WBANs are connected to medical servers that monitor patients' health. This type of network can protect critical patients' lives due to the ability to monitor patients' health continuously and remotely. The inter-WBAN communication provides a dynamic environment for patients allowing them to move freely. However, during patient movement, the WBAN patient nodes may become out of range of a remote base station. Hence, to handle this problem, an efficient method for inter-WBAN communication is needed. In this study, a method using a cluster-based routing technique is proposed. In the proposed method, a cluster head (CH) acts as a gateway between the cluster members and the external network, which helps to reduce the network's overhead. In clustering, the cluster's lifetime is a vital parameter for network efficiency. Thus, to optimize the CH's selection process, three evolutionary algorithms are employed, namely, the ant colony optimization (ACO), multi-objective particle swarm optimization (MOPSO), and the comprehensive learning particle swarm optimization (CLPSO). The performance of the proposed method is verified by extensive experiments by varying values of different parameters, including the transmission range, node number, node mobility, and grid size. A comprehensive comparative analysis of the three algorithms is conducted by extensive experiments. The results show that, compared with the other methods, the proposed ACO-based method can form clusters more efficiently and increase network lifetime, thus achieving remarkable network and energy efficiency. The proposed ACO-based technique can also be used in other types of ad-hoc networks as well.

Keywords: Wireless body area network; clustering; internet of things; evolutionary algorithm; ant colony optimization



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1 Introduction

A wireless body area network (WBAN) is a small-size, lightweight, low-power network consisting of wearable or implantable sensors. These sensors monitor human physiological parameters, such as a patient's heartbeat, blood pressure, electrocardiogram (ECG) data, and electromyography (EMG) data. Multiple sensors can be placed on the human body, and these sensors are regarded as nodes of a WBAN. Every WBAN has a centralized entity called the personal server (PS), and the collection of other sensors' data is performed by the PS, which also acts as a gateway. The PS is connected to a remote base station (RBS) either directly or via a multi-hop link. In WBANs, connectivity of heterogeneous body sensors to a portable hub is allowed, which provides a connection to the external internet. There are a variety of applications of WBANs in different fields. For instance, in military applications, WBANs are used to monitor physical location, physical conditions, and vital signs of a field soldier. In medical applications, WBANs are used to monitor patient medical conditions to provide to medical facilities, and data collected by WBAN sensors are transmitted to a remote medical server, which is situated in a hospital [1]. WBANs can be roughly divided into two communication types, intra-WBANs and inter-WBANs. In an intra-WBAN, communication is performed within the WBAN, and in an inter-WBAN, communication is performed between multiple WBANs. An inter-WBAN provides dynamic access to the patient's data as the patient performs their normal daily routines (e.g., at home or at the market, playground, or office). However, in the course of the patient's activities, the WBAN sensors may not be in the range of a particular RBS. Hence, cooperation between multiple WBANs is required for multi-hop communication in order to reach the corresponding RBS. The RBS further transmits the medical server data via the internet. Use of WBANs in the medical field can protect human lives by timely detection of a patient's critical condition; thus, human lives depend on the performance of WBANs. Routing strategy is crucial for the network efficiency in WBANs. It should be noted that different routing mechanisms are used in inter-and intra-WBANs. Every WBAN is connected to an external network via a gateway. This gateway can be a cellular device, a computer system, or a router that can establish a connection between WBAN nodes and the external internet. The problem occurs when a WBAN cannot access the gateway device or RBS due to the low node density. This is a common situation in a crowded area, such as an international sports stadium or any type of international event, where a large number of people access the same network and share their data. In such situations, significant degradation of network performance can occur. Although current cellular networks provide highly efficient network services, they are still not sufficient in certain cases, which is why a public safety radio system operating in a separate frequency band is available for police, emergency medical services, and firefighters. Another scenario in which gateway connection is difficult is a battlefield, where there can be no available access point in the vicinity of each of the soldiers, as shown in Fig. 1.

Inter-WBAN communication can be useful in solving the communication obstacles in both of the aforementioned scenarios, but because WBANs consist of low-power nodes, an efficient energy consumption routing technique is required for realizing inter-WBAN communication. Clustering is one of the best solutions for efficient routing, where a cluster head (CH) is responsible for the transmission of data of multiple WBANs. However, network efficiency is dependent on the cluster's lifetime. To address the aforementioned problem, this study proposes an optimization algorithm of cluster formation based on evolutionary algorithms. In the proposed algorithm, each CH represents a gateway between cluster members (i.e., PSs) of multiple WBANs and the external network, and CHs are selected based on fitness.

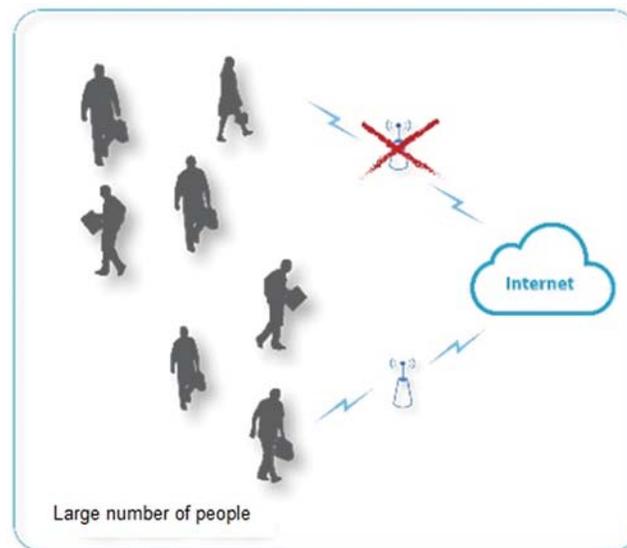


Figure 1: Illustration of a basic WBAN scenario

2 Related Work

As patient lives are dependent on the accuracy of data transferred from both inter- and intra-WBANs, this data transmission must be secured. Different methods have been proposed to protect data in inter-and intra-WBAN communication. In some approaches, clusters between the sensor nodes on a single body are formed to efficiently use the energy of the nodes in tier 1 transmission. In addition, cluster formation in inter-WBAN nodes of different WBANs can provide efficient multi-hop routing for tier 2 transmission. For instance, a multi-hop routing protocol proposed by Adhikary et al. [2] performed well in terms of energy consumption, packet delivery ratio, and network lifetime. In the aforementioned protocol, several fixed nodes were deployed in the network, and the cost function was proposed for the selection of a forwarding-node; the cost function was based on distance from the coordinator nodes, transmission range, residual energy, and velocity vector of the receiver.

In the dual-sink approach using clustering in body area network (DSCB) [3], two sinks are used. The authors use the cost function for the selection of forwarding nodes. The forwarding node is selected by measuring the distance of nodes from the sink and their residual energies and transmission powers. This clustering mechanism can provide better clustering performance in terms of network scalability, energy, and end-to-end delay. In load balancing, not all clusters include the same number of nodes, and nodes are assigned to clusters according to their fitness and feasibility values; also, the balancing function is used for realizing the load balancing. A balanced energy consumption (BEC) protocol was designed in [4]. In this protocol, the relay node is selected using a cost function based on the distance of nodes from the sink. To distribute the load uniformly, each relay node is selected for a specific round. If nodes are near the sink, they can transmit data directly to the sink; otherwise, data are passed to the closest relay node. In this protocol, a threshold value of residual energy is fixed, and only nodes that satisfy the threshold requirement can send critical data to the sink. The simulation study on this protocol has shown that it can achieve better performance than the other routing protocols in terms of network lifetime.

Another method to improve network throughput in terms of energy consumption in heterogeneous WBANs was achieved in [5]. In this method, the residual energy, data rate, and distance from the sink are used as selection criteria of the relay node. It should be noted that the key requirement of WBANs is to minimize delay and increase energy efficiency. To improve the clustering performance of WBANs, a load balancing and position adaptive technique was proposed in [6], where for the CH selection, the probability distribution method is used. In [7], a centralized clustering method was proposed to optimize the energy consumption of a WBAN, and a cluster tree-based structure was designed for the formation of uniform clusters.

An adaptive routing protocol was developed in [8], where the channel/link information is used for the selection of the best relay node regarding the reduction of energy consumption per bit. The sender node sends data to the sink via relay nodes when the link quality reaches the predefined threshold level; otherwise, it transmits data directly to the sink. Omar et al. [9] proposed an energy-efficient routing protocol for WBANs. They used residual energy to increase the network lifetime. This method was used to select energy-efficient stable links. In [10], a fuzzy adaptive routing protocol was proposed. This protocol uses a clustering mechanism for achieving direct communication between the nodes and the sink.

In [11], another routing protocol in which routing is managed by a mobile sink was proposed. In this protocol, the shortest route between numerous unequal clusters is determined to address the problem of the network energy gap. The results showed that this clustering technique performed better than the other techniques in the comparison. A secure cluster-based strategy for both inter- and intra-WBANs was developed in [12]; for intra-WBANs, a pairwise key was generated. The advantage of pairwise keys is that key generation is the same on both the sending and receiving ends. As a result of the highly dynamic nature of the human body, generated key is time-variant. In inter-WBANs, clusters are formed based on two parameters, the residual energy and distance between nodes. A node that has more energy is more likely to form a cluster. In addition, nodes closer to the RBS have a higher probability of becoming the CHs. Other authors have used genetic algorithms in WBAN [13–16]. A concept of a virtual cluster was proposed in [17], wherein clusters were formed only between intra-WBAN nodes. Although the nodes in intra-WBAN were close to each other, due to energy limitation in sensor nodes, this technique provided remarkable results. Currently, several e-health systems and health monitoring applications are available [18–20]. All the above-mentioned techniques have certain shortcomings, specifically in terms of the network lifetime. The proposed ACO-based technique exclusively addresses this issue.

3 Proposed Method

In this work, multiple WBANs are considered, and the frequent route search is reduced by the generation of long-lasting clusters. In the proposed method, WBANs are not directly connected with the RBS; instead, a WBAN-to-WBAN communication is obtained directly via the PS. The sensor nodes send their data to the PS that is responsible for further transmission of data. In the proposed method, PSs of different WBANs form clusters. Each cluster contains a CH and cluster members (CMs) in its vicinity. ACH is a selected PS of a WBAN among the WBANs of a cluster. All other WBANs will be connected to the CH. Also, CHs of different WBANs can have multi-hop communication, and in this way, data are passed to the nearest access point.

The communication in the proposed method can be classified into the three hierarchal groups: sensor node to PS, PS or CM to CH, and CH to an RBS. During the network creation, nodes are randomly deployed on the grid. In the experimental verification of the proposed method, three algorithms were used.

The illustration of the inter-WBAN clustering is presented in Fig. 2. As shown in Fig. 2, WBANs of cluster A and its CH are not in the range of the RBS, but cluster B is in the vicinity of the RBS, so cluster B can communicate with the RBS. In this case, cluster A needs the help of cluster B to communicate with the RBS. Members of cluster A have a direct link with the CH of cluster A, and this CH can establish a connection with the CH of cluster B, thus achieving a simple mechanism of cluster communication.

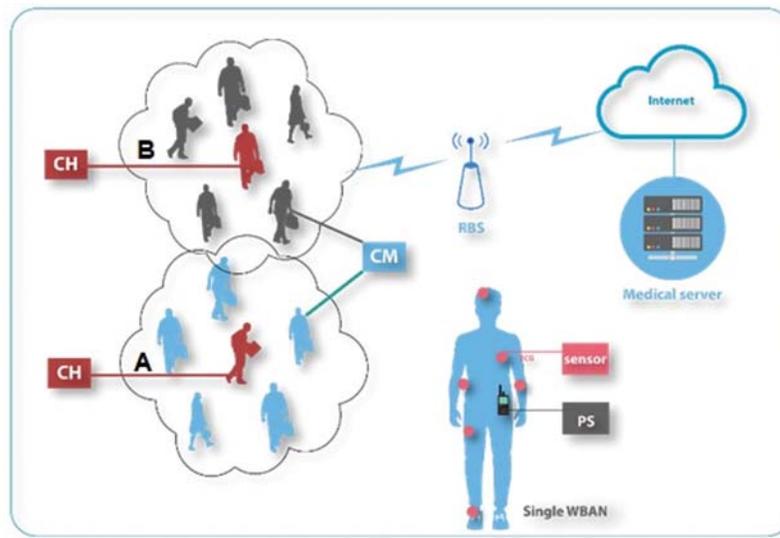


Figure 2: Illustration of inter-WBAN clustering

3.1 Evolutionary Algorithms

In the proposed method, evolutionary algorithms are employed for optimal cluster formation. These nature-inspired algorithms pick the most suitable solution (cluster) from the solution set according to the fitness criteria. Clustering in inter-WBANs also represents a non-polynomial (NP)-hard problem. For an NP-hard problem, there is no known polynomial algorithm, so the solution selection time grows exponentially with the problem dimension. For solving this type of problem, the desired termination criterion of the proposed method is defined. In most real-world problems, it is necessary to achieve multiple objectives simultaneously, so these multi-objective problems require simultaneous optimization. Each objective can be modeled mathematically via a specific objective function. These objective functions consider different parameters, and usually, they are conflicting and competing. A multi-objective function, where $f_1(d)$, $f_2(d)$, and $f_n(d)$ are objective functions and W_1 , W_2 , and W_n are the weights assigned to them, can be expressed as

$$f = W_1 (f_1 (d)) + W_2 (f_2 (d)) + \dots W_n (f_n (d)). \quad (1)$$

Suppose the main objective is to buy a railway ticket with a low cost and less time to reach the destination. On the one hand, for cheap tickets, railway service will be compromised and will stop at every station, which will increase the time cost. On the other hand, for expensive tickets, the train will cost less time to reach the destination. It should be noted that multi-objective functions with conflicting objectives increase the size of the optimum solution set. Thus, there

is no solution that is the best regarding all objectives, and the solutions can be classified into dominated and non-dominated sets.

3.2 Fitness Calculation

Evolutionary algorithms can provide different solutions, each of which can be denoted as a string of binary numbers (chromosome). To determine the best solution, it is required to evaluate all solutions, so the fitness of each solution should be calculated to find how closely it meets the desired result. The fitness function is created by incorporating the objective(s). The fitness function used in the proposed method is presented in [Eq. \(1\)](#).

3.3 Local and Global Best Values Updating

The local or personal best value represents the fitness value of an individual. This value is updated in each iteration of the algorithm based on the comparison with the current local best value. If the current value is better than the previous value, the local best value will be updated. The global best value denotes the best value among all individuals, and it is also updated in each step.

The proposed algorithm consists of two parts. The first part is the network creation part, where the basic network parameters are specified. As shown in [Tab. 1](#), in the simulations, the transmission range varied from 2 to 10 m with a step of 2 m, and the node number varied from 50 to 300 with a step of 50.

The flowchart of the proposed method is presented in [Fig. 3](#).

The suitable CH is a node that increases both network efficiency and overall network lifetime. The CH selection is performed based on defined criteria. To find the optimum solution, the current fitness value of each node is compared with the previous fitness value. If the current fitness value is better than the previous one, the old value is replaced by a new one; otherwise, it stays the same. The flowchart of the proposed scheme is presented in [Fig. 3](#).

3.4 Proposed Method Steps

The ant colony optimization (ACO) method is based on the behavior of ants. A single solution is considered as an ant, and the entire set of solutions is regarded as a swarm. To obtain the best solution, the mechanism of hunting the food of ants is adopted. The ACO models the natural environment of ants in the form of a graph, where candidate solutions are represented as graph vertexes. The proposed method is based on the ACO method, and its pseudo-code is presented in [Tab. 1](#).

Ants travel through the edges and create trails. Ants used the chemical substance called the pheromone to mark the route. In the proposed algorithm, artificial values of pheromone are correlated with the edge, and the edge is updated on the basis of the trail quality. Higher trail quality increases the concentration of the pheromone, and a higher pheromone attracts more ants. In the proposed method, ants create a candidate solution by adding up solution components one by one. Before determining the complete candidate solution, the problem-dependent heuristic is applied by collaborating pheromone values to optimize the route of ants. Ants construct their optimal solutions and help other ants to determine the optimal solution. The components having greater pheromone values are considered as contributors to an optimized solution. After sufficient

iterations, the optimal solution is found. The pheromone is initialized by

$$\tau_{ij}(\text{iteration} = 1) = \frac{1}{\text{Node}}, \quad (2)$$

where *Node* denotes a single sensor in the WBAN.

Table 1: The pseudo-code of the proposed ACO-based method

1.	Randomly initialize WBANs in the network
2.	Define random direction of WBANs
3.	Initialize velocity of each WBAN
4.	Create mesh topology of WBAN nodes
5.	Initialize the pheromone value on edges of the mesh created in Step 4
6.	Calculate distance between all WBANs, and then normalize and associate the distance values with the corresponding nodes
7.	WHILE (<i>Iteration</i> == <i>Maximum iteration</i>)
8.	FOR <i>Ant(i) = 1</i> to <i>swarm size</i>
9.	<i>Ant(i)_tour</i> == empty, <i>cost</i> == infinite
10.	<i>Nodes for clustering</i> = <i>All nodes</i>
11.	WHILE (<i>Available nodes for cluster formation!</i> = empty)
12.	<i>Ant(i)_cost</i> = <i>evaluation (Ant(i)-tour)</i>
13.	IF (<i>Ant(i)_cost</i> < <i>Best Ant_cost</i>)
14.	<i>Best Ant</i> = <i>Ant(i)</i> ; <i>Ant(i)</i> ++
15.	END WHILE
16.	END FOR
17.	FOR <i>Ant(i) = 1</i> to <i>swarm size</i>
18.	1. Update Pheromone (<i>Ant(i)_tour</i> , <i>Ant(i)_cost</i>)
19.	a. Evaporate
20.	b. IF (<i>BestAnt_cost</i> == <i>Last iteration Best_Ant_cost</i>)
21.	2. Stall <i>Iteration</i> ++;
22.	c. ELSE
23.	3. <i>Stall iteration</i> = 0;
24.	d. END IF
25.	e. <i>Iteration</i> ++;
26.	END FOR
27.	END WHILE
28.	<i>CH</i> = <i>Best Ant_tour</i>

The vertex is selected from the search space using the following probability function:

$$P_{ij} = \frac{\text{Pheromone}_{i,j} \times \text{Heuristic}_{i,j}}{\sum_{k \in S} \text{Pheromone}_{i,k} \times \text{Heuristic}_{i,k}} \quad (3)$$

where *i* denotes the label of the vertex last entry in the tour, and *j* is the label for the next candidate vertex for the ant selection. The set of vertices for selection is denoted as *S*. The optimal edge is selected by dividing the selection probability of an edge by the summation of selection probabilities of all available edges.

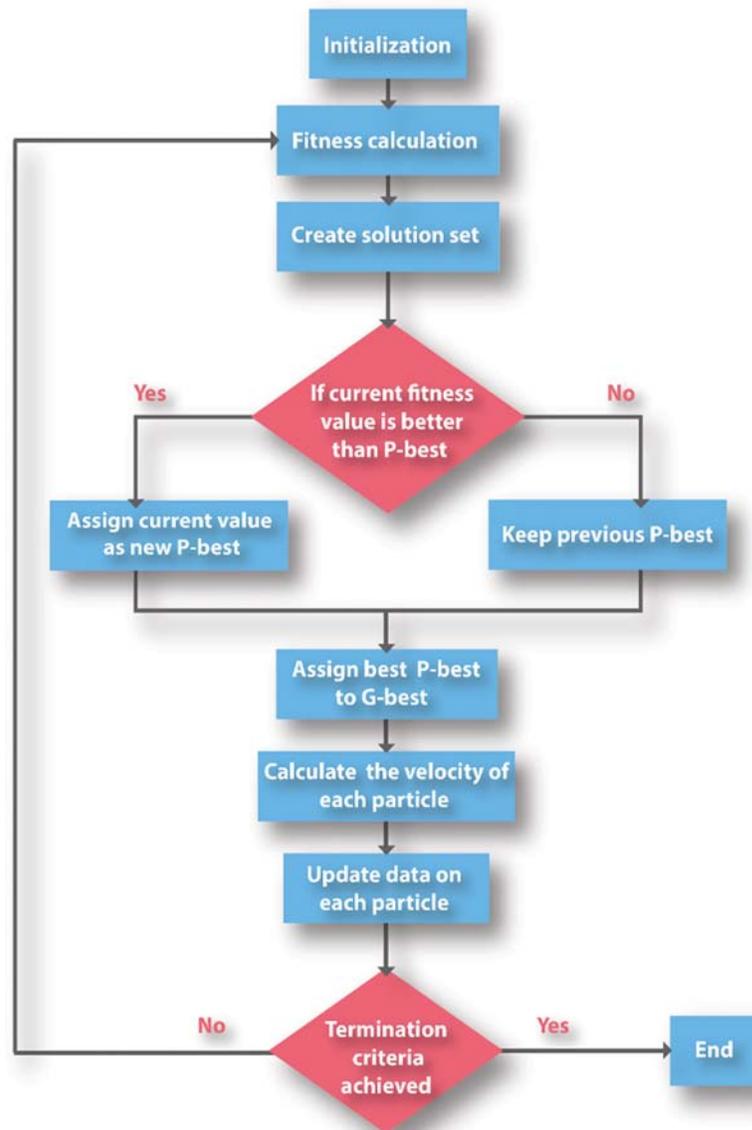


Figure 3: Flowchart of the ACO-based proposed method

4 Results and Discussion

Several scenarios with different node density, grid size, and transmission range were created for simulation purposes. The scenarios were created by varying the parameters' values. The transmission range for all the nodes in a single scenario was kept the same. The performance of the proposed method was verified by the experiments. In the experiments, the grid size varied to the following values: $100\text{ m} \times 100\text{ m}$, $200\text{ m} \times 200\text{ m}$, $300\text{ m} \times 300\text{ m}$, and $400\text{ m} \times 400\text{ m}$. The node number was changed from 50 to 200 with the Step of 50. The detailed simulation parameters are given in [Tab. 2](#).

The optimized solution was determined for each transmission range. Commonly, a shorter transmission range results in a higher number of clusters because, at a short transmission range, the nodes have less coverage area, so each node has only a few other nodes in its vicinity. Thus, by shortening the less transmission range, the cluster number increases, having a smaller number of CMs.

Table 2: Simulation parameters

Parameters	Values
Population size	100
Maximum iteration number	150
Lower bound (lb)	0
Upper bound (ub)	100
Dimension	2
Transmission range (m)	2 m, 4 m, 6 m, 8 m, 10 m
Node number	50, 100, 150, 200, 250, 300
Mobility model type	Freely mobility model
W_1	0.5
W_2	0.5
Grid size	100 m \times 100 m, 200 m \times 200 m, 300 m \times 300 m, 400 m \times 400 m
Simulation software	Matlab 2018a
CPU	intel i7-5500u
CPU frequency	2.4 GHz
RAM	8 GB
Operating system	Windows 10 (64 bit)

The results of all three algorithms in the comparison for the grid size of 100 m \times 100 m are presented in Fig. 4. In Fig. 4, the x-axis denotes the transmission range, and the y-axis depicts the total number of CHs. The experimental results showed that the proposed ACO-based method had a smaller number of CHs compared to the CLPSO and MOPSO methods. Also, the increase in the number of nodes remarkably affected the number of CHs. As shown in Fig. 4, at the node numbers of 50, 100, 150, and 200, the highest number of CHs was 19, 25, 32, and 28, respectively. The obtained numbers of CHs were relatively closer to each other, which was due to the relatively small grid size, which was only 100 m \times 100 m. With the increase in the transmission range, more nodes became available in the vicinity of each node, so the number of CHs decreased.

The comparison results of the three algorithms for the grid size of 200 m \times 200 m are presented in Fig. 5. In Fig. 5 similar trend can be observed as in Fig. 4—the ACO outperformed the other methods. The graphs in Fig. 5 show, at the same transmission range, the CH number slightly increased with the node number. Namely, as the grid area increased, nodes were slightly away from each other.

The results of the three methods for the grid size of 400 m \times 400 m are presented in Fig. 6. As shown in Fig. 6, at the node number of 50 and the transmission range of 2 m, there were no nodes in the vicinity of any of the nodes. Thus, at the transmission range of 2 m, no clusters were formed. By increasing the transmission range, the clusters started to form. However, at the grid size of 400 m \times 400 m, as the overall area increased and node density decreased, a fewer number

of clusters were formed compared to the cases with small grid sizes and high node density. This was because of the sparsity of nodes.

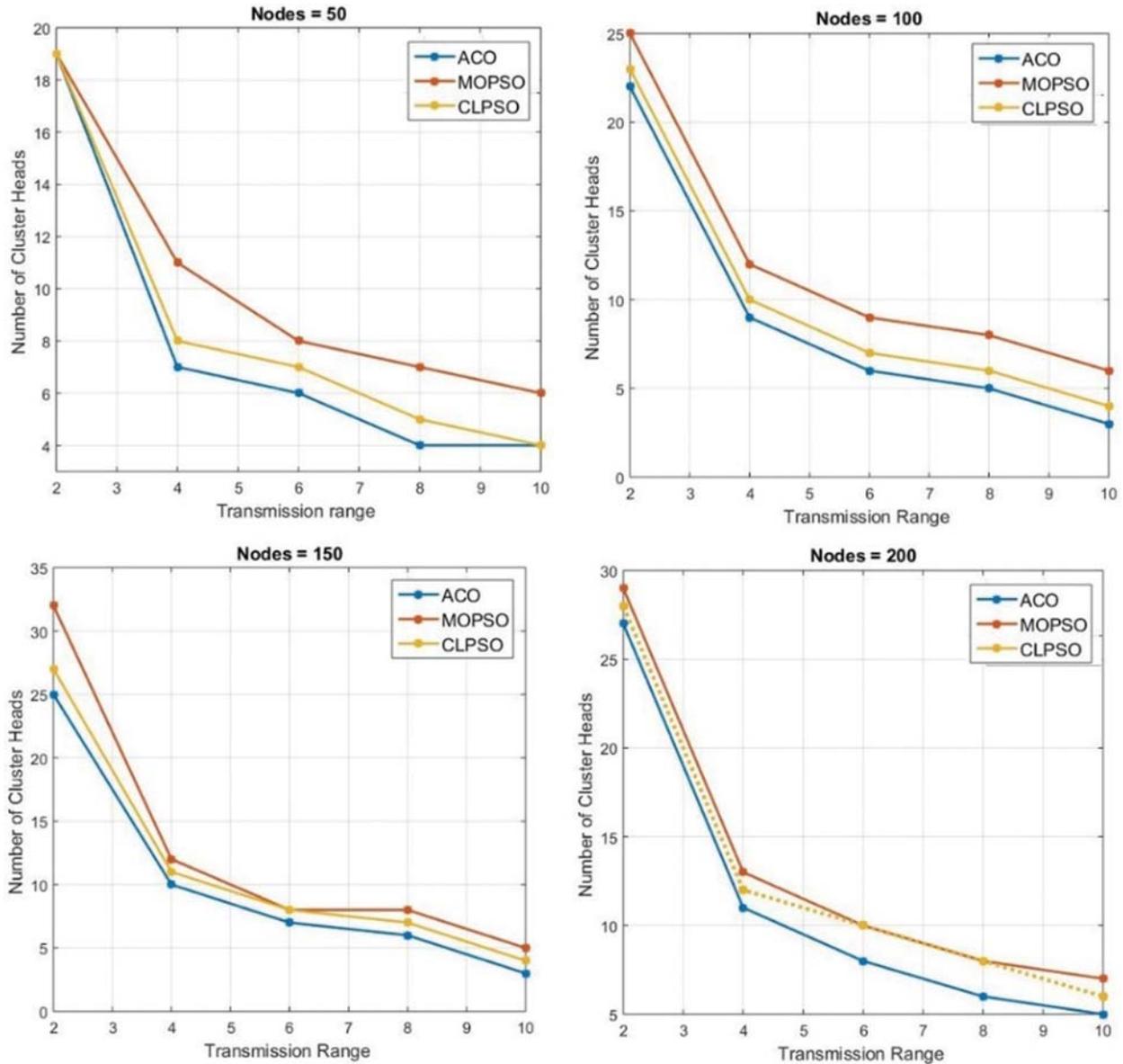


Figure 4: Transmission range vs. CH number under the grid size of 100 m × 100 m and the node number changing from 50 to 200

In Fig. 7, the percentage of CH formation with respect to the total number of nodes available for clustering under different transmission ranges is presented. As presented in Fig. 7, at the node number of 50 nodes and the grid size of 100 m × 100 m, the percentage of cluster formation of the ACO, MOPSO, and CLPSO methods was 16%, 20.4%, and 17.2%, respectively. The percentage

was very low because of the small grid size. With the increase in the grid size, the percentage also increased. In the largest grid size of 400 m × 400 m, the percentage of cluster formation of the ACO, MOPSO, and CLPSO methods was 56.4%, 62.4%, and 58.4%, respectively. The same trend was observed for all other node numbers.

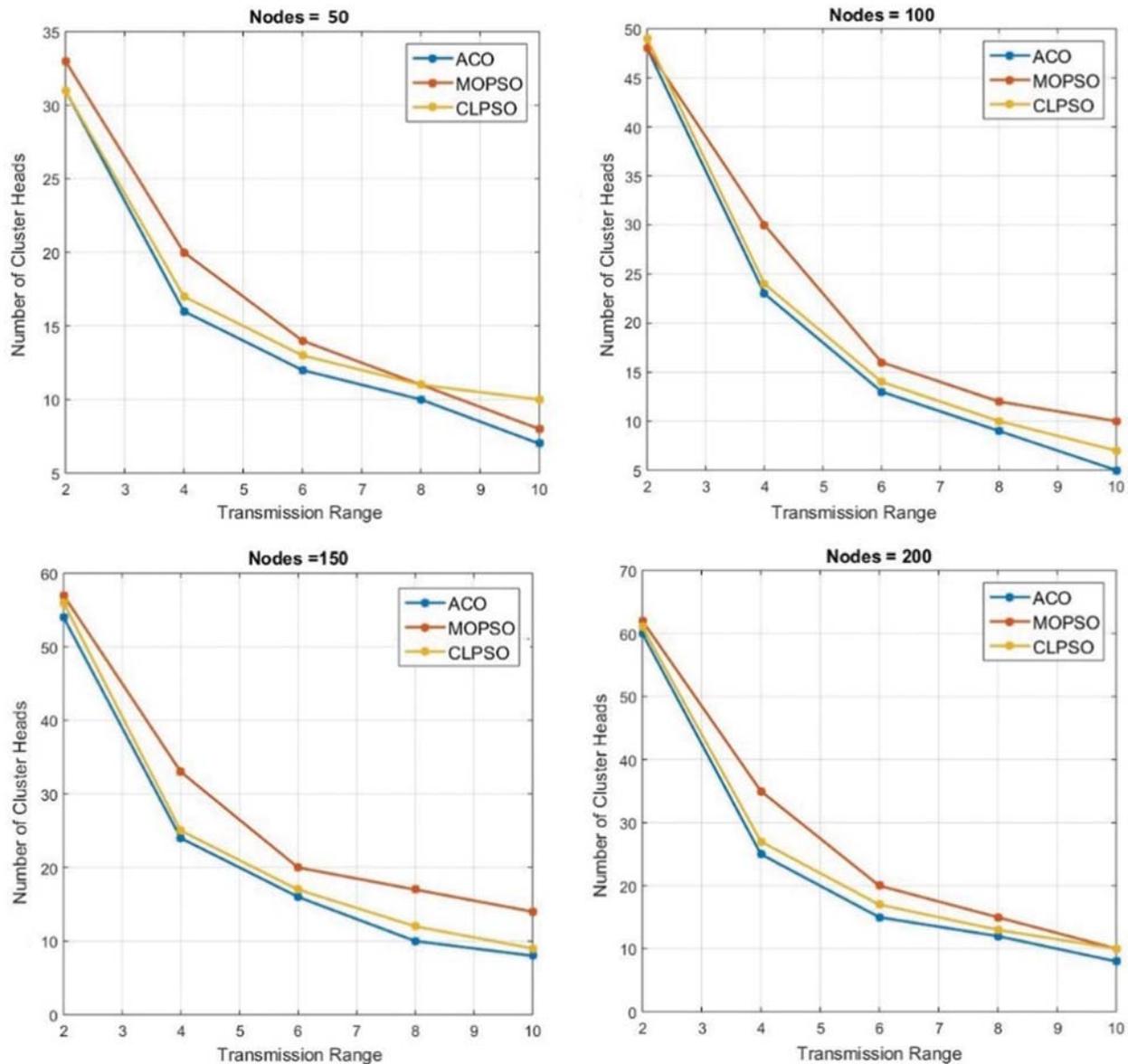


Figure 5: Transmission range vs. CH number under the grid size of 200 m × 200 m and the node number changing from 50 to 200

Based on the experimental results, it can be concluded that the increase in the overall area and decrease in the node density result in a smaller number of formed clusters compared to the cases with small grid sizes with high node density. In other words, the sparsity of nodes

directly affects the number of clusters. Moreover, in the proposed method, the role of the CH as a gateway between the CMs and the external network helps to reduce the network's overhead, and the cluster's lifetime is a vital parameter for network efficiency. The main limitation of the proposed method is its high computational complexity.

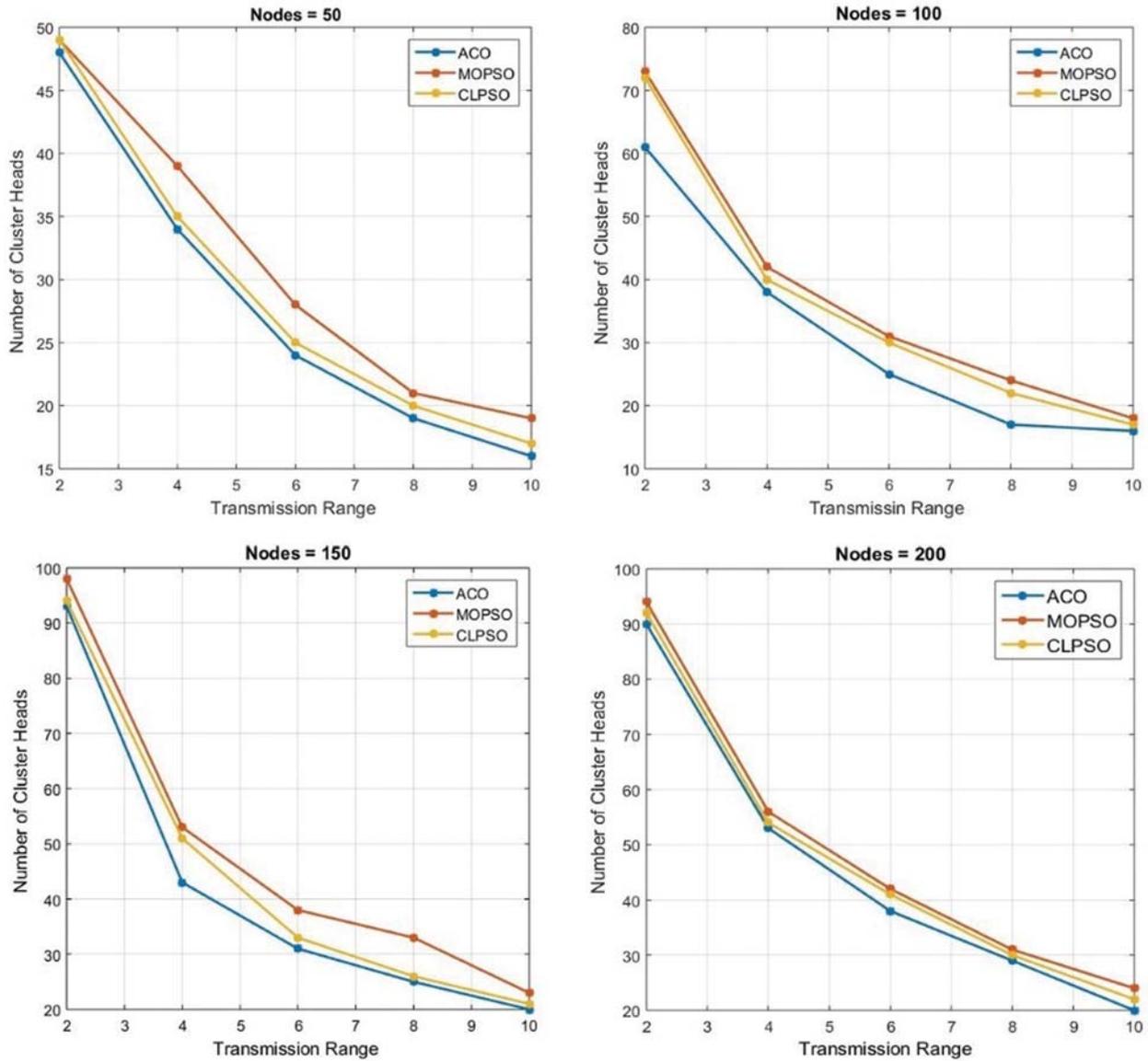


Figure 6: Transmission range vs. CH number under the grid size of 400 m × 400 m and the node number changing from 50 to 200

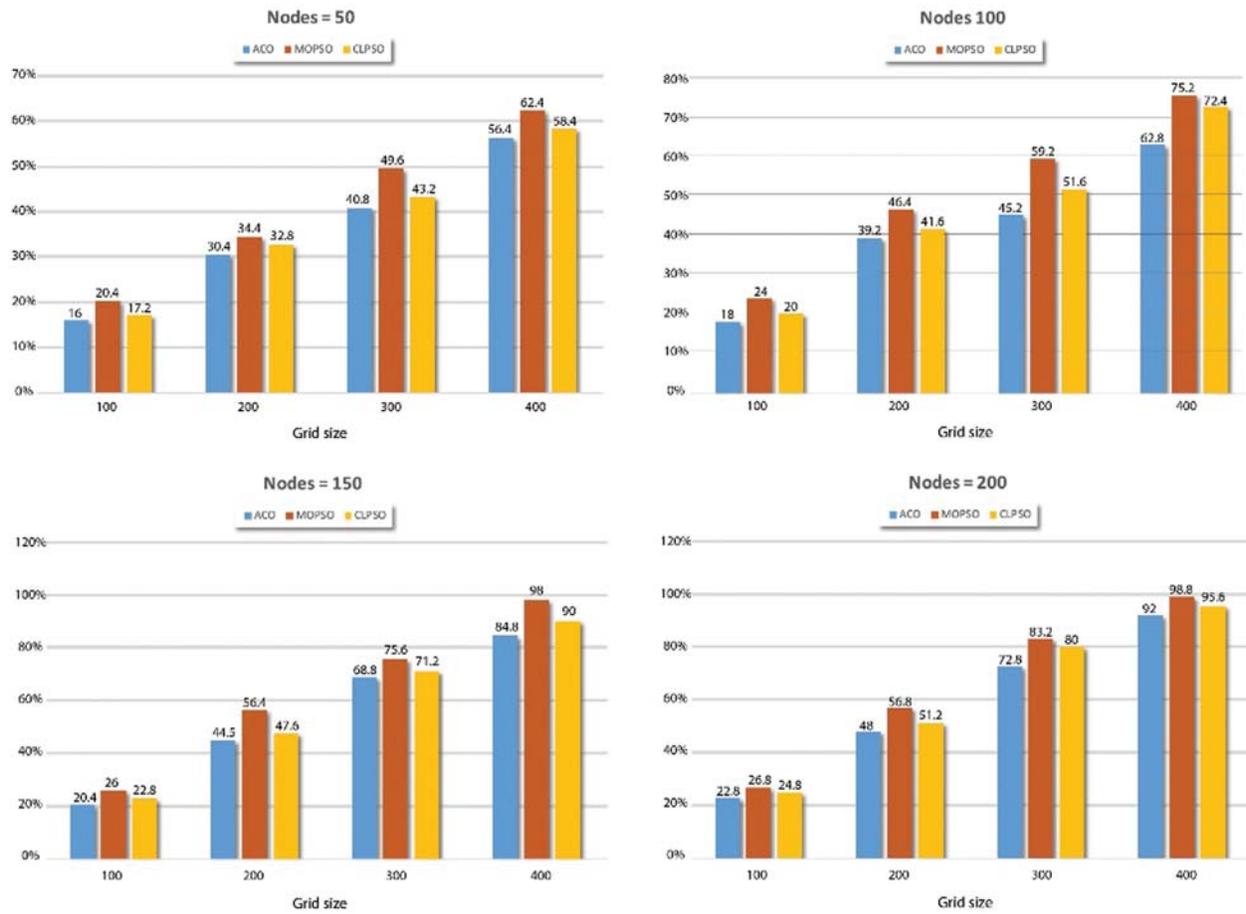


Figure 7: Grid size vs. cluster percentage with respect to the total number of nodes

5 Conclusion

Using WBANs in medicine can protect patients’ lives by continuous monitoring and transmission of patients’ data. However, how to balance the network load is one of the most important challenges in WBANs, and clustering can provide a practical solution to the energy optimization problem of nodes. This paper proposes a cluster formation method based on evolutionary algorithms. In the proposed method, a cluster-based routing is adopted, where CH act as a gateway between the CMs and the external network, which helps to reduce the network overhead. Moreover, the optimum CH selection is performed using the three evolutionary algorithms, namely, the ACO, MOPSO, and CLPSO methods. The proposed method is verified by extensive experiments by varying values of different parameters, including the transmission range, node density, and grid size. The experimental results show that the proposed method can form clusters efficiently while increasing the network lifetime, thus achieving remarkable network and energy efficiencies.

The performance of the proposed method is verified by extensive experiments by varying the values of different parameters, including the transmission range, node number, node mobility, and grid size. A comprehensive comparative analysis of the three algorithms is also conducted. The results show that, compared with the other methods, the proposed ACO-based method

can form clusters more efficiently and increase the network lifetime, thus achieving remarkable network and energy efficiency. The main limitation of this proposed method is its computational complexity. This limitation can be addressed in future work by using more efficient techniques for node clustering.

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Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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