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Joint Clustering and Routing Optimisation for Low-power Wireless Sensor Networks

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Abstract

Wireless sensor networks (WSNs) have been one of the fields that have attracted a lot of attentions from many scientific researchers in recent years. The sensor nodes of the network are fixed or moved to detect the environment and impart the data accumulated from the remote monitored regions via wireless connections. It is indicated in complex environments such as forests, deep seas, urban areas, etc., the sensor nodes in WSNs are usually tiny and battery-driven devices. Thus, energy-effective data accumulation methods required to improve the network's lifetime are very necessary. In this paper, we propose a joint technique of fuzzy clustering and heuristic ant routing (FCHAR) to save the energy for low-power WSNs. Simulation results are shown to demonstrate the benefits of the proposed FCHAR compared to other conventional ones.

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1. Introduction

The rapid development of information and communication technology (ICT) has made an impressive role in modern society and in people's lives. In an ICT system, wireless networks can be integrated as a major part of conveying data, e.g., capturing data from remote environments and delivering them to the data centers for monitoring and analysis. Recently, wireless sensor networks (WSNs) have become one of the fields that have attracted a lot of attention from researchers in both academic and industrial sectors [1]. WSNs are also considered as one of the typical examples of technological solutions that meet many social needs, such as surveillance and management in disasters, structural health of buildings, urban transportation, security, urgent situations, and public safety, to create an intelligent living environment [2–4].

The general WSNs are described in Figure 1, including the sensor nodes, cluster heads (CHs), the base station (BS), Internet connection, and data center. WSNs have outstanding advantages such as rich applicability, low deployment costs, and low energy consumption while ensuring high quality of service. However, one of the biggest challenges of the WSNs is the energy resource of the sensor nodes, which is limited and unrechargeable. To solve this problem, many research directions have been focusing on improving energy efficiency to expand the lifetime for WSNs [5, 6].

An effective method for energy efficiency improvement is joining clustering and routing in which a CH is selected for data transfer over hierarchical routes. Low energy adaptive clustering hierarchy (LEACH) is a conventional but efficient clustering routing protocol in terms of energy saving [7]. A centralized LEACH (LEACH-C) was proposed to improve the performance of LEACH by adding the average energy conditions to choose the CHs done by the base station (BS) [8]. Another extension from LEACH is a combination of LEACH-C and Dijkstra (LEACH-CD). LEACH-CD has further applied the Dijkstra algorithm to determine the shortest path from the CH to the BS [9]. However, LEACH, LEACH-C, and LEACH-CD protocols cannot

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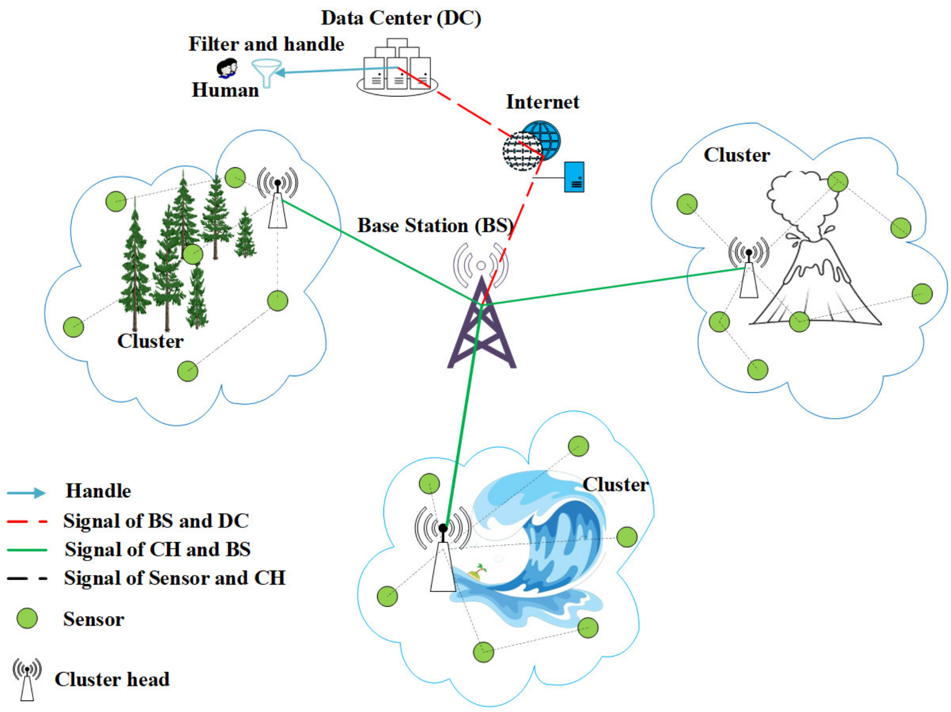

Figure 1. Wireless Sensor Network.

provide the best energy efficiency due to the lack of 1) considering the most important input parameters, i.e., density of sensor nodes, remaining energy of CH, distance from the CH to the BS and to its neighbors, for clustering and 2) the available paths for routing.

In this paper, we address the problems of the protocols above by proposing a joint technique of fuzzy clustering and heuristic ant routing (FCHAR). The fuzzy clustering considers not only the density of sensor nodes but also the remaining energy of the CH and the distance from the CH to the BS and its neighbors to balance the internal cost (CH-neighbors communications) and the external cost (CH-BS communications). Furthermore, the heuristic ant routing can find alternate paths to avoid unexpected situations when too much traffic always goes into only one path. This way can prolong the lifetime of WSNs efficiently.

The rest of this paper is organized as follows. In Section 2, we present the related works. We introduce the energy consumption model in Section 3. Section 4 proposes the FCHAR solution in detail. The simulation results are shown in Section 5. Finally, we conclude the paper in Section 6.

2. Related Works

In [10], Mukhtar et al. proposed a mobile-based routing protocol to improve the network's life in the WSNs. First, the network is divided into two parts based on the distance from BS. The CHs of area 1 are closer to the BS, who communicate directly with the BS about average energy consumption. The BS is placed in the center of the network. The mobile routing nodes are deployed in area 2, moving on the road designated to collect data from the CHs, and sending it to the BS after synthesizing and preserving the energy of nodes to nodes. Therefore, it increases the lifetime of the network.

The works in [11] introduced a fuzzy logic method to improve the energy for WSNs. Particularly, the Leach-Fuzzy clustering (LEACH-FC) protocol has been proposed to solve the problem of two or more CHs located in close vicinity leading to the result of inefficient energy usage. The LEACH-FC protocol considers three input variables, i.e., energy, concentration, and centrality, to select each CH and then gather its members in a cluster. The results show that the proposed protocol is more effective in terms of lifetime than other energy protocols.

In [12], the authors proposed an algorithm to plan the path and the sensor cluster, namely ISCTO (Iterative Sensor Clustering and mobile sink Trajectory Optimization), for the WSN that deploys the sensor nodes unevenly with many mobile sinks. This algorithm repeats two stages of the clustering and optimizes the trajectory to minimize energy consumption by the WSN components. According to Xiao *et al.* [13], an algorithm is proposed based on the ant colony system to reduce the communication distance and energy of neighboring nodes, leading to balanced network energy.

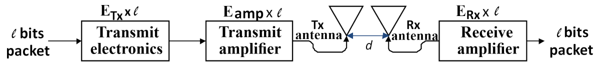

Figure 2. Transceiver model of sensor network.

This paper compares their algorithm with particle swarm optimization and genetic algorithm about the convergence rate. This way can improve the stability of the WSNs and the energy consumption balance for ultimately prolonging the lifetime of the WSNs.

In another study, Xingxing Xiao *et al.* [14] proposed a WSN routing algorithm in a complex underwater environment for efficiently transferring data from underwater sensor nodes to the BS over many difficulties and obstacles. To process the complex challenges of data loss in the water environment. The authors proposed a routing ACO algorithm to reduce the distance of CHs. The result shows a close distance of CHs can improve the energy of CHs and ensure the data transfer quality in the water environment. The authors in [15] addressed a problem of forest fire monitoring which was a challenge for the environment management. Once again, a route optimization algorithm based on the information heuristic is used to reduce the energy consumption for WSNs. The authors applied energy-efficient and reliable parameters to increase node sensors' efficiency and the network's lifetime.

Interestingly, a joint solution of fuzzy and ant colony have been studied in [16] to select the next node to be accessed by the ants. In this work, the authors use fuzzy inference with fuzzy information variables of pheromone power, length, and traffic conditions at a delivered span. The output result of the fuzzy logic system is the probability value of an ant stay that will be the base for choosing the call to the next node. In [17], fuzzy inference was used to calculate the total node cost by considering the node's traffic load and energy. Ant colony system optimization was used to discover and select the shortest route between the source node and the destination node evaluated by the shortest length. Using the ant-swarm algorithm and combining fuzzy inference have improved the node's energy consumption efficiency, leading to a longer lifetime of the WSNs.

3. Energy Consumption Model

In this paper, we apply the energy consumption model studied in LEACH protocol [7] as shown in Figure 2. This model allows us to compute the energy consumption to transmit ℓ bits of information over a distance d, given by

$$E_{Tx}(\ell, d) = \ell \times (E_{ele} + E_{amp}(d)) = \begin{cases} \ell \times E_{ele} + \ell \times \epsilon_{fs} \times d^2, d < d_0 \\ \ell \times E_{ele} + \ell \times \epsilon_{mp} \times d^4, d \geq d_0 \end{cases}. \quad (1)$$

In (1), the energy of the transmission amplifier to maintain the acceptable signal ratio is E_{amp}.

Furthermore, the energy consumption to receive ℓ bits of information is expressed as

$$E_{Rx}(\ell, d) = \ell \times E_{ele}, \quad (2)$$

where d_0 is the reference distance between the transmitter and the receiver, computed as

$$d_0 = \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}}. \quad (3)$$

The above parameters used to simulate in our paper are presented in the Table 1.

We can see that the CHs consume more energy than the others because they need to receive information from all the nodes in the same cluster and transmit them to the BS. Each node n randomly selects a value in [0, 1] for the LEACH algorithm. If it has a smaller value than the threshold $T(n)$, the node will become a CH in the current round (r). The nodes in the network are randomly distributed to make the cluster based on the arrangement algorithm. $T(n)$ is shown below

$$T(n) = \begin{cases} 0 & , n \in G \\ \frac{p}{1 - p \times (r \bmod \frac{1}{p})}, & n \notin G \end{cases}, \quad (4)$$

where G is a set of network nodes that have been in $1/p$ previous round and p is the desired percentage to become a CH.

With the LEACH-C algorithm, the BS makes the cluster and selects the CH based on the information of all the nodes in the WSN sent to it, including the reserve energy and the location of the sensor nodes. The BS uses the optimal algorithm to identify the CH and the clusters. In LEACH-CD, the LEACH-C is combined with the Dijkstra algorithm to find the shortest path through the nodes to the CH to minimize the transmission distance.

However, if a CH has a lot of reserved energy, but its location is quite far from the BS, and the number of nodes in the same cluster is numerous, the CH needs too much energy for transmitting and receiving. In addition, the non-CHs (neighbors) in the same cluster must transmit the signals directly to its CH without transmitting through the intermediate node, or they can be used as an intermediary node (relay node). This may cause the CHs and the neighbors to become exhausted after just a short lifetime. For the above reasons, we propose an improvement presented below

Table 1. Simulation parameters [18]

Parameters	Value
Simulation area	$100m \times 100m$
Number of sensor nodes used (N)	100
Percentage desired to become the cluster head out of the total number of nodes in the network (p)	0.05
Number of bits transmitted	4000
Initialization energy of nodes (E_0)	$0.1J$
The power dissipation factor of the transmitting and receiving circuits (E_{ele})	$50nJ/bit$
Channel parameter in multi-path model (ϵ_{mp})	$0.0013pJ/bit/m^4$
Channel parameter in free-space model (ϵ_{fs})	$10pJ/bit/m^2$
Power factor of transmission amplifier circuit (E_{Tx} , E_{Rx})	$50nJ/bit$
Simulation time (r_{max})	1000 rounds

Table 2. Input language values

Input variables	Language value
Retention energy	Small, Average, Hight
Distance to BS	Near, Modarate, Distant
Neighbor density	Sparse, Fair, Dense
Neighbor cost	Low, Adequate, High

Table 3. Output language values

Output variables	Language value
Output	Very very small, very small, small, medsmall, medium, medlong, fairy long, long, very long

- Choose a CH with a high energy level to ensure data transferred to the BS and data received from the neighbors in the same cluster without interruption.
- Choose a CH close to the BS to reduce data transmission distance.
- Distribute the sensor nodes in clusters to balance the energy for the CHs.
- Consider the node-to-node distance in the same cluster, which is one of the energy saving factors for WSNs.

4. FCHAR Solution

From the above four ideas for improvement, we propose the following FCHAR solutions to gain high energy efficiency for WSNs. First, in the clustering phase, we use the fuzzy inference model to select the CHs and the clusters. Second, we use the ACO-based routing algorithm from the neighbors to the CH in the routing phase. The detailed FCHAR is presented in the sequel.

4.1. Fuzzy-based Clustering Phase

In this paper, we use fuzzy inference model [19–21] with four input variables and corresponding output values listed in Table 2 and Table 3. The fuzzy inference system has three fuzzy inference models named fuzzy logic models 1, 2, and 3. Each model has two input and one output variables, as shown in Figure 3.

Language Variables.

- Retention energy

Retention energy is the linguistic variable in the fuzzy system 1, defined in the range of [0, 0.1]; the number of fuzzy variables includes Small, Average, and High belonging to the range of values in the interval [0, 1]. When a sensor node is selected as the CH, the value of the node's sustained energy variable is considered. Therefore, the network needs to choose the CH with the most sustained energy possible in the sensor node set. Figure 4 shows the membership functions of the linguistic energy variable.

- Distance to the BS

The distance from the CH node to the BS is the second language variable in the fuzzy system 1, defined in the range of [0, 120], measured in meters, and it has the fuzzy variables of Near, Moderate, and Distant in the domain value in the range of [0, 1]. If a CH has a shorter distance to the BS, that node has a better chance of becoming the CH. Figure 5 shows the membership functions of the distance linguistic variable.

- Neighbor density

The density of the neighbors around the CH is a linguistic variable in the fuzzy system 2 defined in the range of [0, 1], with the variables of Sparse, Fair, and Dense belonging to the value domain in the range of [0, 1]. If a CH has a higher link density than other CHs in the list, it will likely run out of energy sooner than the rest. Figure 6 shows the membership functions of the density linguistic variable.

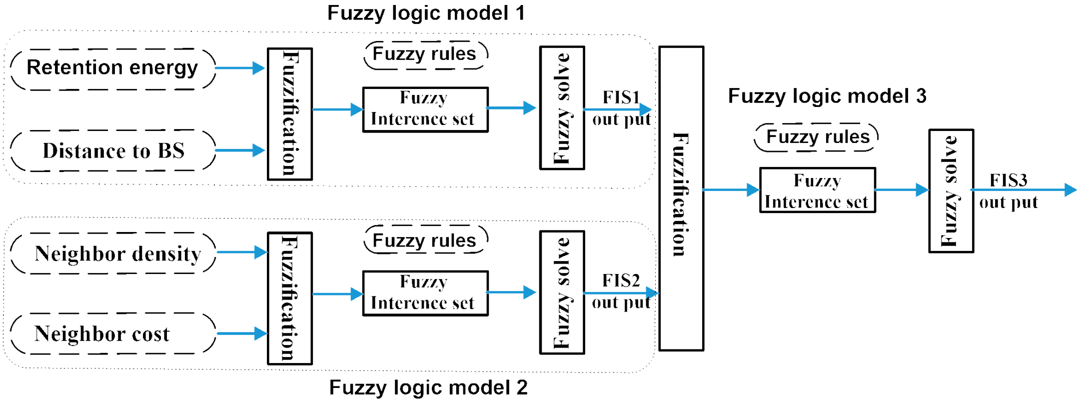

Figure 3. Fuzzy logic system model.

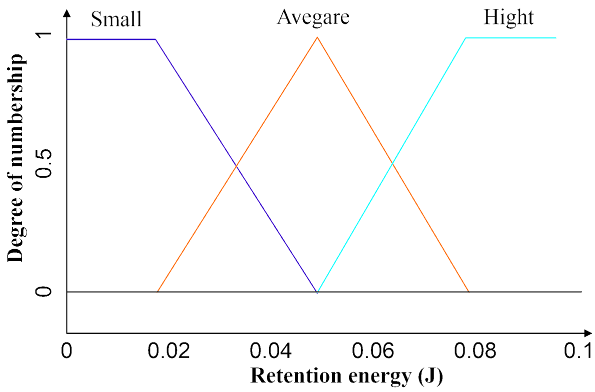

Figure 4. The dependency functions of the sustained energy variable.

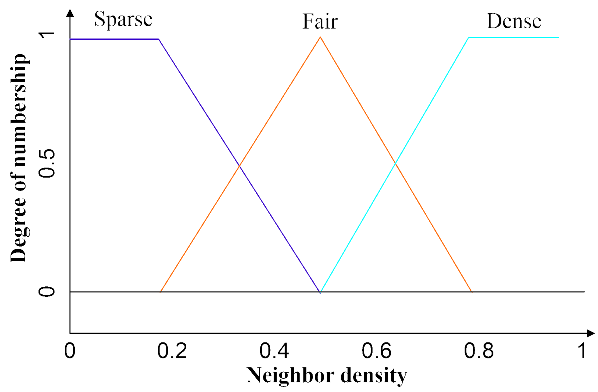

Figure 6. Density variable's membership functions.

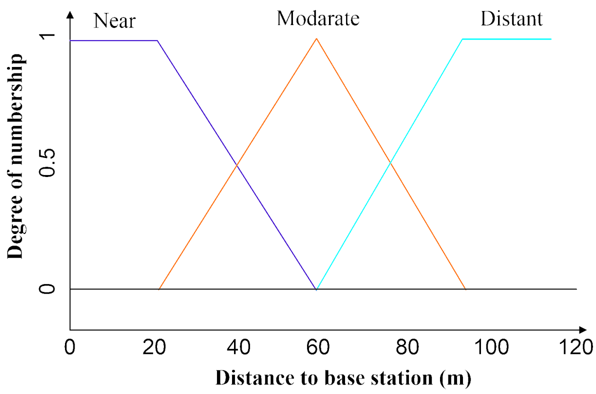

Figure 5. The membership functions of the distance variable.

- Neighbor cost

The node-to-node distance in a cluster is a linguistic variable in the fuzzy system 2, defined in the range of [0, 1], and with the variables of Slow, Adequate, and Dense, in the domain of values in the range of [0, 1]. Suppose the sensor nodes transmit the information to the CH effectively. In that case, the shortest possible distance from the transmission node to the intermediate node in the cluster is an advantage in saving energy for the transmitting node. Figure 7 shows the membership functions of a link-local value language variable.

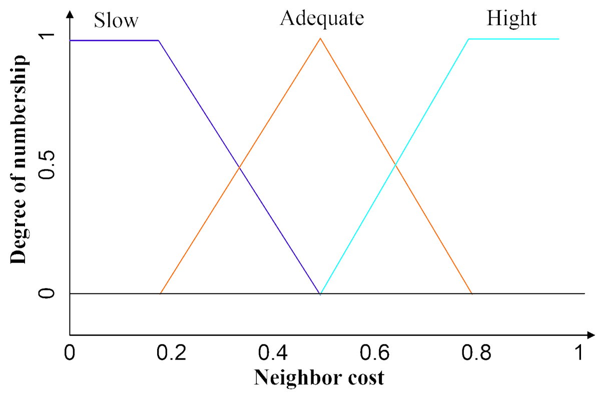

Figure 7. Link-local value membership functions.

Fuzzy Rule Basis. We then apply the fuzzy if-then rule based on the output data of the fuzzy process. The number of fuzzy rules depends on the number of input language variables. Figure 3 shows the fuzzy rule base used in the model, including; the first fuzzy inference system performs inference on two input linguistic variables, namely the retention energy and the distance to the BS with the output fuzzy variable value of the fuzzy inference system 1 ($FIS1$); the second fuzzy inference system performs inference on two input linguistic variables, which is the local association degree function, and the local distance with the output fuzzy variable value of the fuzzy inference system 2 ($FIS2$). The results of $FIS1$ and $FIS2$ are the input variables for the fuzzy inference model 3 ($FIS3$). According to [21], we apply the logical operation and combine the fuzzy values of the three fuzzy inference models, and form the corresponding if-then statements as shown in Tables 4, 5, and 6.

Table 4. Fuzzy inference basis of first fuzzy inference.

Energy level	Distance to BS		
	Near	Modarate	Distant
Small	Medium	Weak	Very weak
Average	Strong	Medium	Very weak
High	Very strong	Strong	Weak

Table 5. Fuzzy inference basis of second fuzzy inference.

Neighbor density	Neighbor cost		
	Low	Adequate	High
Sparse	Very high	High	Low
Fair	High	Medium	Low
Dense	Medium	Low	Very low

CH selection and Clustering. The CH selection and clustering scheme is done in the 3 following steps:

- Step 1: Determine the node information

First, the nodes in the network send their location information and energy reserves to the BS. From the received information, the BS determines the distance d_{ij} from any i^{th} node ($i \in N$, N in Table 1) to all the remaining nodes j in the network

$$d_{ij} = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2}, \quad (5)$$

where (x_i, y_i) and (x_j, y_j) are the coordinates for the i and j nodes, respectively.

The density of the i^{th} node is determined by its number of neighbors ($N_{num-neigh-i}$) within the maximum radius between a node in the network and the BS (R_{max}), given by

$$Neighbordensity_i = \frac{N_{num-neigh-i}}{N}. \quad (6)$$

Another critical factor is to choose a CH in the center of a cluster. Due to the node distance of the member being inversely proportional to its data transmission energy to the CH in the same group, if the CH has the position in the middle of the cluster, it will save the power of the neighbors to the CH. The neighbor cost of the i^{th} node in radius R_{max} is given by

$$Neighborcost_i = \frac{\sqrt{\sum_J distJtoI^2 / N_{num-neigh-i}}}{R_{max}}, \quad (7)$$

where $distJtoI$ is distance from node J to I in radius R_{max}.

From the fuzzy if-then rule in Table 6, we can get the fuzzy output variable $FIS3$. This fuzzy variable has to be converted into a single crisp number. That is a condition we can use in training. This so-called defuzzification method is written in (8), where A is the fuzzy set of $FIS3$, $\mu_A(z)$ is membership function of the fuzzy set A, the variable z belongs to the base of the fuzzy set A.

$$FIS3 = \frac{\int z\mu_A(z)d(z)}{\int \mu_A(z)d(z)}. \quad (8)$$

- Step 2: Select the CH

From the output results of $FIS1$, the BS builds the probability function (Td) for N nodes in the network. If the i^{th} node has the minimum Td_i, non-CH, and does not belong to the radius of other CH, it is potentially to become the CH in the current round. The function Td_i is given by

$$Td_i = \delta \times (1 - FIS1_i), \quad (9)$$

where δ is the random value in the range of [0.9, 1].

- Step 3: Find the candidate CH and cluster

The CH_i has a crisp value corresponding to $FIS3_i$, here $FIS3_i$ is the radius of the CH_i. If the node j in the non-CH set has a distance from it to the CH_i smaller than or equal to the radius of $FIS3_i$, the CH_i is the fellow node of the j node. A node j may have many CH_i, so the BS finds only one CH_i for the node j. After seeing only CH_i for node j, the network is formed with many clusters, each containing only one CH.

4.2. Routing Phase

After clustering, routing is the essential task that can reduce energy consumption. In other words, the total transmission distance can be reduced if we find the optimal route from the node-to-node and the node-to-CH. Dijkstra is the algorithm to discover the route from one vertex to the remaining vertex of the diagram

Table 6. Fuzzy inference basis of third fuzzy inference.

		Fuzzy inference system 2 ($FIS2$)				
		Very low	**Low**	**Medium**	**High**	**Very high**
Fuzzy inference system 1 ($FIS1$)	**Very weak**	MedLong	MedLong	Very Small	Fairlylong	Fairlylong
	Weak	Very long	MedLong	FairlyLong	Long	Long
	Medium	Very Very Small	Very Small	MedSmall	MedSmall	Medium
	Strong	Very Very Small	Very Small	Small	Small	MedSmall
	Very strong	Medium	Medium	MedLong	MedLong	Long

with the lowest expense. The algorithm is applied to routing from any node to the CH in the same cluster. This algorithm has given the possible results of saving energy for nodes to transmit data and maintain lifetime for WSNs. After each round, the algorithm completes the process of finding the route. The route is established with the lowest consumption level to transfer data from the nodes to the CH. This route only changes once the process of finding new ones is repeated. The problem is that if $d > d_0$ in the equation (1), the route remains unchanged, and thus when the network has non-energy nodes to receive and transmit data, the remaining nodes in the cluster change to the direct transmission to the CH. This may cause an unbalanced energy consumption problem among sensor nodes, especially over a long transmission distance to the CH. Therefore, the ACO-based routing algorithm is applied to solve this problem. The ACO-based routing flow chart includes initial setup, build solution, heuristics, and update pheromone, as shown in Figure 8 and presented in detail below.

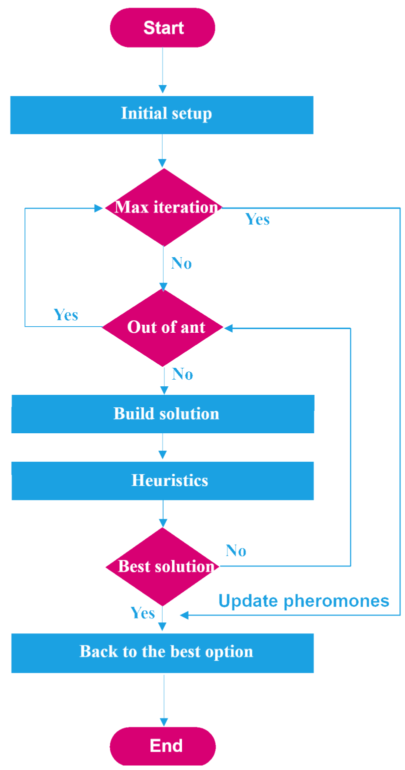

Figure 8. ACO-based Routing Flow Chart.

- Initial setup

Initially, each ant is assigned to a cluster, randomly selected as the first node that the ant visits from the BS. Then, at each construction step, an ant k at the current node i will choose the next node j to visit from a possible neighborhood according to the probability distribution

$$P_{ij}^{k} = \frac{(\tau_{ij})^{\alpha}(\eta_{ij})^{\beta}}{\sum_{j \in N_i^k}(\tau_{ij})^{\alpha}(\eta_{ij})^{\beta}}. \tag{10}$$

where $\eta_{ij} = \frac{1}{d_{ij}}$is the heuristic value, τ_{ij} representing the pheromone level on the edge connecting nodes i and j. The parameters α and β are biased effects of pheromone levels and heuristic values.

Based on (10), the selection of the next node will depend on the following criteria.

- Pheromone level, τ_{ij} which indicates how good the selection of the next node j compared to the current node i in the past.
- The heuristic value, η_{ij}, indicates how promising the next node choice is compared to the current node i.
- The possible neighborhood N_i^k is also known as the candidate list, which includes only the nodes closest to the current node i so that it can be selected as the next node to be visited in the route. The probability of choosing a specific branch τ_{ij} will increase when the value of the corresponding pheromone level is τ_{ij} added. In contrast, the value of the heuristic information N_i^k will not automatically change over time.

- Build solution

In ACO, each artificial ant simulates a transmission from the nodes back to the clusters and the BS. Its complete set of routes is constructed by successively selecting the nodes to propagate until all nodes have been transmitted to the BS. A new route will be started from the BS whenever the choice of the next node leads to an unfeasible solution due to the lack of sensor nodes in the cluster or the limitation of the total route length. Therefore, a total of m sequentially constructed solutions equal the total number of m artificial ants in one iteration.

- Heuristics

After an artificial ant has finished building a path but before the following ants start building their tour, the pheromone will be updated. The ant's solution will be improved by applying the method random change heuristic. This method modifies a sequence of CHs in the current solution by selecting a subsequence of CHs and randomly inverting the order of pheromones.

- Update pheromones

After the artificial ants have improved the solution through testing, the pheromone trails will be updated. This is a crucial feature of the ACO algorithm that improves future solutions, as the updated pheromone paths will reflect the performance of the ants and the quality of the solutions found. The details of the pheromone update procedures performed in the proposed ACO are modeled according to the below formula

$$\Delta\tau_{ij}^k = \begin{cases} \frac{1}{L_k} & k^{th} \text{ ant travel on the edge } i, j \\ 0 & \text{otherwise} \end{cases}, \quad (11)$$

where L_k is the cost of the k^{th} ant's tour.

After ants have completed their tour, each ant k deposits a quantity of pheromone.

To control the activities, a negative response, the operation of the evaporation of pheromone after the travel is also performed, we have

$$\tau_{ij} = \rho \times \tau_{ij}, \forall(i, j). \quad (12)$$

Increasing the amount of pheromone on the paths according to the length of the tours, the ants leave the amount of pheromone on the roads they have passed, so

$$\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^k, \forall(i, j). \quad (13)$$

After the evaporation of the pheromone, only the best and most elite ants will deposit the pheromone on the roads they have followed by the following method

$$\tau_{ij} = \tau_{ij} + \sum_{k=1}^{m} \Delta\tau_{ij}^k, \forall(i, j), \quad (14)$$

where m original number of ants.

In simulations, the parameters of ACO are $\alpha = 1$, $\beta = 2$, $\rho = 0.5$, and $m = 50$ [22].

5. Simulation and results

The initial simulation parameters are listed in Table 1. Assume that the sensor nodes are randomly distributed in the considered area, with an energy limit, and the BS without an energy limit is located in the center of the area.

5.1. Criteria for Evaluating

The proposed FCHAR is compared to the LEACH, LEACH-C, and LEACH-CD protocols based on the following criteria:

- The lifetime is calculated from the initialization of the grid until all sensor nodes are no longer active.
- The number of sensor nodes can exchange data at the time of the survey.
- The remained energy level of the sensor network after finishing the transceiver of information from the CH to the BS.

We further compared FCHAR to FLEACH-CD, which is an extension of LEACH-CD with only fuzzy clustering assistance. Thereby, we show that the FCHAR solution achieves better energy efficiency, thus prolongs the lifetime of WSNs.

5.2. Results and Discussions

To evaluate the performance of FCHAR, we first investigate the convergence of ACO and then the lifetime, average energy consumption, and residual energy of WSNs, which are presented in detail below.

- ACO Convergence

Figure 9 shows the convergence results of the ACO algorithm implemented in a simulation environment of about 100 rounds. From round 1^{st} to round 25^{th}, the ants find their random path and are started from the source sensor node to the sink. After each round, the distance from the source node to the destination node is fixed, and the path is gradually reduced. From round 25^{th} to round 40^{th} ant colonies begin to converge to a single common path slowly and after round 40^{th} ant colonies begin to join entirely and find the optimal way to round 100^{th}.

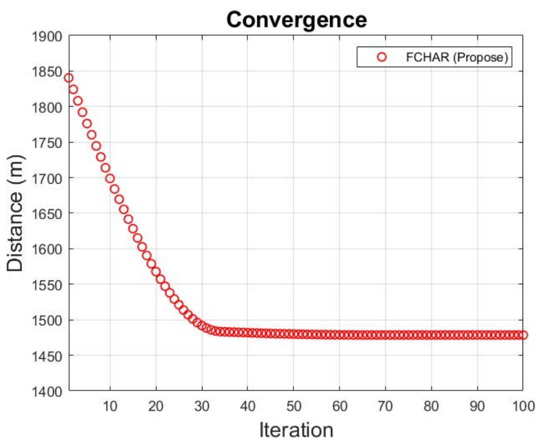

Figure 9. Convergence rate of ACO

- Lifetime of WSNs

Figure 10 depicts the lifetime of WSNs represented by the remaining number of sensor nodes versus simulation time r_{max}. The result shows that all the protocols work well and have no difference before the 100^{th} round. Until the 200^{th} round, LEACH-C, LEACH-CD, FLEACH-CD, and FCHAR have sensor nodes that still work stably, but LEACH has about fifty sensor nodes alive. From the 300^{th} round, all the nodes in LEACH are not alive; LEACH-C and LEACH-CD have only several nodes alive, and FLEACH-CD and FCHAR are still working stably. From the 400^{th} round, the LEACH, LEACH-C, and LEACH-CD stop working, and FLEACH-CD has about 92 dead nodes. Meanwhile, there are about 90 nodes alive in FCHAR. By this, there is a significant improvement in the number of live sensor nodes and network lifetime by using FCHAR.

- Average Energy Consumption

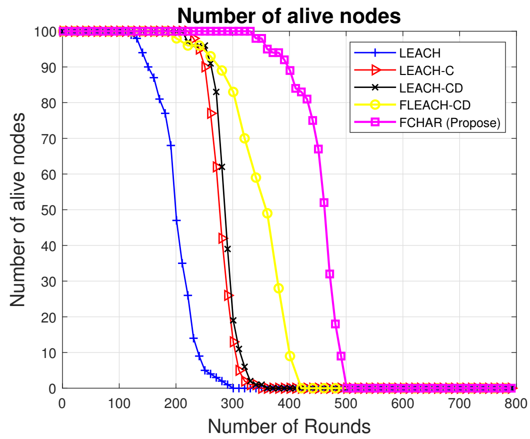

Figure 10. Remaining number of sensor nodes

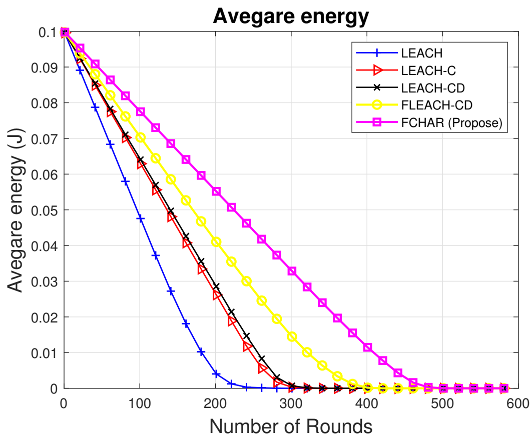

Figure 11. Average energy consumption

In Figure 11, we describe the average energy consumption of the protocols versus simulation time r_{max}. The average energy consumed in each round includes the energy used to select the CHs, and clusters and to transmit and receive the data from the sensor nodes. In this section, we present the average energy consumption of each protocol in some corresponding rounds such as 100^{th}, 200^{th}, 300^{th}, 400^{th}, and 500^{th}. The statistics are presented in Table 7. The result shows that the energy consumption in each round of the FCHAR is less than LEACH, LEACH-C, LEACH-CD, and FLEACH-CD. This indicates that FCHAR can save the sensor network's average energy consumption.

- Residual Energy

Figure 12 and Table 8 describe the remaining energy level versus simulation time r_{max}. After each round, the remaining energy level of all the protocols decreases. We can see that the proposed FCHAR outperforms the others in terms of maintaining the energy resource to prolong the lifetime of WSNs.

Table 7. Average energy consumption

	Residual energy				
	100^{th}	200^{th}	300^{th}	400^{th}	500^{th}
LEACH	0.0480	0.0958	0.1	0.1	0.1
LEACH-C	0.0367	0.0734	0.1	0.1	0.1
LEACH-CD	0.0355	0.0716	0.1	0.1	0.1
FLEACH-CD	0.0294	0.0587	0.0853	0.1	0.1
FCHAR	0.0223	0.0446	0.0668	0.0873	0.1

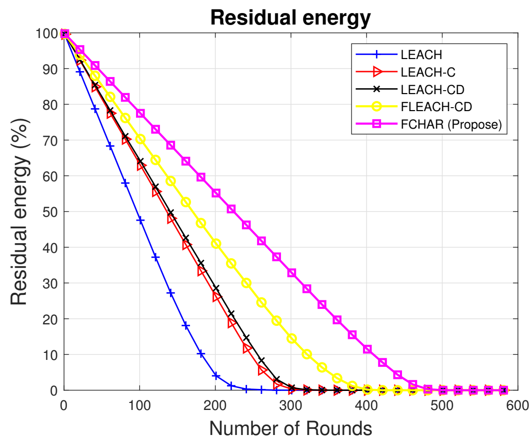

Figure 12. Residual energy

Table 8. Remaining energy

	Residual energy				
	100^{th}	200^{th}	300^{th}	400^{th}	500^{th}
LEACH	49%	4%	0%	0%	0%
LEACH-C	63%	26%	2%	0%	0%
LEACH-CD	64%	28%	3%	0%	0%
FLEACH-CD	70%	41%	15%	1%	0%
FCHAR	79%	55%	32%	12%	0%

6. Conclusion

In this paper, we have proposed the joint solution of fuzzy clustering and heuristic ant routing (FCHAR) for low-power WSNs. The proposed FCHAR combines fuzzy-based clustering and ACO-based routing to save the energy consumption of WSNs. The fuzzy logic is used to locate the CHs and the clusters for the network, and then the ACO is applied to find the optimal route from the sensor nodes to the CHs. As a result, our proposed solution provides a significant improvement in terms of energy saving compared to the other conventional ones.

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