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A Hybrid Approach for Prolonging Lifetime of Wireless Sensor Networks Using Genetic Algorithm and Online Clustering

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Abstract
Currently, the technology advancements have led to significant growth in the application of wireless sensor networks (WSNs) and its remarkable developments. WSNs are the most applicable and least-cost sub-category of existing computer networks. However, WSNs still suffer from energy limitation challenges. Since the energy limitation challenges are not appropriately resolved, prolonging the lifetime of nodes by reducing energy consumption has obtained more attention in this literature. In this paper, while routing is being performed an online clustering approach has been developed for updating the sensors' clustering, if it is required. The proposed clustering is carried out based on three objectives including reducing the distance between nodes within a cluster, reducing the distance between the cluster head (CH) candidate nodes and the sink node, and online appropriate energy distribution of the nodes in each cluster for each routing round. The improved fuzzy C-means (FCM) algorithm is applied to perform clustering. Additionally, the genetic algorithm (GA) is used as the routing algorithm. In order to evaluate the performance of the proposed FCM-GA algorithm, the DirectTransmission, SH-MEER, and MH-FEER algorithms are compared with FCM-GA. The results show that the proposed FCM-GA algorithm outperforms other algorithms in terms of network lifetime and the number of sent packets.

Category: Smart and Intelligent Computing

Keywords: Wireless sensor networks; Online clustering; Improved FCM algorithm; Genetic algorithm.

I. INTRODUCTION

Wireless sensor networks (WSNs) are composed of a plethora of tiny nodes. Each node includes sensors and actuators. WSNs closely interact with their surroundings so that they can collect information from the environment using their sensors and react with their actuators. As the name reveals, inter-nodes communication is accomplished

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by wireless technology. In fact, every node works independently and without human intervention, and is typically very small. Consequently, it has limitations with regard to processing power, storage capacity, power supply, and so on. The above-mentioned limitations raise challenges thereby attracting more attention in this research area [1, 2]. Despite the substantial advancements in WSNs, a large number of tiny sensor nodes that establish WSNs still apply low-power batteries for supply of their energy. In addition, since WSNs are often deployed in rough, dangerous or even inaccessible places, recharging or replacing sensor nodes is almost impossible. Thus, efficient energy management and prolonging the network lifetime are the most important issues in WSNs [3]. The lifetime of WSN is defined as the time from the network starting until the first node depletes its energy [4].

As a matter of fact, the lifetime of sensor nodes in WSNs determines the lifetime of the whole network. WSNs lifetime is one of the most fundamental parameters of Quality of Service (QoS) in WSNs and is remarkably important in sensing applications. The lifetime of sensor nodes is directly related to their energy consumption. Basically, numerous sensor nodes are deployed in WSNs to achieve a particular purpose. The purpose is extracting and accumulating information from the environment by sensors and forwarding to a central gathering node (central station). Obviously, longer distances consume higher energy to forward information. The clustering techniques are scalable and extendable to be applied for hundreds and/or thousands of nodes. In other words, despite extending the network size, it would be possible to efficiently utilize the resources and balance the load on the network. Also, applications that require effective data collection are other suitable use cases of clustering techniques. Analogously, routing protocols can also be applied on clustering techniques basis [5, 6].

So far, a vast number of protocols for clustering in WSNs are presented, but the majority of them addressed only the network topology and geographical location of nodes in clustering technique [2, 7]. The purpose of this paper is to present an online clustering algorithm to set sensor nodes in similar clusters along with performance of routing rounds. To accomplish this goal, we use a combination of genetic algorithm (GA) and fuzzy C-means (FCM) clustering.

FCM algorithm is a data clustering technique in which a data set is grouped into *C* clusters. FCM algorithm enables the dataset to contain data belonging to multiple clusters by considering its degree of membership within each cluster [8]. Pattern recognition is one of the prevailing appliers of this algorithm. It is developed by Dunn [9] and improved by Bezdek [10]. In the FCM approach, data are bound to each cluster by means of a membership function, which represents the fuzzy behavior of this algorithm. In this case, the membership function follows a smoother line to indicate that every datum may belong to several clusters with different values of the membership coefficient.

A genetic algorithm is a search heuristic that is inspired by Charles Darwin's theory of natural evolution [11]. This algorithm reflects the process of natural selection where the fittest individuals are selected for reproduction in order to produce the descendants [12]. The process of natural selection starts with an initial population and the selection of fittest individuals is conducted from the designated population. Accordingly, offsprings that inherit the characteristics of the parents are spawned and would be appended to the next generation. The more the parents have fitness, the higher the chance their offsprings acquire to survive. This process constantly iterates until a generation with the fittest individuals is found.

In Section II, the most recent attempts in the literature are investigated. In Section III, the proposed method of reducing energy consumption is presented which is based on GA and online clustering. The results of the evaluation of the proposed method are elaborated in Section IV and finally, the conclusion and future works are presented in Section V.

II. RELATED WORKS

In this section, some of the approaches for reducing energy consumption in WSNs are investigated. Moh'd Alia [13] developed a dynamic movement of the mobile sink in WSNs using a cluster-based harmonic search algorithm. In [13], the location of the central station is considered mobile, in order to reduce the distance in communication establishment. In another research, Kong et al. [14] presented the energy balancing strategy based on the Hilbert diagram and the GA for WSNs.

Agrawal and Pandey [15] proposed the hybrid algorithm FLIHSBC for increasing the network lifetime. The FLIHSBC is based on a fuzzy logic and harmony based clustering algorithm. Kumar et al. [16] proposed an opportunistic void avoidance routing (OVAR) for underwater wireless sensor networks (UWSN). OVAR utilizes distributed beaconing to construct the adjacency graph at each hop and then selects a forwarding set with the highest reliability and energy efficiency. In analogous research, Patil and Mishra [17] presented an improved Mobicast (also known as mobile geocast) routing protocol in order to minimize the energy consumption of UWSNs. The purpose in [17] is to overcome the unpredictable holes problem and minimize energy consumption of sensor nodes. Akbar et al. [18] proposed an efficient data gathering approach in WSNs utilizing mobile sink. In the proposed scheme of [18], a mobile sink, as a vehicle, along with several courier nodes, are applied to minimize the energy consumption of sensor nodes.

Yao et al. [19] proposed an improved GA, in order to overcome the problem of generating invalid solutions in routing optimization utilizing GA in WSNs. Dasarathan and Kumar [20] introduced the quality of service improvement in MANETs. In this schema, network performance is realized by avoiding link breakage. Barzegari and Masdari [21] presented an FCM-based clustering schema for routing in WSNs in which the total distances of intra-cluster communications are reduced by creating symmetric clusters. Accordingly, Bouyer et al. [22] proposed a new approach for reducing the energy consumption of WSNs by combining LEACH and FCM algorithms. Applying FCM algorithm in WSNs changes the LEACH protocol parameters during the execution. Ravi Chandra and Reddy [23] are benefited from orthogenesis evolution based GA technique for QoS fitness scope aware routing in MANETs. Ghasemzadeh and Latif [24] improved the LEACH protocol utilizing the SFLA algorithm. Paul et al. [25] developed the analysis and improvement of DSDV routing protocol in vehicle ad-hoc networks (VANETs).

Rasheed et al. [26] proposed a method to reduce energy consumption by removing energy holes in WSN in which an energy level threshold is considered so that only nodes with energy levels higher than the considered threshold would be able to transmit data. Elleuchi et al. [27] performed an evaluation of the DEEC protocol in WSNs. They carried out a comprehensive analysis of distributed energy efficient clustering (DEEC), developed DEEC (DDEEC), enhanced DEEC (EDEEC) and threshold DEEC (TDEEC). Kaur and Sharma [28] introduced improved enhanced developed distributed energy efficient clustering (iEDDEEC) in order to prolong the lifetime of WSNs. iEDDEEC protocol was proposed for three types of nodes to prolong the lifetime and stability period of the network, thereby resulting in an increase in the heterogeneity and the energy level of WSN. Thirumala et al. [29] presented a version of zonal-stable election protocol (Z-SEP) for WSNs. According to Z-SEP protocol, some of the nodes directly forward data to sink node, while some others forward their data to sink by applying clustering approaches such as SEP.

In all the investigated methods, the number of clusters is manually determined by the user. However, the most natural number of clusters in a real environment of sensors is usually unknown for the user in advance. A widely known and simple approach to get around this drawback consists of getting a set of data partitions with different numbers of clusters and selecting that particular partition that provides the best result according to a quality criterion. But this method is not suitable for clustering nodes in WSNs, as many states need to be investigated. Also, changing the active nodes in the WSN may require updating the clustering, which is not feasible using the number of fixed clusters. Hence, this paper presents a method that determines the number of clusters in the optimal state according to the properties of the WSN problem.

III. PROPOSED METHOD

In this paper, an online clustering method is developed. That way, while the routing is in progress the sensors clustering in case it is required is updated. In fact, the proposed clustering is carried out based on three objectives including reducing the distance between the nodes within a cluster, reducing the distance between the cluster head (CH) candidate nodes and the sink node and online appropriate energy distribution of the nodes in each cluster for each routing round.

The improved FCM algorithm is applied to perform clustering. Since the number of clusters is input for the FCM algorithm, it is modified to determine the number of clusters automatically. Additionally, the GA is applied as the routing algorithm. The next-hop node in the routing process would only be selected among those with distance to the current node lower than a threshold. This model controls the use of power consumption in multi-hop mode and ultimately prolongs the network lifetime. Fig. 1 illustrates the flow of the proposed model.

The sink node plays a key role in the WSN. In fact, it is an interface between the sensing field and the user agents and applications. The collected data of sensor nodes from the environment is forwarded to the sink nodes. The sink node is like a base station that collects and processes data in a centralized manner. Therefore, sink is a special node that has unlimited energy and in charge of computing the GA operations. In addition, the essential demand of most of the clustering protocols is location and energy level information. Here, it is assumed that the node location and energy level are accessible to the sink node using GPS, compass or directional antennas.

A. Experimented Network Topology

The topology of the network is considered in a 2D $M \times M$ geographical scope in which N sensor nodes are randomly distributed. Accordingly, $d_{i,j}$ and $d_{i,sink}$ notations, respectively, demonstrate the distance between i and j nodes and distance between i and sink nodes in which distance is considered to be Euclidean. In fact, the distance matrix is symmetric so that if $i = j$, $d_{i,j} = 0$ otherwise $d_{i,j} = d_{j,i}$. The radio range of the sensor nodes in the experimented network is limited, and each node has d_0 sensing radius. Thus, if $d_{i,j} > d_0$ then $d_{i,j} = \infty$. In our experiments, the initial energy of all the sensor nodes is assumed as equal. Thus, $E_i = E_0$, where E_0 is the initial energy in Joule.

B. Clustering of Nodes Using FCM Algorithm

In order to avoid high energy consumption of Direct-Transmission approaches, sensor nodes are clustered and only CH of each cluster is determined as responsible for transmitting data towards the sink node. All the nodes

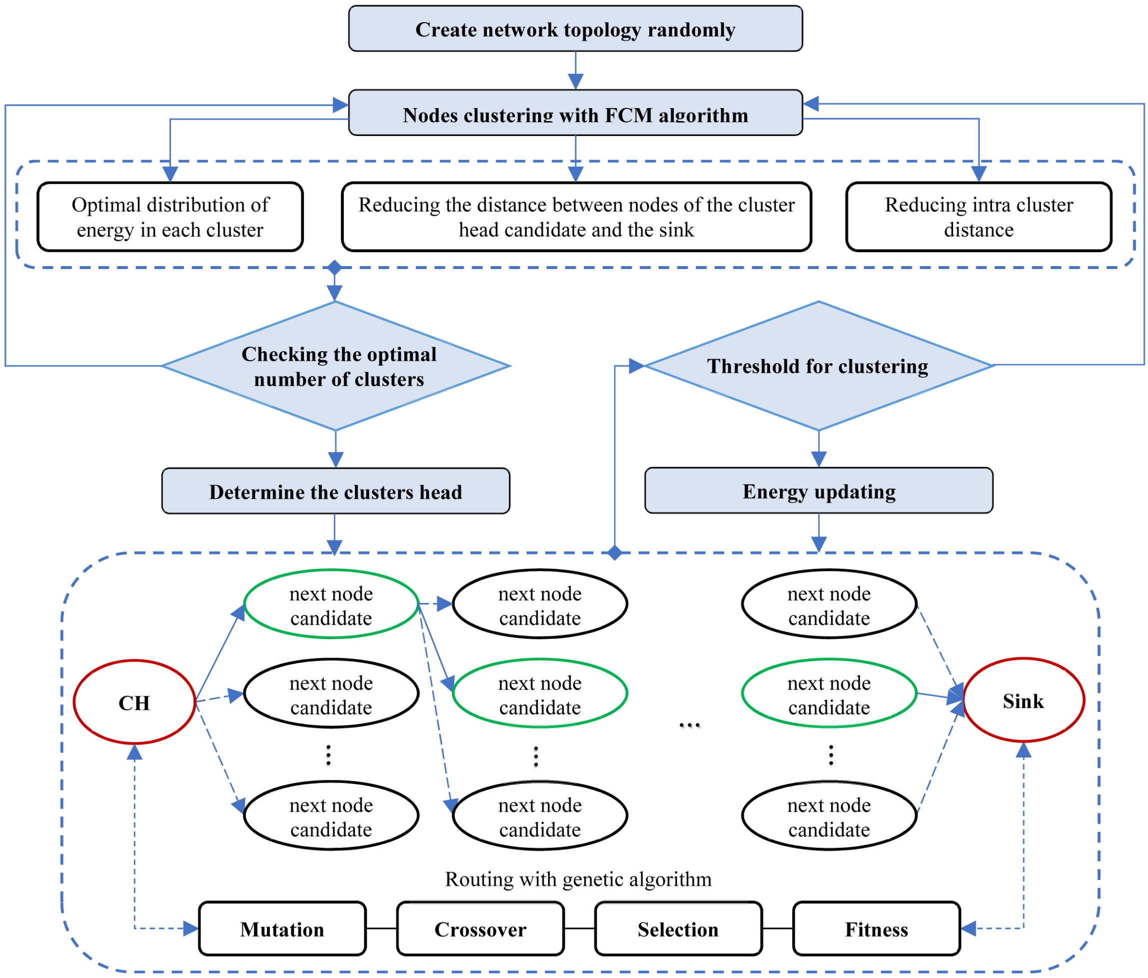

Fig. 1. The flow of the proposed model.

forward their data to their CH via a single-hop path. Then, the process of transferring data to the sink is performed using multi-hop routing. Therefore, reducing the number of clusters leads to reduction in the number of data transmission paths and consequently reduces energy consumption. In this study, we use an improved FCM algorithm for clustering. In fact, FCM algorithm only uses the distance from cluster centroid metric for clustering. According to high importance of energy distribution in clustering, the objective function of this algorithm is customized in order to consider the remaining energy and the distance from sink in this case.

$$J = \sum_{k=1}^{N}\sum_{i=1}^{C}\frac{E_{k,i}}{u_{ik}^{m}[d_{k,v_i}+d_{k,sink}]} \tag{1}$$

where N is the number of nodes and C is the number of clusters. d_{k,v_i} demonstrates the distance from the cluster centroid v_i to the node k and $d_{k,sink}$ is the distance between the node k and the sink node. $E_{k,i}$ is also the remaining energy level of the node k in the cluster i. Forming the numerator of the fraction with the energy value and the denominator with the total distances leads to construction of clusters with minimum distances among the cluster members and minimum distance between the cluster members and sink along with maximizing the remaining energy level of clusters.

According to the sensing radius of nodes, the distance between the CH nodes and other cluster members should be less than d_0. In order to set this constraint and determine the number of optimized clusters, we applied a heuristic clustering technique based on the FCM algorithm with customized objective function. Fig. 2 demonstrates the proposed clustering algorithm.

Considering the location of nodes in each cluster, every cluster should at least have Γ node with the capability of being CH (distance less than d_0 to other members). In fact, the number of optimized clusters is determined while all clusters satisfy this constraint. Starting the clustering algorithm with 1 cluster as the initial value and increasing one unit ensures that the minimum number of clusters is considered in our clustering algorithm.

The proposed clustering algorithm based on FCM
1. Start **2.** Set the initial number of clusters to 0 ($C = 0$). **3.** Increase C value 1 unit ($C = C + 1$). **4.** Perform FCM algorithm with C cluster over the network nodes. **5.** Repeat for all clusters $c = 1,2, \dots, C$: – Consider nodes of cluster c with distances less than d_0 to other members. – Check if this number is less than Γ then go to 3. **6.** Consider C as the number of optimized clusters. **7.** End

Fig. 2. The proposed clustering algorithm.

The Γ parameter demonstrates the minimum candidate nodes of each cluster to be CH. This parameter is defined probabilistically and as a proportion of the number of members in the cluster.

$$\Gamma = \alpha \times N_c \tag{2}$$

where N_c is the number of members of the cluster c and α is a constant number between [0-1]. The α value indicates the percentage of N_c that has the capability of being CH.

C. Cluster Head Determination Based on LEACH Protocol

The LEACH protocol is one of the most prominent protocols in the energy-saving literature of WSNs in which CHs are selected based on their remaining energy level. In fact, the energy level of CHs is diminished during the network transmission and finally depleted. Accordingly, the LEACH protocol repeatedly changes CHs in a rotating manner. Therefore, the energy consumption throughout the whole network is balanced that leads to prolonging the lifetime of the network.

CH determination among the candidate nodes
1. Start **2.** Repeat steps 3 to 6 for all clusters $c = 1,2, \dots, C$: **3.** $CH = \{\}$ **4.** Repeat for all candidate nodes within cluster c ($h_c = 1,2, \dots, H_c$): – Add the node h_c to the CH set, if its energy is higher than the average energy of all members within cluster c. **5.** Select a node with maximum energy from the CH set, and select that as the CH of cluster c. **6.** Go to 7 and perform the clustering algorithm again, if the CH set is empty. **7.** End

Fig. 3. The cluster head determination algorithm.

In this paper, we select CHs based on the LEACH protocol. The CH candidates are determined in the clustering phase. Here, the most appropriate node is selected as CH node among CH candidates within all the clusters. Fig. 3 demonstrates the algorithm of determining CHs.

D. Genetic Algorithm Routing

Basically, single-hop routing protocols in WSNs directly transmit data packets from CHs to sink nodes. However, the single hop approaches suffer from high-energy consumption in CH nodes due to the application of radio wave for transmitting data. The intrinsic constraints of WSNs and distributed structure of WSNs topology have led to application of multi-hop routing approaches. Through the proposed routing approach, the GA searches for a path from the CH as the source node to the sink as the destination node. The GAs solutions structure is often considered as a vector with n elements (n refers to nodes of the path). The GAs solutions structure is illustrated in Fig. 4, where p_1 and p_n are, respectively, the CH and the sink node and p_i and p_j are two consecutive nodes of the path. In fact, the constraint for consecutive nodes to construct the initial population is to have distance less than d_0 threshold.

The lower energy consumption of the path (in other words the higher remaining energy of the participating nodes in the path) indicates that the energy is appropriately distributed among the nodes with a higher energy level. Additionally, the amount of energy required for transmitting data between pair of nodes is deeply dependent on their distance from each other. Therefore, decrease in this distance leads to reduction in energy consumption. On the other hand, reducing the number of participating nodes in the path requires the distance to sink in each hop. Therefore, the remaining energy of nodes, distance to next node and distance to the sink factors should be considered in the objective function, in order to properly distribute the energy consumption in the path. The objective function for calculating the fitness of a path with n length is defined as follows.

$$Fitness = \frac{\sum_{(p_i,p_j) \in path} d_{p_i,p_j}}{\sum_{(p_i,p_j) \in path} d_{p_i,sink} - d_{p_j,sink} + \sum_{p_i \in path} E_{p_i}} \tag{3}$$

where $(p_i,p_j) \in path$ denotes successive nodes p_i and p_j in the path. d_{p_i,p_j} demonstrates the distance between p_i and p_j nodes and $d_{p_i,sink}$ is the distance between p_i and sink

p_1	p_2	...	p_i	p_j	...	p_{n-1}	p_n

Fig. 4. A representation of the GA solutions.

<table>
<tr><td>First parent path</td><td colspan="2">$CH \rightarrow A \rightarrow B \rightarrow C \rightarrow D \rightarrow E \rightarrow F \rightarrow sink$</td></tr>
<tr><td>Second parent path</td><td colspan="2">$CH \rightarrow K \rightarrow D \rightarrow L \rightarrow M \rightarrow C \rightarrow N \rightarrow sink$</td></tr>
<tr><td>Mutual nodes</td><td colspan="2">C , D</td></tr>
<tr><td>Random selection</td><td colspan="2">C</td></tr>
<tr><td rowspan="2">Creating a child</td><td rowspan="2">$CH \rightarrow A \rightarrow B \rightarrow \boldsymbol{C} \rightarrow N \rightarrow sink$</td><td>$CH \rightarrow A \rightarrow B \rightarrow \boldsymbol{C}$</td></tr>
<tr><td>$\boldsymbol{C} \rightarrow N \rightarrow sink$</td></tr>
</table>

Fig. 5. An example of the proposed crossover operator over two assumed paths.

nodes. E_{p_i} refers to the remaining energy of the node p_i. According to the objective function, minimization of the fitness function is considered.

Fundamentally, the operators of the proposed GA consist of the selection, crossover and mutation. In this paper, the roulette wheel method is applied for selecting two parents according to their fitness. The distance between each pair of nodes in the path should be lower than the threshold d_0 and this constraint should be considered in creating new solutions. Fig. 5 illustrates the presented crossover operator which is conducted over two assumed paths with C_r probability.

In the proposed crossover operator, if there is a mutual node between parents, the child path is created from the mutual node; otherwise, one parent is randomly duplicated to the child. In the next level, the mutation operator is conducted over each element (participating nodes in the path) in the created child with M_r probability. According to the proposed mutation operator for each element, a node is randomly selected among all the appropriate cases (according to the threshold d_0). If the selected node already exists in the path, it will be deleted in the sub-path between the two selected nodes, thereby reducing the number of participating nodes in the path. For instance, if we assume the path $CH \rightarrow A \rightarrow B \rightarrow C \rightarrow N \rightarrow sink$ and the mutation operator presents the path $CH \rightarrow C \rightarrow B \rightarrow C \rightarrow N \rightarrow sink$, the resulting path would be $CH \rightarrow C \rightarrow N \rightarrow sink$.

E. Update Clustering Threshold

The iterated routing procedure leads to diminished CH nodes energy. In order to cope with this challenge, the CH nodes repeatedly change in a rotating manner in each routing iteration. This technique can greatly improve system performance. Nevertheless, the energy level of the cluster members may be diminished to the extent so that there are no nodes to perform the CH role, while there are nodes in other clusters with high remaining energy levels. Thus, changing the clusters and conducting an online clustering approach can prolong the lifetime of the network. Technically, performing the clustering is not feasible in every single routing iteration due to its complexity. So, a threshold is considered for iterating the clustering procedure.

The considered threshold is determined based on the minimum energy of the candidate nodes of all clusters in an adaptive manner. If the remaining energy of one of the candidate nodes (from all clusters) degrades from the threshold a_1, then the clustering is iterated. The initial value of a_1 is considered equal to half of the initial energy and this value halves in each iteration. The adaptive adjustment of the threshold prematurely prohibits depletion of the energy of the nodes and consequently leads to the proper distribution of the energy within clusters.

F. Energy Consumption Model

In this paper the energy consumption pattern according to [30] and [31] is applied. The following equations represent the energy consumption for the transmitter nodes E_{tx} and the receiver nodes E_{rx}.

$$E_{tx}(d) = \begin{cases} E_{elec} \times l + \varepsilon_{fs} \times l \times d^2, & d > d_0 \\ E_{elec} \times l + \varepsilon_{mp} \times l \times d^4, & d \leq d_0 \end{cases} \tag{4}$$

$$E_{rx} = E_{elec} * l \tag{5}$$

where E_{elec} represents the needed energy to send or receive one bit data, $\varepsilon_{fs} \times d^2$ and $\varepsilon_{mp} \times d^4$ are the amplifier energy which is set based on the distance and the propagation model (free space or multipath environments). l represents the length of the sent packet, and d is the distance to the receiver node. d_0 is the threshold to transmit packets.

To calculate the energy consumption per routing iteration, the steps for sending a data packet after a node's waking-up and the arrival of these data to the sink should be investigated. The steps consist of:

1. Data extraction from the environment: the required energy to extract one-bit data equals to E_s.
2. Data transmission from cluster members to the CH: according to the energy model, the consumed energy for each cluster member equals $E_{tx}(d_{i,CH})$ and for the CH node is E_{rx}.
3. Data combination and generating packets by the CH: the required energy to combine and generate packets for one bit data is E_d.
4. The energy consumption of the participating nodes in routing: the consumed energy for each node in the path equals to $E_{tx}(d_{p,q}) + E_{rx}$, where $d_{p,q}$ demonstrates the distance between two consecutive nodes p and q in the path.

Table 1. WSN parameters in the simulation

Parameter	Value
Number of sensor nodes (N)	100
Initial energy of nodes (E_0)	0.5, 0.2 J
Length of packets (K)	4 kB
Geographical environment ($M \times M$)	100×100 m
Required energy for sending or receiving one bit data (E_{elec})	50×10^{-9} (Joule/bit)
Required energy for amplifying the signal in short ranges (ε_{mp})	100×10^{-12} (Joule/bit)
Required energy for amplifying the signal in long ranges (ε_{fs})	1000×10^{-12} (Joule/bit)
Required energy for sense of data and combination of packets (E_{DA})	2000×10^{-9} (Joule/bit)
Required energy for extracting one bit data (E_s)	5×10^{-9} (Joule/bit)
Required energy to generate the packet for one bit data (E_d)	2×10^{-9} (Joule/bit)

IV. RESULTS AND DISCUSSION

In this section, we investigate the simulation results of our method along with the evaluation of its performance and comparison with other similar methods. The simulation and evaluation of the proposed method are accomplished in MATLAB version 2016a environment. The proposed algorithm notated FCM-GA in entire experiment results and comparisons. The comparison is conducted between the proposed method performance and DirectTransmission, SH-MEER and MH-FEER.

SH-FEER is a fuzzy-based energy-efficient algorithm in which the process of forming clusters is accomplished by the FCM method [32]. The SH-FEER operation is composed of three stages: clusters are formed during the first step. In the second stage, the CHs are selected. Finally, the data transmit toward the sink node in a single-hop routing manner. MH-FEER algorithm has a high resemblance with SH-FEER in two first stages (i.e., clusters formation and CH selection) [32]. However, the process of data forwarding towards the sink node is different. It utilizes multi-hop routing between CHs and sink.

Table 1 represents the characteristics of the simulated WSN which is considered equal for all the experimented algorithms. In addition, the proposed algorithm incorporates several parameters, whose setting is given in Table 2. Some of the initial parameter values are taken from [19] and [33], including the parameters M_r, C_r and $Iter_{max}$, and other parameters are determined by the trial and error method.

In the first experiment, the average and standard deviation of all the network nodes remaining energy for 1,500 routing iteration are calculated in DirectTransmission, SH-MEER and MH-FEER along with the proposed method FCM-GA. Fig. 6 illustrates the comparison of results with 0.2 and 0.5 Joule initial energy level.

In both of the experiments, the average of the nodes remaining energy is close to zero in DirectTransmission and SH-MEER approaches. These two approaches consume a lot of energy due to the direct transmission of data by each node according to their structure. In fact, low standard deviation of these two approaches indicates that all the nodes energy is degraded equally. The comparison of the proposed method with the MH-FEER method shows that the remaining energy with 0.2 Joule primary energy is lower, whereas this amount is higher with 0.5 Joule initial energy. Although the lower acquired standard deviation for the proposed FCM-GA method in comparison with the MH-FEER method indicates more appropriate distribution of energy between the sensor nodes, it is necessary to carry out other experiments to investigate and analyze the performance of these two methods.

Table 2. Proposed algorithm parameters

Parameter	Value
The probability of determining CH candidates (α)	0.3
Number of routing iterations (*nRounds*)	1500
Population (*nPop*)	5
Mutation operator ratio (M_r)	0.1
Crossover operator ratio (C_r)	0.8
Maximum GA iteration ($Iter_{max}$)	30

For further investigation, we compare the performance of the proposed method with DirectTransmission, SH-MEER and MH-FEER approach via the number of live nodes metric. Fig. 7 shows the experiment results according to number of routing iterations.

Furthermore, in this experiment, both DirectTransmission and SH-MEER create zero energy nodes (dead nodes) in the initial iterations and quickly lose all the network nodes. The results also indicate that the first nodes death

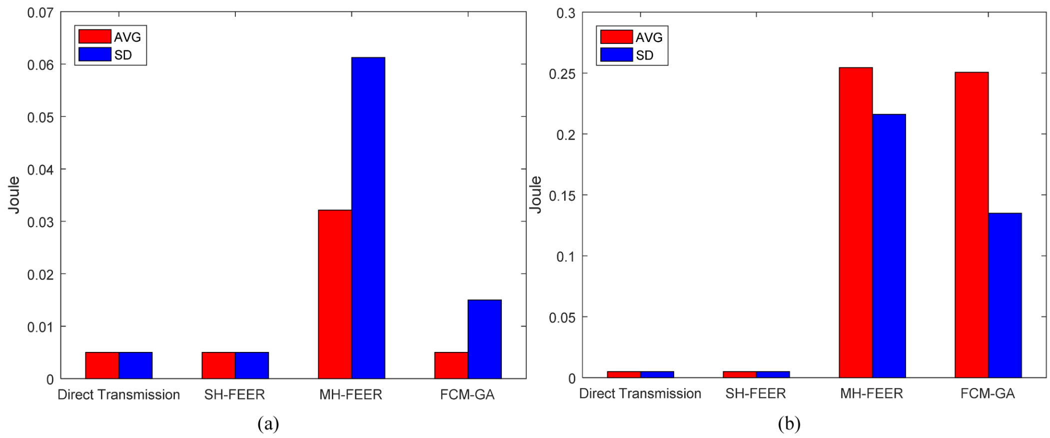

Fig. 6. The average and standard deviation of remaining energy of all the network nodes: initial energy level equal to 0.2 Joule (a) and 0.5 Joule (b).

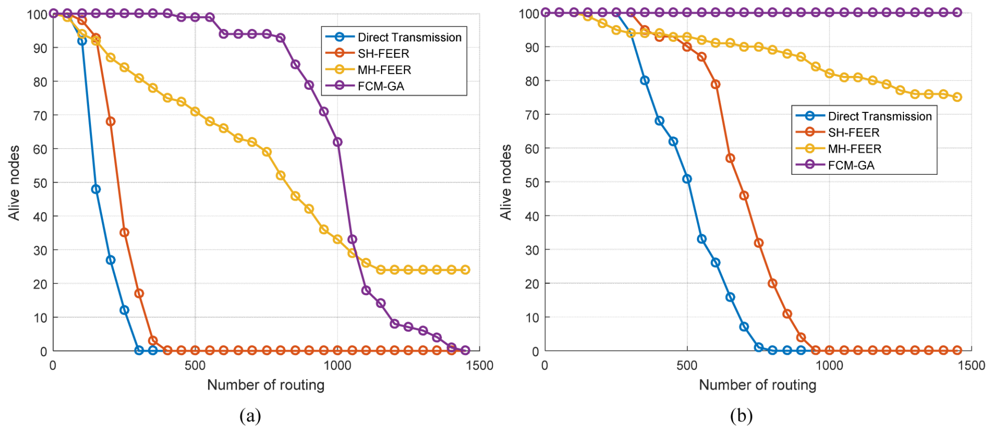

Fig. 7. The number of live nodes over routing iterations: initial energy level equal to 0.2 Joule (a) and 0.5 Joule (b).

(the network lifetime) in our proposed method occurs later than the MH-FEER method. As a matter of fact, updating clusters as well as the CHs in our proposed method leads to the proper distribution of the energy and ultimately prolongs network lifetime. Involving high-energy nodes in routing is also another cause for prolonging the lifetime of the network.

The number of live nodes with 0.2 Joule initial energy is higher for the MH-FEER than FCM-GA at the end of the routing iterations. The MH-FEER loses its first node in the iteration 41, and proceeds to lose the live nodes with a slight descent until it finally has 23 live nodes after the end of iterations. While the proposed method FCM-GA loses its first node in iteration 440, it proceeds to deplete other nodes energy with an exponential rate so that only 2 live nodes remain at the end of the routing iterations. For further investigations, we scrutinized the remaining energy level of each of the nodes for both MH-FEER and FCM-GA. The results of this experiment for 0.2 and 0.5 Joule initial energy are indicated in Fig. 8.

The results show that involving the nodes with higher energy levels has led to the proper distribution of energy consumption in the whole network by the FCM-GA approach. This issue is obvious due to the close proximity of the nodes remaining energy level, which is reported to be approximately 0 and 0.25 Joule, respectively, in the experiments with 0.2 and 0.5 Joule initial energy.

There are only 3 live nodes for experiments with 0.2 Joule initial energy in the proposed method, while there are 23 in the multi-hop MH-FEER method. The distribution of the energy of these 23 nodes is obvious. Nevertheless, in experiments with 0.5 Joule energy, all 100 nodes of the network in the proposed method are alive, while there are only 68 nodes with energy greater than zero in the MH-FEER method. Meanwhile, the results of the proposed method for experiments with 0.5 Joule initial energy indicate that the remaining energy level of about 60% of the nodes is in the range [0.05 J–0.25 J]. It is clear that these nodes were the CH candidates in the simulation. Only about 25% of nodes have an energy higher than

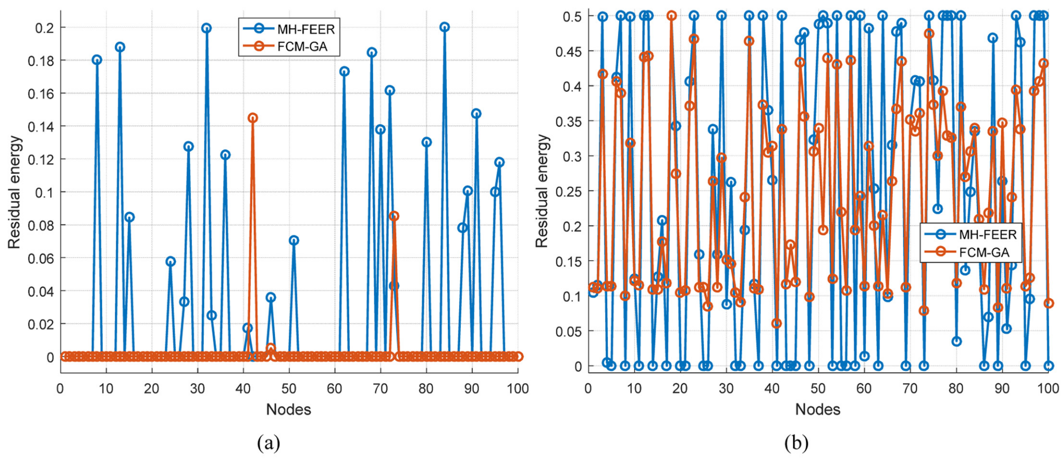

Fig. 8. The remaining energy level of the nodes after the end of the routing iterations; MH-FEER and FCM-GA methods comparison: initial energy level equal to 0.2 Joule (a) and 0.5 Joule (b).

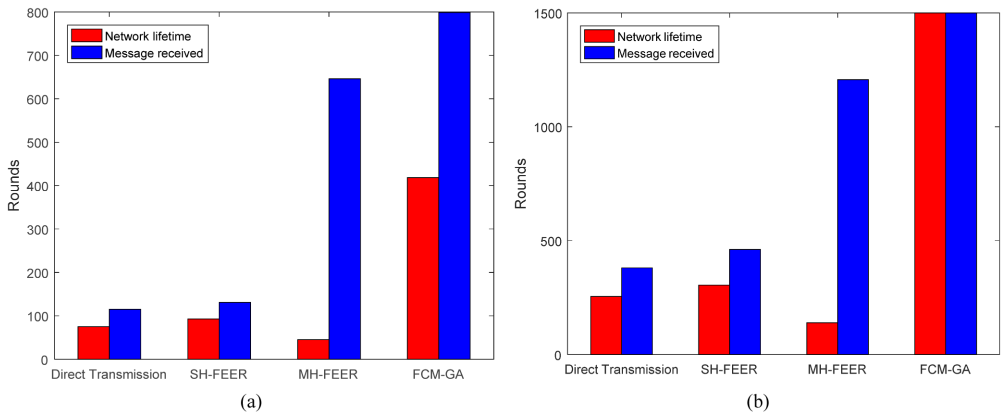

Fig. 9. Network Lifetime and the number of transmitted packets: initial energy level equal to 0.2 Joule (a) and 0.5 Joule (b).

0.35 Joule, which are only used as participating nodes in routing throughout the simulation. The dense presence of nodes proves that the proposed method outperforms other methods in distributing the energy. A large number of nodes with a near-zero remaining energy levels confirms this issue.

The experiment with 0.5 Joule initial energy level in the MH-FEER method indicates that about 50% of the nodes have energy lower than 0.1 Joule revealing that these nodes were often the CH. Furthermore, about 30% of nodes have energy close to the initial value, which demonstrates that they have been unselected. Therefore, MH-FEER method is unable to utilize nodes around the geographical area (distant points) due to the lack of use of cluster update mechanisms and leads to a lack of proper distribution of energy. Accordingly, all the mentioned methods are compared via metrics such as the number of transmitted packets and the network lifetime. Fig. 9 illustrates the result of experiments.

The network lifetime and the number of transmitted packets for the proposed method equal to 425 and 798, respectively throughout experiments with 0.2 Joule initial energy. From this perspective, the proposed method remarkably outperforms all other methods. Technically, the use of all the nodes of the network by updating the clusters has led to the correct distribution of energy and consequently prolongs the network lifetime. Analogously for experiments with 0.5 Joule initial energy, the proposed algorithm with 1,500 transmitted packets and the network lifetime outperforms other methods.

Table 3 gives the numerical results of comparison of the proposed FCM-GA method with other methods based on the network lifetime, the number of live nodes, the total remaining energy of the network, the average and standard deviation of the remaining energy of the network and the number of transmitted packets. The results are reported for both the experiments with 0.2 and 0.5 Joule initial energy and for 1,500 routing iterations.

Overall, the proposed FCM-GA method outperforms other methods. MH-FEER method is in the second rank.

Table 3. The comparison of the proposed method and other methods for 1,500 routing iterations

Initial energy	Methods	Lifetime	#Live nodes	Remaining energy	Avg of the remaining energy	SD of the remaining energy	#Transmitted packets
0.2	DirectTransmission	81	0	1e-10	1e-10	1.5e-25	115
	SH-MEER	93	0	1e-10	1e-10	1.5e-25	126
	MH-FEER	41	23	2.02	0.015	0.062	648
	FCM-GA	425	2	0.24	0.002	0.014	798
0.5	DirectTransmission	218	0	1e-08	≈ 0	≈ 0	483
	SH-MEER	324	0	1e-08	≈ 0	≈ 0	497
	MH-FEER	190	76	25.99	0.251	0.225	1181
	FCM-GA	1500	100	24.25	0.245	0.128	1500

The proposed method exhibits superiority to the MH-FEER method and is based on the number of transmitted packets which is about 30%.

V. CONCLUSION AND FUTURE WORKS

In the majority of the methods, clustering of nodes is performed only based on reduction in the total communication distance between the members; while applying the remaining energy criterion effectively improves the clustering algorithms performance. Thus, the FCM clustering algorithm is customized based on the parameters such as intra-cluster distance, distance to the sink and the remaining energy of sensor nodes. Accordingly, routing of the network packets is accomplished online and through the improved FCM algorithm, which represents appropriate performance in experiments. Moreover, applying the GA for routing packets according to the sensing range of nodes provides acceptable results. In future works, it is suggested to customize the proposed method for networks with mobile base stations, and to make the routing algorithm smart on this basis.

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