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A Firefly Algorithm for Energy Efficient Clustering in Wireless Sensor Networks

Mohamed Sahraoui and Abd Elmalik Taleb-Ahmed

¹ LIAM laboratory Mohamed Boudief University of M'sila, Algeria

² IEMN DOAE Laboratory Hauts de France Polytechnic University of Valenciennes, France

mohamed.sahraoui@univ-msila.dz

taleb@uphf.fr

Abstract. The fundamental metric taken by clustering algorithms in Wireless Sensor Networks (WSN) is energy enhancement to maximize network lifetime. One of the crucial issues is network coverage in order to use all of the network's resources, which increases the lifetime of the network. Moreover, load balancing techniques play an essential role in improving network lifetime due to their efficient way of distributing the load between nodes. The goal of this work is to assemble these two approaches in clustered WSN in order to improve resources utilization and increase network lifetime. Thus, we present a new clustering algorithm named Firefly optimization based Adaptive Clustering for Energy Efficiency (FACEE) which uses a novel clustering based firefly optimization algorithm for coverage improvement and load balancing. The simulation results indicate that our proposed algorithm can significantly improve the network lifetime as well as the delivery rate.

Keywords: WSN, Firefly · Clustering · Optimization · Coverage · Load balancing.

1 Introduction

In order to sense and monitor certain events in the environment, such as temperature, sound, and pressure, numerous sensors are placed across the concerned area to form a wireless sensor network (WSN). Then, the gathered information is transmitted via the network to the sink node which is typically more potent than the other nodes. To this end, The BS allows for the analysis and transmission of information via the internet [1]. Every sensor node is a low-power, single-antenna device with a half-duplex radio that should operate for a very long time as much as possible. In the absence of an energy-efficient method, a node's battery would quickly run out. Furthermore, the energy consumed in communication is more significant than the energy consumed in computations [2].

Over the last decade, extensive research has been done on clustering, one of the most effective power-saving techniques. The use of clustering allows for energy-efficient communication between sensor nodes, which are organized into

various clusters. The node in charge of each cluster is called the Cluster Head (CH). The goal of clustering is to reduce the number of nodes or CHs that may communicate with other clusters and shorten the distance that data must travel. Additionally, clustering stops redundant information from being transmitted utilizing data aggregation [3]. Although clustering is energy efficient, it is difficult to exploit routing information to achieve clustering process with proper load balancing. As a result, the issue becomes NP-hard, and is made considerably more difficult in wide WSNs because the weight of overhead has to be shared by all the nodes. Hence, an appropriate clustering strategy has become to be crucial for extending the WSN's lifetime.

Consequently, many optimization algorithms have been used to propose different clustering solutions such as in [9–16]. The use of Firefly optimization Algorithms (FAs) can be either independently such as in [14–16] or hybridized with another optimization algorithm such as in [12, 13].

However, the absence of a good clustering strategy that focuses on optimal coverage and load balance aspects between the nodes can lead to the disjointing of a certain number of nodes and overloading of some clusters compared to the others. Thus, the network lifetime can be decreased by the loss of the disjointing nodes and the fast death of the overloaded cluster members which can occur due to the increased level of both collisions and communication overhead. To overcome this limitation, we have proposed the Firefly optimization based Adaptive Clustering for Energy Efficiency (FACEE) Algorithm to improve coverage and balance the load between the cluster heads in the network. The purpose is to improve the network lifetime and the delivery rate which ultimately makes the entire network reliable and live more time.

The remainder of this paper is structured as follows: In Section 2, a summary of related work is provided. In Section 3, we present our algorithm FACEE. In Section 4, the simulation experiment findings and discussions of those results are provided. In section 5, we conclude this work with further extension proposals.

2 Related works

Clustering methods have been widely used in wireless sensor networks to provide efficient routing algorithms. Some of them don't take into account the load balance aspect. The most popular algorithms for WSNs is the Low Energy Adaptive Clustering Hierarchy (LEACH) protocol introduced by the authors of [4]. According to LEACH, an ideal number of cluster heads is estimated to be 5% of the total nodes. Also, the CH list change randomly from a round to another in order to balance the energy consumption of nodes. The node makes this determination by selecting at random a value between 0 and 1. If the number is below a predetermined threshold, the node n becomes a CH for the current round. This protocol has seen several enhancement giving rise to new versions of hierarchical routing protocols. The literature contains numerous proposals for improved versions of LEACH, such as the LEACH-C presented in [5] by the same authors of LEACH. Hence, the energy level is included in the cluster selection process

in LEACH-C made by the BS, which leads to an improvement in the network lifetime. In [6], an other improved version of LEACH is suggested to guarantee scalability and speed up broadcasting by adding static and dynamic periods utilized for broadcast messages, however the finding results reveal increased energy usage.

Some other works have focused on load balancing issue such as the load-balanced clustering protocol for WSNs (LBCP) proposed in [7]. It is a compromise between three models: an energy-aware cluster head selection model (EACH) for optimal cluster head selection, which performs clustering based on distances and residual energy, giving clusters the ability to choose their CHs with the least amount of intra-cluster distance, and a delay and energy-aware routing model (DEAR) for optimal inter-cluster communication, which is used to provide the best routes to the BS and calculates the amount of energy used. Furthermore, In order to perform load-balanced clustering according to the amount of energy consumed by given CH nodes, which can be reduced by supporting fewer cluster members, equal traffic for energy-efficient clustering (EQTEEC) is applied. Based on routing overhead, EQTEEC is performed to redistribute cluster members among CHs. Even though this protocol resolves the load balance problem, it suffers from the huge communication overhead needed to route the necessary information to the sink in order to execute the three models. In [8], the authors have proposed a hybrid unequal clustering algorithm for load balancing which focuses on partitioning the network into number of layers and cluster of various groups. The number of neighboring nodes, energy available, available data in the node and the distance to the sink are parameters considered to select the nodes as CHs. Clustering is formed with unequal number of nodes with an equal load to balance the data in the network in such a way that the nodes which are present within a threshold distance will become a part of cluster.

Since the clustering process with adequate load balancing is an NP-hard problem, many optimization algorithms have been used to propose different clustering solutions such as Ant-Colony Optimization (ACO) in [9], Particle Swarm Optimization (PSO) in [10,11] and Firefly optimization Algorithms (FAs) which are detailed in this section due to their relevance to our proposed algorithm. Hence, FA based algorithms can be categorized into two types: independent FAs and FAs hybrid with an other optimization algorithm such as the hybridization with the ACO algorithm in [12], where the authors developed the Butterfly Optimization Algorithm (BOA) and ACO based energy efficient cluster based routing scheme for WSNs. Using the BOA, a number of factors are taken into account for choosing optimal CH, including node degree and centrality, distance to the sink node, distance to neighbors, and node residual energy. The ACO is used to determine the best route between the CH and the sink node while taking into account a number of factors, including distance, residual energy and node degree. An other hybridization between FA and fuzzy logic approach is made in [13], where the authors suggested a three-phase multi-phase routing system, consisting of clustering the network nodes, figuring out the paths between CHs and maintaining the paths. The nodes are clustered using the firefly technique,

then the proper primary path and backup path using fuzzy logic is determined. Hence, CHs use backup paths in the event that the primary paths fail while still transmitting data packets to the sink node.

Although the hybridization of the FA can achieve good results in terms of latency and delivery rate, it requires more data control exchanges resulting in more collisions and overhead communication costs.

As mentioned before, some other works are based on the independent FAs. In [14], routing using firefly algorithm in wireless sensor networks is used. To convey aggregated data, a spanning tree is used in the routing process. Thus, each node in the network reports its energy consumption, and based on various including throughput, packet lost rate, distance between nodes and residual energy, each node compares the obtained values to find the best attracted rout. The network lifetime has been increased in [15] by using an enhanced firefly algorithm. The clusters are formed with based on the firefly algorithm, which is also utilized to choose the cluster head. Two critical aspects in the CH selection are token in the proposed function: first is the energy dissipation of the communication between cluster members and the CH, and second, the energy required for data aggregation and transmission to the sink. Furthermore, the technique includes a step that substitutes a pseudo-random solution produced inside the search space for the worst solution from the population. In [16], an approach called EM-FIREFLY is proposed in order to increase the power of WSN by gathering common data based on efficient clustering. In this method, the network is divided into hexagon which is divided into equal zones. For each zone a fixed sink is assigned to rely data to the BS. Thus, the firefly algorithm replaces the light intensity with the remaining energy of the node, making attraction inversely proportional to distance and directly correlated with energy. Using the four criteria of residual energy, noise rate, number of hops, and distance, the most optimal node is selected as a CH based on the fitness function to transfers the data packets of its cluster to the dependent sink.

It is observed that the main focus of all the previous works is the energy balancing issue with giving less consideration to the coverage aspect even though it plays an important role in reliability guarantees as it increases the use of the network resources, and thus improves the network lifetime and delivery rate. Consequently, our proposed FA takes into account the coverage aspect in addition of the energy balancing one.

3 Firefly optimization based Adaptive Clustering for Energy Efficiency (FACEE)

3.1 Network model

We define a WSN as a set G of N nodes. We denote the i_{th} sensor by n_i and the corresponding sensor node set $SN = \{n_1, n_2, \dots, n_N\}$. The network's nodes are dispersed across a square region, with M denoting the length of each side.

We suppose that:

- Every node also knows the BS coordinate value in addition to its own.
- BS is situated in a predetermined location, either within or outside the sensor field.
- Nodes in the network are pseudo-static.
- The energy of the BS is unlimited.
- Battery power restrictions apply to all sensor nodes. They have a limited communication range too.

3.2 Firefly Optimization Algorithm

Firefly algorithm (FA) was introduced in 2008 which is inspired by the behavior and flashing patterns of fireflies in nature [17]. FA belongs to swarm-based meta-heuristics and replicates the way that fireflies communicate by flashing their lights. Since all fireflies are assumed to be unisex, any firefly can be attracted to any other firefly, and a firefly's attractiveness is directly proportionate to its brightness, which depends on the objective function. Hence, a firefly will be drawn to a firefly that is more visible and the brightness diminishes with distance according to the inverse square law as in 1.

$$I \propto \frac{1}{r^2} \quad (1)$$

The light intensity with a light absorption coefficient λ at a distance of r from the source can be described as in 2.

$$I = I_0 \exp^{-\lambda r^2} \quad (2)$$

where I_0 represents the source's light intensity. The brightness can also be expressed as in 3.

$$\beta(r) = \beta_0 \exp^{-\lambda r^2} \quad (3)$$

The algorithm assigns a light intensity to fireflies, which are randomly produced feasible solutions, based on how well they perform in the objective function. The brightness of the firefly will be calculated using this intensity. For minimization issues, the solution with the lowest functional value will receive the most light. Each firefly will thereafter follow fireflies that have better light intensity. A firefly that shines the brightest will conduct a local search by randomly walking around its neighborhood. However, for two fireflies i and j , firefly i will migrate in the direction of firefly j using the updating method in 4, if firefly j is brighter than firefly i .

$$X_i = X_i + \beta_0 \exp^{-\gamma r^{(i,j)^2}} (X_j - X_i) + \alpha(rand - 1/2) \quad (4)$$

Where $rand$ is the random number drawn from either a uniform distribution or a Gaussian distribution, and α is the randomization parameter.

The flow diagram of the firefly algorithm is shown in Fig 1.

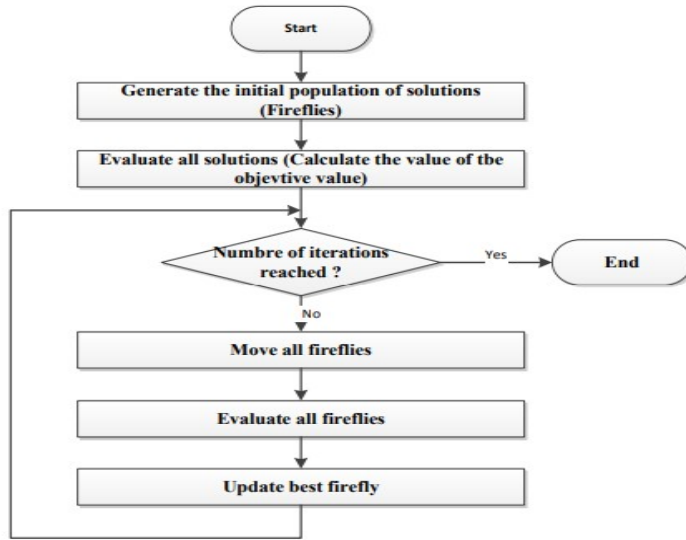


Fig. 1: The firefly algorithm's flowchart.

3.3 FACEE Proposed Algorithm

FACEE approach utilizes adaptive clustering scheme in such a way that if the number of clusters changes over time and the nodes' membership changes, a clustering system is referred as adaptive. For absorbing data transmission overload in FACEE, nodes with a specific high condition (Ich) can serve as the CH. All nodes should alternately take turns serving as CH in order to prevent early mortality from high energy consumption. Hence various considerations must be taken into account when choosing a CH candidate. Node-weight, residual energy, node-to-node distance and distance from the BS are taken into account in FACEE. Consequently, we define the following equations :

$$IW_{ij} = 1 - \frac{W_i}{W_j} \quad \forall i, j \quad (5)$$

Where, W_i and W_j are node-weight of nodes i and j respectively. The node-weight of node n represents the length of its the cluster members and it defined by 6 as follow:.

$$W_n = |CL_n| \quad (6)$$

Where CL_n represents the cluster headed by the node n which includes the node n to initialize the length of the CL_n list by 1. Note that each node have two lists: cluster list (CL) for the cluster members and parent list (PR) for the temporary elected CHs.

$$ID_{ij} = \begin{cases} 1 - \frac{D_{Bs,i}}{D_{Bs,j}} & \text{if } i \neq j \\ 1 - \frac{D_{Bs,i}}{D_{Max}} & \text{otherwise} \end{cases} \quad (7)$$

The Cartesian distances between the node i and the sink (s) and the node neighbor j and the sink are denoted as $D_{Bs,i}$ and $D_{Bs,j}$ respectively. D_{Max} is the maximum distance between all the nodes and the BS, and it is equal to M that represents the length of the side. The equation 8 calculates the Cartesian distance between nodes (i and j).

$$D_{i,j} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (8)$$

Where, (x_i, y_i) and (x_j, y_j) are the coordinate values of the node i and j respectively.

$$IE_{ij} = \begin{cases} \frac{Er_i}{Er_j} & \text{if } i \neq j \\ Er_i & \text{otherwise} \end{cases} \quad (9)$$

Where Er_i and Er_j are the residual energy of the nodes i and j respectively. According to 10, the residual energy of the node n Er_n is determined as follows:

$$Er_n = \frac{E_{Rm}(n)}{E_{Init}(n)} \quad (10)$$

$E_{Rm}(n)$ and $E_{Init}(n)$ are the remaining and initial energies of the node n .

Finally, the different node compete to be a Ch by the maximization of the sum of the equations 7, 5 and 9 according to the equation 11.

$$Ich_i = Max \sum_{j=1}^{W_i} \lambda_1 IE_{i,j} + \lambda_2 ID_{i,j} + \lambda_3 IW_{i,j} \quad (11)$$

Where λ_1, λ_2 and λ_3 are parameters that control the importance of the metrics in such a way that $\lambda_1 + \lambda_2 + \lambda_3 = 1$.

In order to get a suitable cluster distribution (unresolved problem with several protocols), FACEE algorithm uses threshold distance for each firefly in such a way that the nodes belonging to this distance compete to select the best CH, however the other nodes (far from this distance) have an other choice to select an other CH. By this way, our proposed method can ensure the coverage and thus the reliability of all the network.

Algorithm

The application and adaptation of the FACEE algorithm to address coverage and load balancing in clustered WSN are described in this section. FACEE algorithm is presented in Algorithm1.

In fact, there are 4 phases involved in running the FACEE algorithm:

- Step 1: in first step, all the nodes are taken as population with initialization of the different parameters (line1 to 4).

Algorithm 1: FACEE

1. Generate initial population of solutions n_i , ($i = 1, 2, 3, \dots, N$);
2. Light intensity I_i is defined by Ich_i
3. Define Threshold(Δ), λ_1 , λ_2 and λ_3
4. Define number of iterations Nit
5. **while** $t < Nit$ **do**
6. **for** $i = 1$ to N **do**
7. **for** $j = 1$ to N **do**
8. **if** ($Ich_j < Ich_i$) and ($D_{i,j} < \text{Threshold}(\Delta)$) **then**
9. Move solution j towards solution i (Add j to CL_i)
10. Update parent list of the node i ($PR_i(j)$)
11. Update parent list of the node j ($PR_j(i, Pch_i)$)
12. **end if**
13. **end for**
14. **end for**
15. **end while**
16. **for** $j = 1$ to SN **do**
17. **if** $PR_j \neq \emptyset$ **then**
18. Select the best i as CH
19. **else**
20. Select j as CH
21. **end if**
22. **end while**

- Step 2: In the second stage, The equation 11 is used to determine the attractiveness of each artificial firefly i in comparison to another firefly j . Hence the equation 3 is defined by 12 as follows:

$$\beta_i = Pch_i \quad (12)$$

In our work, we took into account the idea that a firefly's attraction is solely dependent on the amount of light it emits through its objective function. Therefore, the distance between the fireflies does not have the only effect on how attractive they are.

- Step 3: The algorithm explores the search space in this step to produce new solutions. Therefore, Adding the moved fireflies to the destination firefly's cluster list and updating the parent lists of both the moved and the destination fireflies in such a way that the moved firefly updates the parent only if it has the largest β_i , but the destination firefly deletes the moved one from its parent list if it exists, are how new solutions are generated by moving fireflies that are at a certain threshold distance away from better solutions (from 8 to 12).
- Step 4: Any meta-heuristic's effectiveness is achieved by fusing the exploration and exploitation behaviors that are used to find the optimal solution. According to our method, the exploitation is carried out by using a local search around the best solution (solution with the highest light intensity). The local search consists on selecting other CH at a time. This process is

repeated until the number of iterations is reached, then optimal CHs will be selected (from 17 to 21).

4 Simulation and Results

The simulation results of our algorithm FACEE in comparison to the protocols LEACH-C and EM-FIREFLY [16] are presented in this section. In addition to our FACEE algorithm, we have implemented EM-FIREFLY due to the lack of its source code. The simulation is performed in MATLAB and the collection of outputs after specific number of rounds considered by 1000. The same simulation parameters are used for the different protocols. These simulation parameters are shown in Table1.

Table 1: Simulation parameters.

Parameters	Values
Number of nodes	100
Area	150m*150m
Radio range	20m
Initial energy	0.5j
Sink location	In the middle
Data packet size	4000bit
Control packet size	500bit

In order to give priority to the energy parameter in our protocol FACEE, we have fixed the parameters that control the importance of the metrics presented by λ_1, λ_2 and λ_3 by 0.5, 0.3 and 0.2 respectively. Also the threshold(Δ) is fixed by 20m (the same as radio range).

The execution of the different protocols is presented in Figures 2(a),2(b) and 2(c) in which it is demonstrated the well coverage of the protocol FACEE (Figure 2(c)) taking in account the whole network and more precisely the dense eras by specifying more CHs, the case that is not exist in EM-FIREFLY nor in LEACH-C.

For this comparison, Figure 3(a) shows for the network lifetime that is considered here by the number of dead nodes via the different number of rounds for each protocol. We found that our protocol can ensure more life time for the network due to the adaptive clustering with best coverage and balance strategies which are used, unlike the fixed sinks used by EM-FIREFLY in different sides of the hexagonal to collect data that quickly makes them die.

In Figures 3(b), 3(c) and 3(d), the delivery packets to the sink per round in the different protocols is presented. Throughout these figures, it is shown that our protocol succeeds in routing more packets to the sink due to its well strategy of coverage as well as the one of energy conservation.

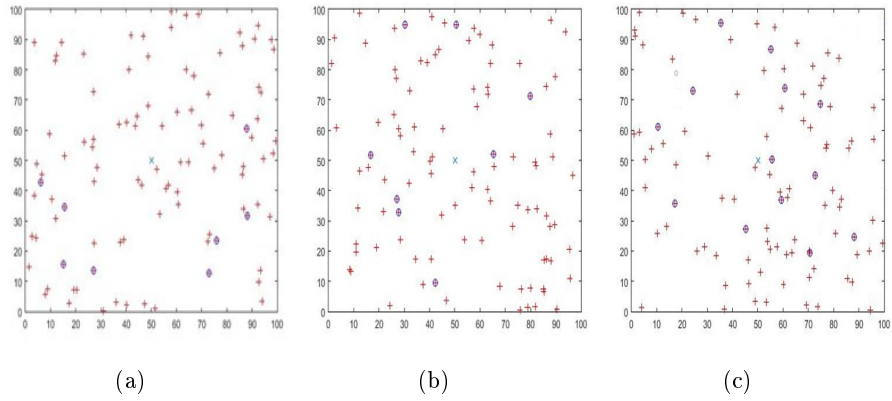


Fig 2: (a) LEACH-C Coverage, (b) EM-FIREFLY Coverage and (c) FACEE Coverage

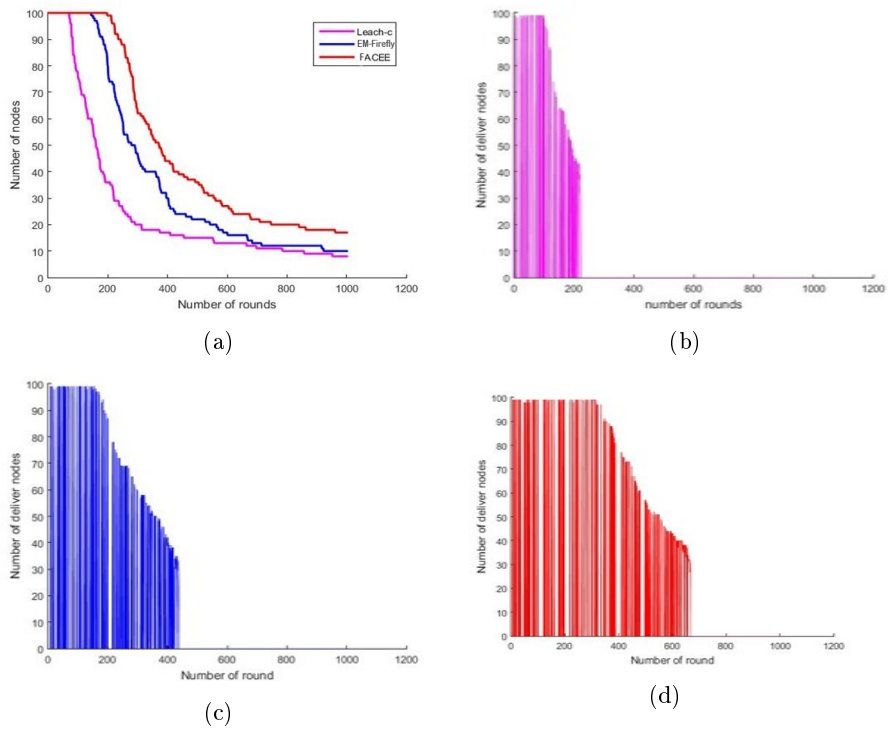


Fig 3: (a) Network lifetime for the three protocols: LEACH-C, EM-FIREFLY, FACEE, (b) Delivery packets in LEACH-C, (c) Delivery packets in EM-FIREFLY and (d) Delivery packets in FACEE.

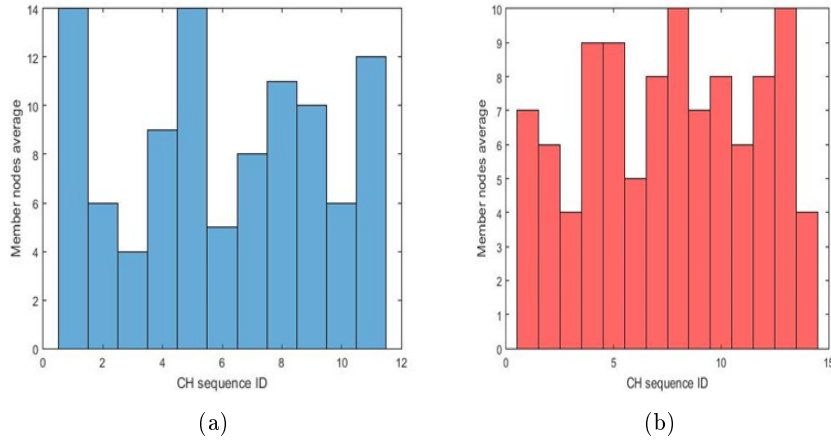


Fig. 4: (a) The average of CHs load in EM-FIREFLY and (b) The average of CHs load in FACEE.

Figures 4(a) and 4(b) show the average of CHs load through the execution in different rounds by the two protocols EM-FIREFLY and FACEE. It must be noted that our protocol succeeds more than the protocol EM-FIREFLY in load balance between CHs. This is proved by the fact of exploiting more number of CHs then EM-FIREFLY in addition of the better dividing of nodes between CHs more than EM-FIREFLY.

5 Conclusion

In this paper, we propose a novel scheme for coverage improvement with energy balancing in clustered wireless sensor networks based Firefly optimization algorithm. The main challenge of such work is the improvement of the network lifetime. For this reason, a special consideration is given to the coverage process that is less considered in the previous works. In addition, a load balance mechanism is added in order to achieve the maximum of the network lifetime improvement. Through simulations and experiments, we demonstrate that our protocol FACEE significantly reduces the energy consumption and improves the network lifetime with good amounts of packet delivery. As a future work, it seems more suitable to design a decentralized version of our technique and compared it with the present work.

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