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Research paper

Better Neighbors, Longer Life: an Energy Efficient Cluster Head Selection Algorithm in Wireless Sensor Networks based on Particle Swarm Optimization

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Abstract

Clustering is one of the most effective techniques for reducing energy consumption in wireless sensor networks. However, selecting optimum cluster heads (CHs) as relay nodes has remained as a very challenging task in clustering. All current state of the art methods in this era only focus on the individual characteristics of nodes like energy level and distance to the Base Station (BS). But when a CH dies, it is necessary to find another CH for cluster, and usually its neighbor will be selected. Despite the existing methods, in this paper, we proposed a method that considers node neighborhood fitness as a selection factor in addition to other typical factors. A particle swarm optimization algorithm has been designed to find best CHs based on intra-cluster distance, distance of CHs to the BS, residual energy, and neighborhood fitness. The proposed method compared with the LEACH and PSO-ECHS algorithms and experimental results have shown that our proposed method succeeded to postpone death of first node by 5.79%, death of 30% of nodes by 25.50%, and death of 70% of nodes by 58.67% compared to PSO-ECHS algorithm.

1. Introduction

The benefits of using wireless sensor network (WSN) in various industries have led to extend WSN, which is a network structure with a large number of sensors that come together to meet a specific purpose and monitor the environment to get data and send them to each other until they are received by the BS. Thus the longer the sensor node's lifetime, the more information we can get from the environment.

Although WSN faces many challenges, the most important one is energy conservation. Thus clustering has been provided to overcome this challenge. In clustering, the network will be partitioned into several groups (which is called cluster) that each group contains nodes closer to each other. In each cluster, one node is selected as cluster heads (CHs) to cope with the heavy responsibilities. CHs should aggregate data from their respective cluster members and send them directly or Hop-by-Hop to the BS. If the communication in the network is Hop-by-Hop, there is an overload on the nodes closer to the BS, which causes faster energy drain in them. It is called hotspot problem. Therefore, the optimal selection of CHs is very important to reduce the energy consumption.

To meet the demand for energy conservation in WSNs, several algorithms have been developed. Among them, LEACH [1] is the basic one, which provides clustering for the first time. Besides, by randomly rotating the CHs among the sensor nodes, load distributes among the nodes and then the longevity of the network will be increased. E-LEACH is another algorithm provided by Xiangning and Yulin [2], which considers energy for optimal CH selection. The other algorithm that tries to find the optimal CHs is provided by Abbas and Khanjar [3]. Furthermore, PSO-ECHS algorithm [4] is a clustering method in which some factors are taken into account to find optimal CHs, but there is no mechanism for replacing the optimal nodes when some CHs die. In this paper, we tackled this shortcoming and proposed a method that remedy this after-death problem by considering the neighborhood fitness of nodes. In other words, when we have two nodes with almost the same quality, we select that node which its neighbors are betters. The reason behind this selection is that when CH dies their neighbors will be next CHs, and that day will come soon.

The rest of the paper is as what follows. Section 2 gives a brief overview of the related works. A brief summary of PSO is provided in Section 3. In Section 4, the proposed method will be elaborated, and Section 5 provides experimental results. Finally, paper will be concluded in Section 6.

2. Related Works

In this section, a comprehensive review of relevant approaches about the CH selection problem is presented. Low Energy Adaptive Clustering Hierarchy (LEACH) [1] is a method for clustering, which was introduced for distributed environment. In each round, we have different CHs that are selected with different probabilities. Although LEACH is a basic algorithm, it has some drawbacks: in the CH selection process, neither the distance of nodes to the base station nor the energy of sensor nodes is considered. Therefore, if a node that is far from the BS and has a low energy is selected, this CH will die soon and as a result, the longevity of the network will diminish.

Centralized Low Energy Adaptive Clustering Hierarchy (LEACH-C) [5] is provided to make LEACH better. It considers not only the distance to the BS but also the energy, although clustering has been neglected in LEACH-C, and this results in network longevity reduction.

E-LEACH [2] was introduced to be an improvement to the LEACH, which considers energy in the CH selection process. This algorithm is superior over LEACH but regardless of the distance, it cannot effectively save energy in the network.

Tillett *et al*. [6] have introduced an algorithm for CH selection. They used PSO to find optimal CHs. In this method, the intra-cluster distance is considered to be low, but the distance to the BS that can enhance energy efficiency is not taken into account. So, if there were some arrangements for replacing optimal nodes at the time of CHs' death, energy consumption would be reduced.

Guru *et al*. [7] have introduced a method for clustering that considers the distance of the member nodes to their related CHs (called intra-cluster distance). But their method ignores the energy of the CHs, which has a negative effect on the network longevity.

Latiff *et al*. [8] have presented a PSO-based method for cluster head selection. They considered the average intra-cluster distance and a parameter for balancing energy consumption in the network but they didn't consider the distance of the CHs to the BS.

Batra and Kant [9] have used MAC layer information for improving network lifetime. Their simulation results showed that first node death(FND) and half nodes alive(HNA) time has been extended 22% and 24%, respectively, over the LEACH.

Chandirasekaran and Jayabarathi [10] have proposed an algorithm in which Cat Swarm Optimization (CSO) is used for finding optimal CHs. The parameters which are considered in this method include residual energy, received signal strength of sensors from the BS and intra-cluster distance. Although CSO performs better than PSO, CSO computation time is a bit more than PSO. The disadvantage of this method is that there are no provisions for replacing the optimal nodes when the CHs die. It incurs an energy cost for re-running of the CH-selection algorithm.

Rao *et al*. [4] have introduced the PSO method for CH selection. This algorithm consists of a clustering method, which can cause balance in energy consumption. CHs are selected based on some parameters, namely energy, distance of member nodes to their related CHs, and distance of CHs to the BS. The parameters that are mentioned for CH selection plus the degree of CHs are considered in clustering. In this method, there is no mechanism for replacing CHs when they are dead.

Iqbal *et al*. [11] have proposed a method in which fuzzy logic system is used to find optimal CHs. They considered recent history of communication, energy consumption, and vulnerability ratio, which means how many of sent packets received by the BS. Kumar and Mehfuz [12] have devised a PSO method, in which malicious nodes are recognized and neglected. Factors involved in this method are energy, coverage and the quality of link. By using this method, cluster overlapping will be reduced and the network will survive for a longer time.

Azizi and Hasnaoui [13] have presented a method for clustering in which one gateway node will be chosen among CHs based on its energy and distance to the BS. In their architecture CHs can't communicate directly to the BS, but CHs should send their data to the gateway and gateway sends their data to the BS. By decreasing long transmission distance to a shorter one, saving more energy will be possible.

Haider *et al*. [14] have introduced a method for finding optimal CHs to augment the lifetime of the network. This method also incorporates energy harvesting, which makes it possible to reuse CHs. In this scheme, there are two factors for finding optimal CHs: nodes' channel conditions with the BS and residual energy. By considering these parameters, data will be transmitted with less delay and the longevity of the network will be increased. They also proposed a method in which an Unmanned Aerial Vehicle (UAV) has been used for selecting optimal CHs [15]. In this method, CHs should communicate with the UAV and then the UAV have permitted to communicate with the BS. Some factors, i.e. the average of residual energy, the channel condition and the distance of node to the UAV are considered. By decreasing long transmission distance to a shorter one, we can save more energy and the link failure rate with the BS will diminish.

in ECAFG method [16] Genetic Fuzzy System (GFS) has been used for selecting optimal CHs and Fuzzy C-means (FCM) for static clustering. In GFS, distance to the BS, residual energy and distance of the node to its cluster center are considered. The benefit of static clustering is that the size of clusters is relatively the same. Therefore, energy is consumed almost equally among all clusters. NEETCH is offered in [17] to find optimal CHs. For CH selection, three parameters, namely Received Signal Strength Intensity (RSSI), mobility and residual energy of the nodes are considered. The more RSSI, the less delay; therefore, having less delay is the benefit of this method. R-LEACH [18] is presented for CH selection with the aim of increasing network lifetime. In this method, some parameters, i.e., initial energy, residual energy and an optimum value of the CHs are considered.

Meta-heuristic algorithms have been vastly used in optimization problems so far. For example Hosseinirad and Basu in [19] modeled WSN design as a multi-objective optimization problem and tried to solve it using GA. PSO is also utilized in PSO-SD [20] for finding optimal CHs. Parameters like residual energy, node degree, intra-cluster distance, and also number of times that a sensor node acts as a CH has been considered in this method. Karthick and Palanisamy [21] have introduced a method to find optimal CHs. This method consists of Genetic Algorithm (GA) and Krill Herd (KH) algorithm. For CH selection, residual energy and a trade-off between intra-cluster and inter-cluster distance are considered.

A Fuzzy Inference System (FIS) is used to select optimal CHs in [22]. In this method, two parameters, i.e. residual energy and RSSI are mentioned to increase the longevity of the network. Yousif *et al*. [23] have proposed a clustering method in which CH selection is done in a distributed manner. Two parameters, namely residual energy and node degree are considered to select optimal CHs. In this method, Multi-Hop communication is used, and several parameters are considered to find the optimal next relay. By using Multi-Hop communication, CHs will consume less energy, d so that network longevity will be increased.

By using a sampling-based spider monkey optimization, Lee *et al*. have introduced SSMOECHS [24] for finding optimal CHs. In this method, candidate CHs are selected by sampling and optimization will be done by SMO.

Lewandowski and Płaczek [25] have devised an algorithm in which the role of CH is substituted among all available sensor nodes. This method prevents transmitting unnecessary data and maximizes lifetime of network. Haseeb *et al*. [26] have proposed RCER to ameliorate next hop selection. To do this, the parameters, i.e. residual energy, hop counts, and weighted value of Round Trip Time (RTT) are considered. By using this method, more data can be delivered to the BS and therefore, the reliability will be increased.

Rout *et al*. [27] have proposed a clustering method based on Fuzzy Logic. For CH selection, the parameters, namely distance to the BS, residual energy and density of the node are considered. For cluster formation phase, the parameters, namely intra-cluster distance, residual energy and density of the CH are considered. By using this method, we can distribute the load almost evenly among sensor nodes and as a result, increase the longevity of the network.

Liu et al. [28] have introduced a method which is called IEE-LEACH. The parameters, namely initial energy and residual energy of the nodes are considered. Of course, total and average energy of the network are considered as well. In this method, the nodes closer to the BS should not join to the cluster. For data transmission, they used not only single hop but also multi hop and hybrid communication. This method can balance the consumption of energy and increases the lifetime of the network.

Lin and Wang [29] have proposed a method called ECGD for clustering. In this method, the role of CH is substituted among all available sensor nodes and a dual-cluster-head mechanism is used to reduce the overhead. Also, a non-cooperative game model is used to balance energy consumption. Finally, by reducing the consumption of energy, we can increase the lifetime of the network.

Wang *et al*. [30] have presented a method for clustering by using PSO. In this method, for detecting optimal CHs, the parameters, i.e. residual energy and position of the nodes are considered. By using mobile sink, we can overcome the hotspot problem and reduce transmission delay. Therefore, the lifetime of the network will be increased. Zeng *et al*. [31] have proposed ECRCP for clustering. In this method, the optimal number of clusters is calculated with regard to energy consumption. The nodes which are candidate to be CHs should support maximum coverage. Furthermore, CH which consumes a lot of energy must be replaced. Eventually, this method leads to extend the lifetime of the network.

Saini *et al*. [32] have proposed a method for energy efficiency by using GA and Virtual Grid based Dynamic Routes Adjustment (VGDRA). By using dynamic approach, data routing can perform better. Consequently, we can achieve increase in energy efficiency and network longevity.

Murugan and Sarkar [33] have used a hybridization of firefly and grey wolf optimization techniques for cluster head selection, and showed that their method has succeeded in prolonging network lifetime. Abbas and Khanjar [3] have proposed a method to find optimal CH by using FIS. In this method, there are some parameters to find optimal CH, namely residual energy, intra-cluster distance and distance to the BS. By using this, we can balance energy consumption and extend the longevity of network.

Shankar and Jaisankar [34] have used an improved version of firefly optimization algorithm with dual update process for cluster head selection. They have compared their method with other optimization algorithms like bee colony and traditional firefly and inferred that their method has a superior performance over others.

The bottom line is that, many research works have been done in the field of cluster head selection. Some of them use meta-heuristic techniques like PSO and GA. But to best of our knowledge, none of them has any intelligent solution for the death of the cluster head. This is what our method tries to do.

3. Particle Swarm Optimization (PSO)

PSO introduced by Kennedy and Eberhart [35] is one of the most applied metaheuristic optimization algorithms and is inspired from the behavior of bird flocks. In PSO, there are some particles that are randomly scattered in the search space, and continuously move with different velocities. Each particle represents a solution for our optimization problem. A cost function (or fitness function) is used to evaluate the quality of solutions, and PSO tries to find the most fitted particles. At the beginning, particles are randomly placed in the search space, and in each iteration, move based on the formulas 1 and 2.

$$\begin{aligned} V_{i,d}(t+1) &= \omega \times V_{i,d}(t) + \\ & C_1 \times \lambda_1 \times (X_{Pbest_{i,d}} - X_{i,d}) + \\ & C_2 \times \lambda_2 \times (X_{Gbest} - X_{i,d}) \end{aligned} \quad (1)$$

$$X_{i,d}(t+1) = X_{i,d}(t) + V_{i,d}(t+1) \quad (2)$$

where i and d stand for particle and dimension indices, respectively. $X_{i,d}$ is the current position of particle in the search space and $V_{i,d}$ is its velocity. $X_{Pbest_{i,d}}$ is the best position of particle up to now and X_{Gbest} is the best position among all particles. ω is the inertia weight ($0 < \omega < 1$), C_1, C_2 are tuning parameters ($0 \le C_1, C_2 \le 2$), and $\boldsymbol{\lambda}_1$ and $\boldsymbol{\lambda}_2$ are random values ($0 < \boldsymbol{\lambda}_1, \boldsymbol{\lambda}_2 < 1$).

After each iteration, $X_{Pbest_{i,d}}$ and X_{Gbest} will be updated based on the fitness computations.

4. Proposed Method

In ad-hoc WSNs, when a certain percentage of nodes die, the network structure will be significantly changed, so that in the current state-of-the-art PSO-based CH selection algorithms there is a need to re-run the PSO algorithm at the base station to find the new optimal CHs. The novelty of our method is that when it is searching for optimal CHs, it considers not only the optimality of CH but also the optimality of some CH's neighbors. By this strategy, after the death of current CH, simply its nearest node can be selected as new CH without a significant loss in network performance.

In other words, in the proposed method, positive factors for selecting CH are:

- more remaining energy of the node
- shorter distance to the BS
- shorter average distance to its cluster members
- having some close neighbors with more remaining energy and less distance to the BS

The method works as what follows. First, all nodes send their situation data to the BS. Secondly, the PSO algorithm is run at the BS to find the optimal

CHs. Thirdly, nodes are informed about selected CHs and finally, nodes begin to sense data and communicate according to the network topology. Details of our PSO design will be explained at the following sub-sections.

4.1. Cost function

The main part of each optimization problem is its cost function. We have considered three objectives in our cost function. The first objective is minimizing the average of sum of intra-cluster distance and distance of CH to the BS for all clusters. As we know, shorter transmission distance causes lower energy consumption and longer network lifetime. The first objective is formulated as formula 3.

$$f_1 = \sum_{j=1}^{m} \frac{1}{l_j} \left(\sum_{i=1}^{l_j} dis(s_i, CH_j) + dis(CH_j, BS) \right) \quad (3)$$

where s_i is the i[th] sensor node, CH_j is the j[th] CH, l_j is the number of sensor nodes in the cluster j, and m is the number of clusters.

The second objective is to minimize the reverse of total energy of the CHs (we converted the objective functions to minimization functions for consistency with the optimization common terminology). The higher total CHs energy, the longer time CHs can survive. This objective is depicted in Formula 4.

$$f_2 = \frac{1}{\sum_{j=1}^{m} E_{CH_j}} \quad (4)$$

where E_{CH_j} is the remaining energy of cluster head CH_j.

The innovation of our method is in the third objective. By neighborhood similarity criteria PSO tries to select a node as CH that its K nearest neighbors are also well-fitted for CH, so that we have devised the third objective as minimizing the reverse of neighborhood similarity, and it is calculated as Formula 5.

$$f_3 = \sum_{i=1}^{m} \sum_{n \in knn_{CH_i}} dist(n, BS) + {}^{1}\!/_{E_n} \quad (5)$$

where Knn_{CH_i} is the set of K nearest neighbors of CH_i.

The linear combination of three objectives has been considered as cost function in PSO:

$$\mathrm{Cost} = \alpha \times f_1 + \beta \times f_2 + \gamma \times f_3 \quad (6)$$

where α, β, and γ are the weighting coefficients used for balancing the effect of objective functions. The pseudo-code of our method has been depicted in Algorithm 1.

4.2. Clustering

The cluster formation phase is the same as the PSO-ECHS algorithm [4]. Sensors use CH_{Weight} to join a CH. In fact, they join to a cluster with the highest amount of CH_{weight}, which is computed based on these four parameters (Formula 7): CH energy, distance of sensor node to CH, distance of CH to the BS, and degree of CH, i.e. number of nodes in its cluster.

Algorithm 1: Neighbor-oriented PSO-based cluster head selection

- Initialize *N* particles with random positions and velocities
for each iteration **do:**
  for each particle **do:**
    - compute fitness value for particle's current position using Cost Fucntion (4.1)
    - **if** current fitness is better than the best fitness of particle **then**:
      - Update particle's best location
    - **if** current fitness is better than global best fitness value **then:**
      - Update global best position
    - Update particle's velocity using PSO formula (section 3)
    - Update particle's position using its velocity (section 3)

$$CH_{weight(S_i, CH_j)} = \frac{E_{residual}(CH_j)}{dist(s_i, CH_j) \times dist(CH_j, BS) \times \mathrm{degree}(CH_j)} \quad (7)$$

5. Experimental Results

5.1. Simulation and PSO settings

The proposed algorithm is implemented in MATLAB (version 9.0). All nodes are assumed to be fixed. The distances of nodes are calculated based on the received signal strength. Therefore, there is no need to have GPS. All the sensor nodes are homogeneous and number of clusters has been set to 15. Network parameters are listed in Table 1. We set number of neighbors *k* to 5 and 7 for simulation and for each of them we ran the algorithm 20 times with random node placement. To normalize three objective functions (*f1, f2, f3*) between zero and one, we set the value α to 0.001, β to 0.999, and γ to 0.00001.

Furthermore, the adsorption rule is used to keep particles in the range of target area. To apply this rule, updated position of particles which have negative value are replaced by zero and of particles which exceed the target area range is replaced by maximum value of range. We have used the same energy model as in [1].

Table 1. Simulation network parameters.

Parameter	Value
Target area	200 × 200 m^2
BS location	(100,100)
Number of sensors	300
Initial Energy of each sensor node	2 J
E_{elec}	50 nJ/bit
ε_{fs}	10 pJ/bit/m^2
ε_{mp}	0.0013 pJ/bit/m^4
d_{max}	100 m
d_0	30 m
Packet length	4000 bits
Message size	500 bits

PSO implementation parameters has been shown in Table 2.

Table 2. PSO parameters. ω is inertia weight and C1 and C2 are tuning parameters. Vmax and Vmin are maximum and minimum velocity of each particle, respectively. D is number of dimensions.

Parameters	Value
Number of particles	30
C_1	2
C_2	2
ω	0.7
V_{max}	200
V_{min}	-200
D	15
Iteration	100

5.2. Evaluation

For evaluation purpose the proposed method has been compared with LEACH and PSO-ECHS. In the PSO-ECHS algorithm, there is no policy about after-death problem, we choose the closest node to the dead CH as new CH as in our proposed method. The following criteria have been considered as evaluation metrics:

1- Energy consumption
2- Network lifetime

Lifetime of network is calculated by averaging on number of communication rounds in which the first node died, 30% of nodes died, and 70% of nodes died. As shown in Figure 1 through Figure 3, it is obvious that performance of our algorithm is better than PSO-ECHS in terms of network lifetime. Because in our method CHs that are selected after the death of primary CHs are almost as good as their predecessors, lifetime of network will be longer than in PSO-ECHS.

For our method we have considered two settings: 5 nearest neighbors and 7 nearest neighbors. It means that in evaluation of the fitness of candidate cluster head, the fitness of its five (or seven) nearest neighbors also will be considered. In Figure 1, it is shown that the first node in PSO-ECHS will be died after 162.2 rounds (averaged on 20 randomized experiments), while in our method (7NN) it will be died after 179.5 rounds. This means that our method succeeded in prolonging the network life time in case of considering death of the first node.

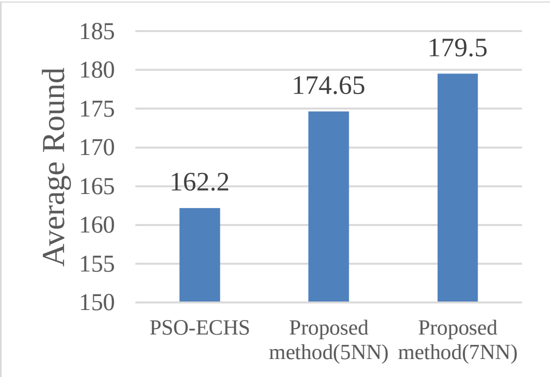

Figure 1. Comparison of averaged network lifetime based on the time when the first node died.

In Figure 2 and Figure 3, death of 30 and 70 precent of nodes has been considered, respectively. Again, it can be seen that if one WSN uses our method for cluster head selection, it can survive more than PSO-ECHS method. Another subtle point is that in our method as much as the number of nearest neighbors increases the network lifetime is more prolonged. It confirms that considering the fitness of neighbor nodes in cluster head selection, has a direct effect on the network lifetime prolongation.

It is noteworthy that when *K* gets bigger the network lifetime also increases. The reason is that when number of well-fitted neighbors, i.e. parameter *K*, increases, there will be better successors (closer to BS and more energetic) for the dead CH in the cluster and so that network lifetime will be extended.

In Figure 4, averaged energy consumption of proposed method has been compared with LEACH and PSO-ECHS after 200 rounds of communication.

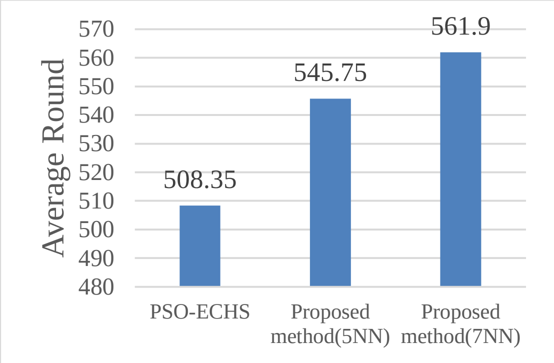

Figure 2. Comparison of averaged network lifetime based on the time when 30% of nodes died.

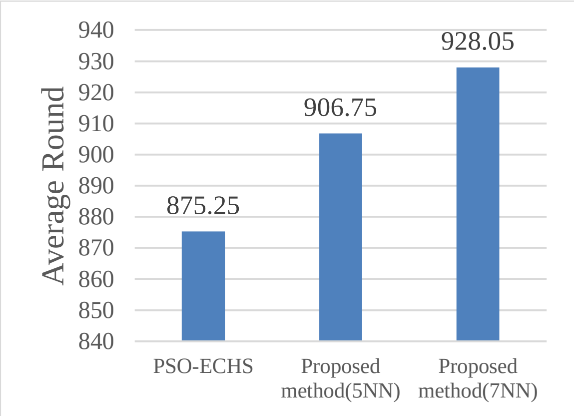

Figure 3. Comparison of averaged network lifetime based on the time when 70% of nodes died.

As it is expected, our method consumes less energy than LEACH and PSO-ECHS because of its conservative attitude about selecting CHs. Also as K gets bigger this energy consumption difference between our method and others gets more obvious.

6. Conclusion and Future Works

In this paper, we provided a sensor network CH selection method, which resolves the need of re-running CH-selection algorithm after death of CH. In this method, nodes with more well-fitted neighbors have more chance for selection. When a CH dies, the closest node to it, that has good criteria will be selected as new CH.

This method has been compared with the LEACH and PSO-ECHS methods, two of prominent methods among CH selection algorithms. Experimental results have shown that our proposed method succeeded to postpone death of first node by 5.79%, death of 30% of nodes by 25.50%, and death of 70% of nodes by 58.67% compared to PSO-ECHS algorithm. Energy consumption has also reduced in comparison with PSO-ECHS and LEACH.

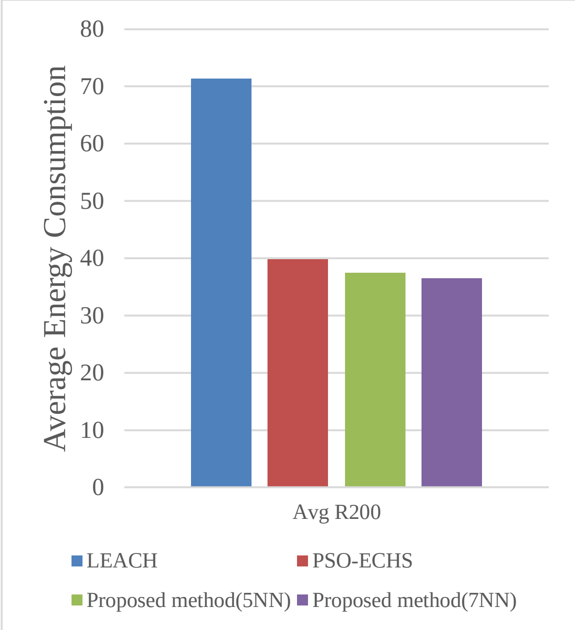

Figure 4. Comparison of proposed method with LEACH and PSO-ECHS on average energy consumption (J) after 200 rounds.

There are some new ideas that we are working on it. One is that we can set a minimum value for the distance of CHs in selection phase, so that CHs will not be too close together. The other is that we can run the proposed method on a heterogeneous network in terms of communication range of sensor nodes and we can also consider energy balancing.

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همسایه های بهتر، زندگی طولانی تر: یک الگوریتم کارا از نظر انرژی برای انتخاب سرخوشه ها در شبکه های حسگر بی سیم با استفاده از بهینه سازی ازدحام ذرات

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چکیده:

خوشه بندی حسگرها یکی از موثرترین تکنیک‌ها در کاهش مصرف انرژی در شبکه‌های حسگر بی سیم می‌باشد. اگرچه، انتخاب بهترین سرخوشه ها به عنوان یک چالش مهم در خوشــه بندی شــناخته می‌شــود. تمامی روشــهای موجود در این حوزه، تنها بر روی ویژگی‌های اختصــاصــی یک گره تمرکز می‌کنند، مانند سطح انرژی آن یا فاصله تا ایستگاه مرکزی شبکه. اما زمانی که عمر یک سرخوشه به پایان می‌رسد، ضروریست که یک سرخوشه دیگر بجای آن انتخاب شود که روشهای موجود معمولا یکی از همسایه های آن سرخوشه را انتخاب می‌کنند که ممکن است ویژگی‌های یک سرخوشه خوب را نداشــته باشــد. ما در این پژوهش، این مســئله را مورد هدف قرار داده‌ایم و ســعی کرده‌ایم روشــی ارائه دهیم که هنگام انتخاب ســرخوشــه، علاوه بر ویژگی‌های متداول، میزان برازندگی همسایه های یک گره را نیز در نظر بگیرد. در این مقاله برای انتخاب سرخوشه ها، یک الگوریتم بهینه‌سازی ازدحام ذرات ارائه شده‌است که ویژگی‌هایی همچون فاصله درون خوشه ای، فاصله تا ایستگاه مرکزی شبکه، انرژی باقیمانده و برازندگی همسایه ها را در تابع هدف خود در نظر می‌گیرد. روش ارائه شده با روشهای معتبر در این حوزه همچون LEACH و PSO-LEACH مقایسه شده است. نتایج نشان می‌دهد که روش پیشنهادی موفق شده است زمان خاموشی اولین گره شبکه را به میزان ۵/۷۹ درصد، ۳۰ درصد گره ها را به میزان ۲۵/۵۰ درصد و ۷۰ درصد گره ها را به میزان ۵۸/۶۷ درصد نسبت به روش PSO-LEACH به تاخیر بیاندازد.

کلمات کلیدی: انتخاب سرخوشه، شبکه های حسگر بی سیم، بهنیه سازی ازدحام ذرات، برازندگی همسایه ها، طول عمر شبکه.