A Distributed Energy-efficient Clustering Algorithm based on Weighted Probability for Wireless Sensor Networks

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Abstract

Clustering problem is one of the significant issues for wireless sensor networks concerned with energy consumption and large-scale deployment. Several energy-efficient clustering algorithms have been proposed to improve the energy utilization efficiency and prolong the network lifetime. In this paper, we propose a new clustering scheme after a comprehensive analysis on existing protocols. In our algorithm, named WPCA (Weighted Probabilistic Clustering Algorithm), every node independently decides whether to be a cluster head according to a weighted probability, which is related to the ratio between node's residual energy and average remaining energy. The nodes with more residual energy are assigned larger weight value to further increase the chances to be elected as cluster heads. In addition, the rotation procedure of cluster heads in previous algorithms is totally abandoned. Simulation results show that WPCA achieves longer lifetime than previous probabilistic-based clustering algorithms and gets a very close approximation compared with a deterministic clustering method.

Keywords: *Wireless sensor networks; Clustering algorithm; Energy-efficient; Probabilistic; Distributed*

1. Introduction

As the maturation of wireless communication technology and development of tiny, low-cost, low-power sensors, wireless sensor networks (WSN) have aroused great research enthusiasm in this decade. A large number of sensors are manually deployed or randomly dropped to a specific application scenario, such as battlefield, virgin forest and agricultural farm. These different environmental conditions have posed many challenges on the designing of sensor networks, for instance, topology control and maintenance, data aggregation and fusing, power management and so on [1]. Among all the considerations, energy utilization efficiency is the most concerned for sensors' batteries are hard to be recharged and replaced. Thus, network lifetime has to be prolonged as much as possible with limited energy.

These years various mechanisms have been suggested from different aspects to save energy of wireless sensor networks. [2] demonstrates an energy-efficient sensor network architecture. [3] compares two important data gathering algorithms using energy metrics while [4] investigates routing protocols from the point of energy efficiency. In all these strategies, the clustering scheme is the most attractive due to the fact that clustering intrinsically realizes the function of data gathering (Cluster head gathers information from cluster members) [3] and packet routing (Packets are routed from low-hierarchical cluster head to high-hierarchical cluster head) [5]. Moreover, each sensor node independently decides to be a cluster head or join a cluster without any centralized instructions. This distributed way enhances the robustness of sensor networks, making it much more fault

tolerant. Clustering mechanism is becoming a first choice for organizing sensor nodes when designing an actual sensor application system.

Many energy-efficient clustering algorithms have been proposed in recent years. Literature [6] presented a detailed taxonomy and classification of these methods. In this paper, we are only concerned with some of the clustering property. First, the algorithm is distributed or centralized. A distributed way means that every node separately runs the program without any information from a central device such as a base station. On the contrary, the algorithm which is executed on a powerful device is centralized. For example, LEACH [7] is distributed and LEACH-C [8] is centralized. Although centralized algorithms are able to achieve a global optimal solution, they increase node interaction and wireless communication burden. Thus, most research work is concentrated on the preferred distributed algorithms. Second, the algorithm is probabilistic or deterministic. In some algorithms, nodes decide to be cluster heads with a certain probability, while in other algorithms, they choose to be cluster heads according to an absolute parameter value. For example, LEACH selects a cluster head based on a randomly generated probability between 0 and 1, while in [9], the node with the largest residual energy is chosen to be a cluster head. Probabilistic-based algorithms are usually distributed as well. By contrast, deterministic algorithms are likely to be centralized because the deterministic value is acquired either from a centralized device or from neighbors' message exchanges.

In this paper, we present a weighted probabilistic clustering algorithm, which we called WPCA. WPCA is both probabilistic and distributed. Every node independently chooses to be a cluster head with a certain weighted probability. The principal innovation of this paper is that the weight coefficient is a non-linear function of the residual energy. The node with more residual energy is assigned a larger weight. In addition, traditional probabilistic methods have all adopted the cluster head rotation strategy to balance energy load among all sensors. However, since our weighted scheme can always make the most energetic sensors to be elected, the meaningless rotation procedure is totally relinquished. Simulation results show that the energy consumption of WPCA is well distributed over the whole network, thereby prolonging the lifetime to a higher stage than preceding algorithms.

The remaining part of this paper is organized as follows. In Section 2, related works are summarized. Section 3 gives an introduction to existing probabilistic clustering algorithms for wireless sensor networks. Section 4 presents our protocol in detail. Section 5 shows the simulation results. A deep analysis and comparison with three other methods is offered as well. At last, the conclusion is drawn in Section 6.

2. Related Works

Self-organization is one of the important characteristics of wireless sensor networks. Many protocols and algorithms have been devoted to solve this issue. For instance, [10] proposes a chain-based protocol PEGASIS to organize sensor nodes. All data packets are transmitted from one node to another on a linked chain till the header of the chain. All nodes take turns to be the header who is responsible for transmitting fused data to the base station. Different from this chain structure, LEACH [7] forms clusters. Each cluster, consisting of a cluster head and several members, constructs a small star topology. Packets are collected and aggregated by the cluster header and then delivered to the base station. In paper [11], the authors combine LEACH and PEGASIS to organize the whole network. The system is divided into several clusters, and then a linked chain is built in each cluster. Generally speaking, the cluster-based algorithms have been a basic method for self-organizing sensor networks.

The key problem for clustering is the selecting algorithm of cluster head. Many kinds of protocols are focused on choosing the most appropriate node as the cluster head by means of

various methods. The simplest LEACH, who picks out a cluster head purely by a randomly generated probability, takes the rotation step as a main strategy for balancing the energy consumption. In order to make the network surviving time as long as possible, other important parameters are further introduced. For example, SEP [12] and EECHE [13] use the initial energy to fix different electing probability. DEEC [14], EDFCM [15], and DEC [9] take advantage of node's residual energy as a reference. Besides, HEED [16] combines a node's residual energy and a second parameter, such as node distance to its neighbors or the number of neighbors, to select cluster heads. ECSA [17] calculates a node's weight composed of its k-density and residual energy in its 2-hop neighborhood. Every node's weight is exchanged within its neighborhood and the node that has the greatest weight value is selected as the cluster head. Another important clustering algorithm based on the weight value is WCA [18]. It takes node's degree, transmission power, mobility and battery power into consideration and assigns these four parameters each a weighted coefficient respectively. Each node updates its combined weight in every round and the node with the smallest weight is chosen as cluster head. According to different parameters, all these algorithms have successfully prolonged system lifetime to some extent. However, more parameters means more complicated information processing. Moreover, some parameters, such as node distance to its neighbors in HEED and node degree in WCA, are acquired at a high price of interchanging neighbor's information, which wastes much energy. In this paper, we only use every node's residual energy as a parameter to get a weighted probability. Although none of the other parameters is adopted, we believe that the residual energy is helpful enough to select the most proper cluster head in our algorithm.

These two or three years, an interesting mathematical method named game theory is introduced to solve the cluster problem of wireless sensor networks. [19] models all sensors as players and ingeniously constructs a Nash Equilibrium for the clustering game. Then each node bids for the cluster head with an equilibrium probability. [20] proposes a repeated game theory with limited punishment mechanism to solve the cheating phenomenon in the clustering algorithm. Although a sophisticated game model is still to be developed, the game theoretical approach has brought new energy to the research of clustering.

3. Probabilistic Clustering for Wireless Sensor Networks

In this section, we introduce some existing probabilistic clustering algorithms. First, let us describe the network model that used in our analysis and simulations. Suppose that N sensor nodes are dispersed to an area of $M \times M$ square meters and a base station is installed at the center of the sensing area. Generally speaking, there are two deployment methods for sensors. The first way is by hand. Therefore, sensor nodes can be uniformly distributed to a district. The second is the random way, which means that nodes are stochastically installed to a specific region. In addition, since the differences of node type, transmitting data packet and computational complexity can all be expressed by the amount of energy consumption, all nodes in our model are treated as the same device but equipped with different initial energy.

Let us assume that the least initial energy of all the nodes is E_0. Each other node s_i have α_i times more initial energy, that is $E_0(1+\alpha_i)$. Thus, the total initial energy of the whole network is given by:

$$E_t = E_{total} = \sum_{i=1}^{N} E_0(1+\alpha_i) \quad (1)$$

If $\alpha_i = 0$ for all nodes, this corresponds to the case of homogeneous wireless sensor networks; if there are only two values of α_i, this is the case of two-level heterogeneous networks [12]; if there are three values of α_i, this is the case of three-level heterogeneous networks [13]; if each node has a different α_i, then this is a multi-level heterogeneous wireless sensor networks. As described in [15], homogeneous sensor network is just a special case of heterogeneous networks. By using energy metrics, our network model has effectively unified homogeneous and heterogeneous networks into the same frame.

3.1. Probabilistic Clustering for Homogeneous WSN

LEACH [8] is the most famous clustering protocol based on probability for homogeneous wireless sensor networks. In LEACH, every node is equipped with the same initial energy and has the same probability p_{opt} to become cluster head. As LEACH does not take the energy consumption into consideration, it introduces a threshold $T(s)$ to rotate the role of cluster head in order to equally distribute the energy consumption among the whole network. The threshold is defined as:

$$T(s) = \begin{cases} \dfrac{p_{opt}}{1 - p_{opt} \cdot (r \bmod (1/p_{opt}))} & \text{if } s \in G \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

where r is the current round. G is the set of nodes that haven't been elected as cluster heads in the current epoch. An epoch is $\frac{1}{p_{opt}}$ rounds. Every node in the current set G selects a random number from 0 to 1. If this number is less than the threshold $T(s)$, then it becomes a cluster head. Due to the introduction of $T(s)$, the role of cluster head is rotated between every two rounds. Meanwhile, all nodes are served as a cluster head once in an epoch. In addition, an optimal number of cluster head is achieved in every round in LEACH:

$$k_{opt} = N \times p_{opt} = (N - \sum_{i=1}^{r \bmod (1/p_{opt})} C_i) \times (\frac{p_{opt}}{1 - p_{opt} \cdot (r \bmod (1/p_{opt}))}) \tag{3}$$

Literature [8] proved that the best k_{opt} is:

$$k_{opt} = \frac{\sqrt{N}}{\sqrt{2\pi}} \frac{\sqrt{\varepsilon_{fs}}}{\sqrt{\varepsilon_{mp}}} \frac{M}{d_{toBS}^2} \tag{4}$$

where ε_{fs} and ε_{mp} are parameters of radio energy dissipation model. d_{toBS} is the average distance between a cluster head and the base station.

3.2. Probabilistic Clustering for Heterogeneous WSN

In heterogeneous WSNs, each node has its own initial battery power. The more powerful and capable nodes ought to serve as cluster heads with more chances. Thus, the clustering probability is naturally related to the energy of each node. Based on this, SEP [12] and DEEC [14] are proposed in succession.

In SEP, nodes are divided into two types according to the amount of initial energy: normal node with little energy and advanced node with α times more energy than normal node. Their selecting probabilities are weighted by the energy and given as:

$$p_{nrm} = p_{opt} \times \frac{E_{nrm}}{E_t} = p_{opt} \times \frac{NE_0}{N(1-m)E_0 + NmE_0(1+\alpha)} = \frac{p_{opt}}{1+\alpha \cdot m} \tag{5}$$

$$p_{adv} = p_{opt} \times \frac{E_{adv}}{E_t} = p_{opt} \times \frac{NE_0(1+\alpha)}{N(1-m)E_0 + NmE_0(1+\alpha)} = \frac{p_{opt}}{1+\alpha \cdot m} \times (1+\alpha) \tag{6}$$

where m is the fraction of advanced nodes and p_{opt} is the optimal clustering probability for corresponding homogeneous WSN. As can be seen from formula (5) and (6), normal nodes are assigned a smaller probability while advanced nodes are assigned a larger one. This can effectively assure that nodes with more energy are more frequently to be elected as cluster heads so that all nodes are nearly at the same time to run out of energy.

The cluster head selection algorithm in DEEC is based on residual energy rather than the initial energy in SEP. Since the residual energy of every node is decreasing as time passes, the probability is dynamically changed. Moreover, each node has its own selecting probability due to its different residual energy. The probability p_i for node s_i is obtained by:

$$p_i = p_{opt} \frac{E_i(r)}{\bar{E}(r)} \tag{7}$$

$$\bar{E}(r) = \frac{1}{N} \sum_{i=1}^{N} E_i(r) \tag{8}$$

where $E_i(r)$ is the residual energy of node s_i in round r and $\bar{E}(r)$ is the average residual energy for every node in round r. Considering the situation of heterogeneous nodes, p_{opt} should be replaced by:

$$p(s_i) = p_{opt} \cdot \frac{NE(s_i)}{E_t} = p_{opt} \cdot \frac{NE_0(1+\alpha_i)}{E_0(N + \sum_{i=1}^{N} \alpha_i)} = \frac{p_{opt} N(1+\alpha_i)}{N + \sum_{i=1}^{N} \alpha_i} \tag{9}$$

Therefore, a more generalized p_i is:

$$p_i(r) = \frac{p_{opt} N(1+\alpha_i) E_i(r)}{(N + \sum_{i=1}^{N} \alpha_i)\bar{E}(r)} \tag{10}$$

Due to the dynamic characteristic, DEEC is more adaptive to balance the energy consumption than SEP. Hence, DEEC get a relatively longer network lifetime compared with SEP.

4. Our WPCA Protocol

This section describes the detail of our WPCA protocol. Like DEEC, WPCA also uses the residual energy to select the cluster head but with a more sophisticated weighting function to obtain the election probability.

4.1. Weighted Probability Calculation

According to the analysis of last section, we can summarize the election probability of LEACH, SEP and DEEC as follows:

$$\text{LEACH:}\quad p_i = p_{opt} = \frac{k_{opt}}{N} \tag{11}$$

$$\text{SEP: } p_i = \begin{cases} \dfrac{p_{opt}}{1+\alpha \cdot m} & \text{s}_\text{i} \text{ is normal node} \\ \dfrac{p_{opt}}{1+\alpha \cdot m}(1+\alpha) & \text{s}_\text{i} \text{ is advanced node} \end{cases} \tag{12}$$

$$\text{DEEC:}\quad p_i = \frac{p_{opt} N(1+\alpha_i)E_i(r)}{(N+\sum_{i=1}^{N}\alpha_i)\bar{E}(r)} \tag{13}$$

In paper [9], the authors propose the DEC algorithm. DEC applies this principle that the k_{opt} nodes with the largest residual energy are designated as cluster heads in the current round. Although DEC is a deterministic method, we can also explain it by a probabilistic way, which is:

$$\text{DEC: } p_i = \begin{cases} 1 & s_i \text{ is one of } k_{opt} \text{ most powerful nodes} \\ 0 & \text{others} \end{cases} \tag{14}$$

In addition, no matter probabilistic or deterministic, all these algorithms aim to expect an optimal cluster number:

$$\begin{aligned} k_{opt} &= Np_{opt} = \sum_{i=1}^{N} p_i = \frac{p_{opt}}{1+\alpha \cdot m} \cdot N(1-m) + \frac{p_{opt}}{1+\alpha \cdot m}(1+\alpha) \cdot Nm \\ &= p_{opt} \sum_{i=1}^{N} \frac{E_i(r)}{\bar{E}(r)} \end{aligned} \tag{15}$$

In fact, from the function point of view, all the above algorithms can be expressed as:

$$p_i = f(E_i / \bar{E}) \cdot p_{opt} \tag{16}$$

Here, E_i is the current residual energy and $\bar{E}$ is the average residual energy of all nodes. According to this relationship, we have:

$$\begin{aligned} &\text{LEACH: } f(E_i / \bar{E}) = 1 \\ &\text{SEP: } f(E_i / \bar{E}) = \begin{cases} \dfrac{1}{1+\alpha \cdot m} & E_i < \bar{E} \text{ when } r = 0 \\ \dfrac{1+\alpha}{1+\alpha \cdot m} & E_i > \bar{E} \text{ when } r = 0 \end{cases} \\ &\text{DEEC: } f(E_i / \bar{E}) = E_i(r) / \bar{E}(r) \\ &\text{DEC: } f(E_i / \bar{E}) = \begin{cases} 1/p_{opt} & E_i / \bar{E} \text{ is the } k_{opt} \text{ largest} \\ 0 & \text{others} \end{cases} \end{aligned} \tag{17}$$

From formula (17), we can see that the fundamental difference of these algorithms is the chosen of weight function $f(E_i / \bar{E})$. A well-designed weight function can select the most appropriate node to serve as cluster heads. Obviously, the nodes with more residual energy deserve the role of cluster head with priority. Thus, a non-linear weight function, which is capable of increasing the probability of larger remaining energy nodes while decreasing the probability of less powerful nodes, is in accord with our assumption. The weight function of our WPCA protocol is shown as:

$$f(E_i / \bar{E}) = \lambda (E_i / \bar{E})^n \tag{18}$$

where λ is a normalized parameter and the power exponent $n > 1$ is used to adjust the degrees of nonlinearity.

Figure 1 gives a visual representative for the weight function of different methods. We can see that the curve of WPCA is in closest analogy to DEC while keeping the probabilistic characteristic.

In order to get an optimal cluster number, we have:

$$\sum_{i=1}^{N} f(E_i / \bar{E}) = N \tag{19}$$

Suppose that the residual energy is averagely distributed between $E_{\min}$ and $E_{\max}$ (this assumption is reasonable because the number of sensors is usually large and the difference of every node's residual energy is small), thus:

$$\begin{aligned} &\sum_{i=1}^{N} \lambda (E_i / \bar{E})^n = \int_{E_{\min}}^{E_{\max}} \lambda (E_i / \bar{E})^n dE_i = N \\ &\Rightarrow \quad \lambda = \frac{N(n+1)\bar{E}^n}{E_{\max}^{n+1} - E_{\min}^{n+1}} \end{aligned} \tag{20}$$

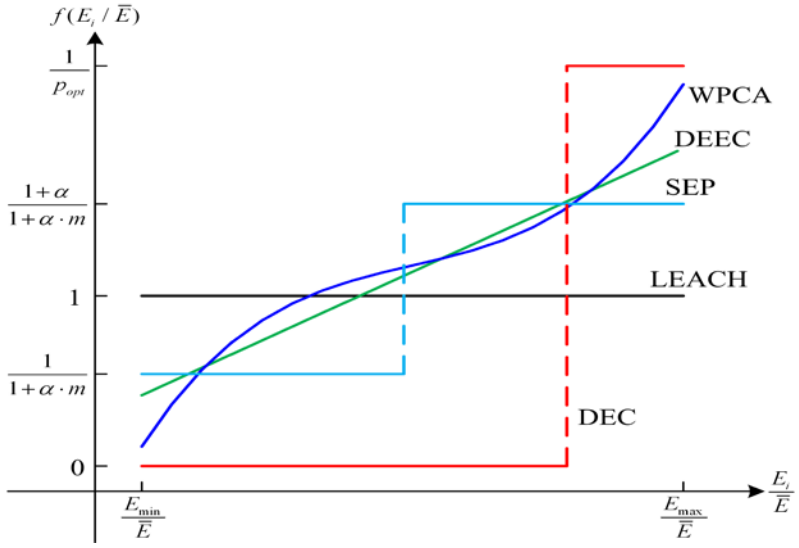

Figure 1. Residual Energy as a Parameter of Weight Function for Different Algorithms

Since we prefer a distributed way to design the network, the average residual energy of the whole network is hardly to know by every node. Here, we apply the same strategy as in [14] to estimate $\bar{E}$:

$$\bar{E}(r) = \frac{1}{N} E_{total}(1 - \frac{r}{R}) \tag{21}$$

$$R = \frac{E_{total}}{E_{round}} \tag{22}$$

$$E_{round} = L(2NE_{elec} + NE_{DA} + k\varepsilon_{mp} d_{toBS}^4 + N\varepsilon_{fs} d_{toCH}^2) \tag{23}$$

where r is the current round, R is the total surviving rounds of the network which is estimated by the base station at the initial time, L denotes the packet size, k is the number of clusters, E_{DA} is the data aggregation cost, d_{toBS} is the average distance between the cluster head and the base station, and d_{toCH} is the average distance between the cluster members and the cluster head. E_{elec} , ε_{fs} and ε_{mp} are radio energy dissipation parameters.

According to the above analysis, the electing probability of WPCA for each node can be obtained by:

$$p_i(r) = \frac{N(n+1)\bar{E}(r)^n}{E_{\max}^{n+1} - E_{\min}^{n+1}} \square (\frac{NE_i(r)}{E_{total}(1 - r / R)}) \square p_{opt} \tag{24}$$

where n and p_{opt} are predefined parameters. N , E_{total} , R , $E_{\max}$ and $E_{\min}$ are calculated by the base station.

4.2. Our Clustering Algorithm (WPCA)

In LEACH, the cluster head rotation scheme has efficiently balanced the energy consumption among all the nodes and resulted in a longer network lifetime. However, when using residual energy as the selecting parameter, the rotation is redundant and sometimes antipathetic. For example, in an extreme situation, due to the rule that every node must serve as a cluster head once in a few rounds (an epoch), the rotation will force a node with little energy to serve as cluster head again and again, thus making this node prematurely exhausted while the other nodes still have enough energy. Hence, the rotation step is thoroughly abandoned by WPCA and the energy equalize procedure is actually realized by our cluster head selection algorithm.

Figure 2 gives out the detailed procedures of our WPCA algorithm. Basically, our algorithm is divided into three steps: initialization step, cluster head selection step and data transmission step. In the initialization step, after nodes have been deployed, they report their initial energy to the base station. On the basis of all nodes' reporting information, the base station then calculates the total energy of the system E_{total} , counts the total number of nodes N , estimates the possible surviving round R and replaces $E_{\max}$ and $E_{\min}$ with the maximal and minimum initial energy of all nodes. These parameters are then broadcasted by the base station to every sensor node. In the cluster head selection step, the base station first updates $E_{\max}$ and $E_{\min}$ according to receiving data of last round. Each node then calculates its electing probability using formula (24) and determines whether to be a cluster head. Once the cluster heads are picked out, they inform their neighbors to join the nearest cluster in the data transmission step. After the cluster head allocates a slot to each of its cluster member, the sensor packets are forwarded from node members to cluster heads and further to the base station. A fixed time later, the current round finishes and the next round begins. New cluster heads are chosen out in the cluster head selection step of the new round.

As we can see from Figure 2, WPCA is very easy to be realized. Compared to previous probabilistic-based methods, WPCA has two improvements. The first is that the non-linear weight function can select the most proper nodes as cluster heads. The second is that the rotation step is discarded, thus avoiding some less powerful nodes to die too early. In the next section, simulation results further verify the effectiveness of our algorithm.

Clustering Algorithm

Initially, r =0. The power exponent n and the time of a round are predefined.

1. Initialization step
   - 1.1 Node i sends its initial energy $E_{\text{in}itial}^{i}$ to the base station.
   - 1.2 According to the receiving messages of all nodes, the base station calculates parameters N, E_{total}, R, $E_{\max}$, $E_{\min}$.
   - 1.3 The base station broadcasts the above parameters to the whole network.
2. Cluster head selection step
   - 2.1 Round r starts. The base station updates $E_{\max}$ and $E_{\min}$.
   - 2.2 According to the receiving parameters from the base station, node i calculates the average remaining energy $\overline{E}(r)$ and the adjustment parameter λ.
   - 2.3 Node i calculates the weight value $f(E_i / \overline{E})$ and the selecting probability p_i.
   - 2.4 Node i randomly generates a value between 0 and 1; if this value is less than p_i, then node i decides to be a cluster head.
3. Data transmission step
   - 3.1 Every cluster head broadcasts a message to announce itself as a cluster head.
   - 3.2 Every non-cluster-head node joins the nearest cluster head.
   - 3.3 The cluster head assigns a transmission slot to each of its cluster member.
   - 3.4 Each cluster member transmits sensing data to the cluster head in the designated slot.
   - 3.5 The current round ends. $r = r + 1$. Goto step 2.

Figure 2. The Procedures of WPCA Algorithm

5. Simulation Results

In this section, we give the comparison results between WPCA and other algorithms according to our MATLAB evaluation. We assume that $N = 100$ nodes are randomly deployed to a district of $100m \times 100m$. Without loss of generality, the base station is presumed to be positioned at the center of the sensing area. The radio energy dissipation model used in our simulation is the same as that in [12]. Table 1 shows some of the parameters.

Table 1. Simulation Parameters

Parameter	Value
E_{elec}	50 nJ/bit
ε_{fs}	10 pJ/bit/m^2
ε_{mp}	0.0013 pJ/bit/m^4
E_0	0.5 J
E_{DA}	5 nJ/bit/message
Message size	4000 bits
p_{opt}	0.1

In order to give a better result, our WPCA protocol is compared with some other algorithms including LEACH, SEP, DEEC and DEC. We mainly consider two scenarios: first there are only two types of nodes with different initial energy; second the initial energy of all nodes is uniformly distributed on the interval of $E_0(1,\alpha)$. In both scenarios, the power exponent n of our nonlinear weight function $f(E_i / \bar{E})$ is chosen to be 4.

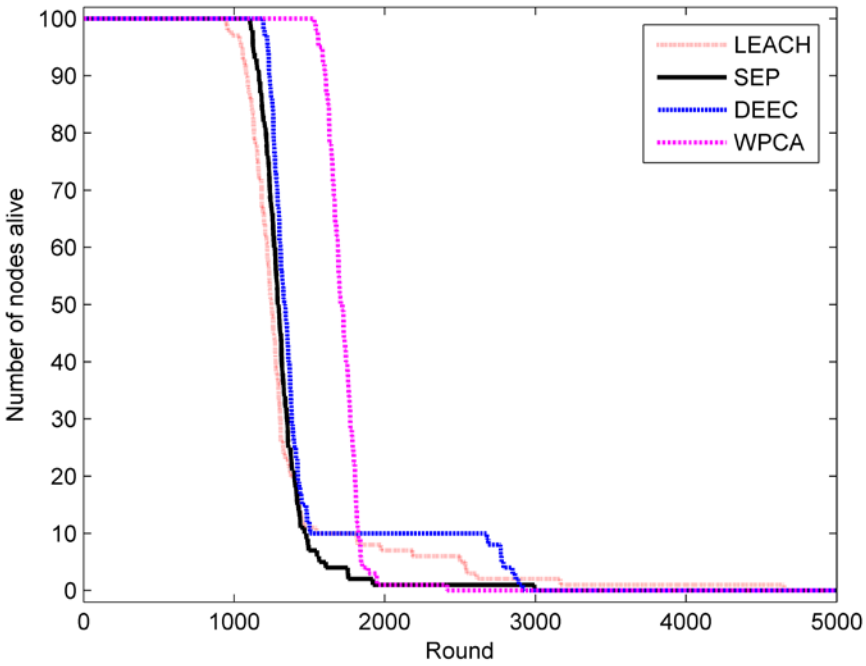

Figure 3. Number of Nodes Alive over Time of LEACH, SEP, DEEC and WPCA for Only Two Types of Nodes when $m = 0.1$ and $\alpha = 1$

Figure 3 shows the number of alive nodes along the axis of round when there are only normal nodes and advanced nodes. Here $m = 0.1$ and $\alpha = 1$. It is obvious that WPCA outperforms the other three algorithms in terms of stability period. To further compare the performance, we change the fraction m of advance nodes from 0.1 to 0.9 and the additional energy factor α from 0.5 to 5. Moreover, the deterministic method DEC is also taken as a contrast. Figure 4 and Figure 5 give the comparison result. Obviously, as m and α are increasing, the total energy of the whole network is increasing. Thus, the network lifetime is also prolonged. This is why most curves in Figure 4 and Figure 5 are uprising. However, the curves of LEACH are nearly flat because the lifetime of LEACH is decided by the least energetic node, irrelevant to the total energy. In addition, we observe that WPCA greatly outperforms the other three algorithms LEACH, SEP and DEEC. Although DEC sometimes performs better than WPCA, it is deterministic and has to consume much energy on localized information exchange, which we do not take into consideration in our simulation.

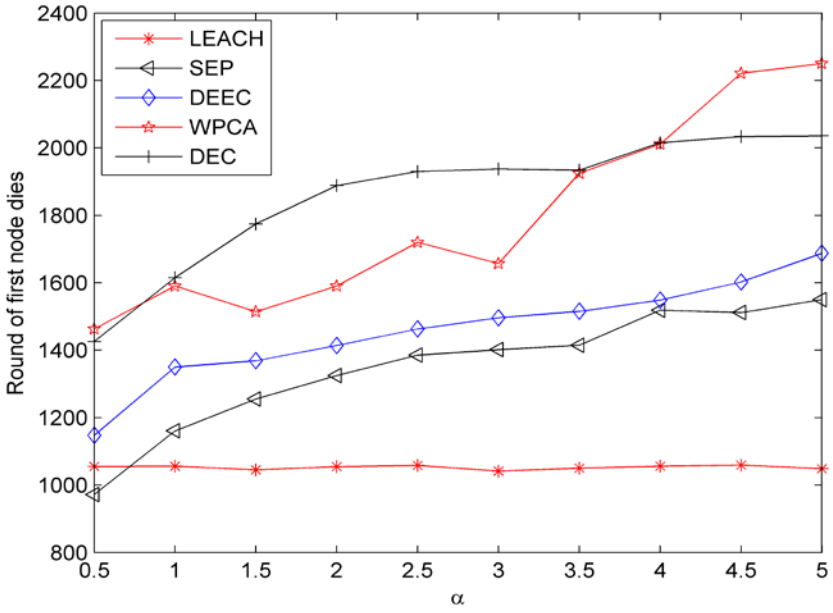

Figure 4. Round of First Node Dies for Different α when $m = 0.3$

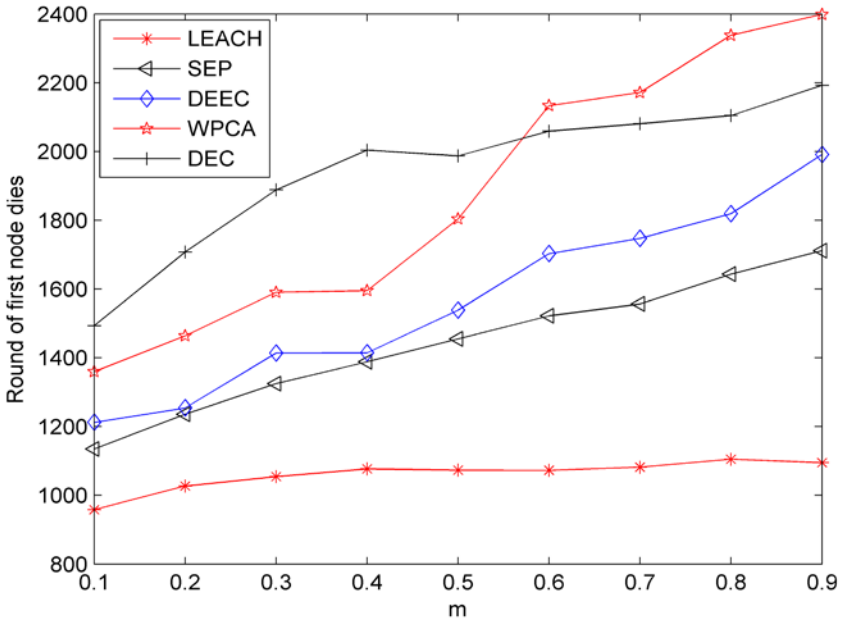

Figure 5. Round of First Node Dies for Different m when $\alpha = 2$

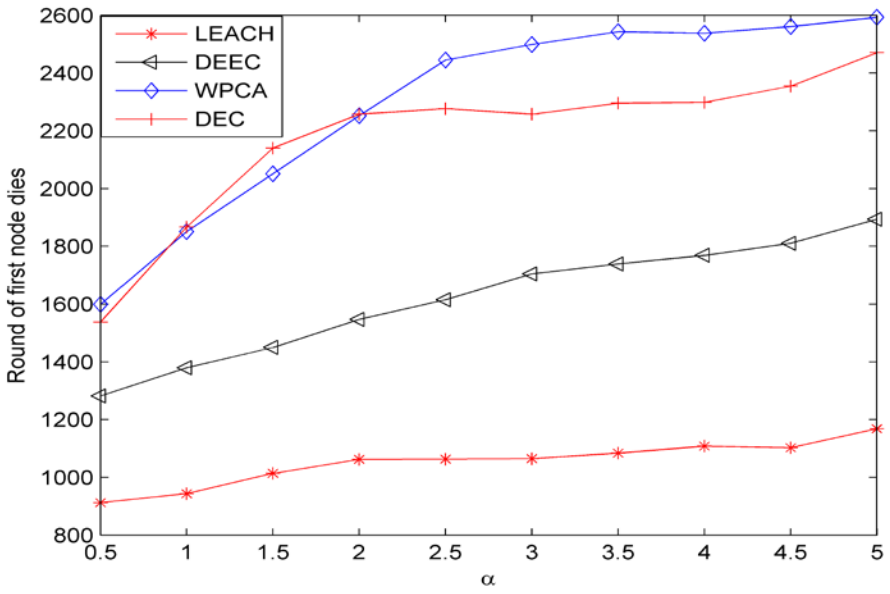

Figure 6. Round of First Node Dies for Multi-level Heterogeneous Sensor Networks when α is Varying

Figure 6 shows the results in the other scenario where a multi-level heterogeneous network is supposed. It can be still observed that WPCA performs better than LEACH and DEEC and gets an approximate result with DEC. Since WPCA globally selects the most energetic nodes as cluster head while DEC is localized and prone to choose the local optimal cluster head, the former usually gets a better solution than DEC.

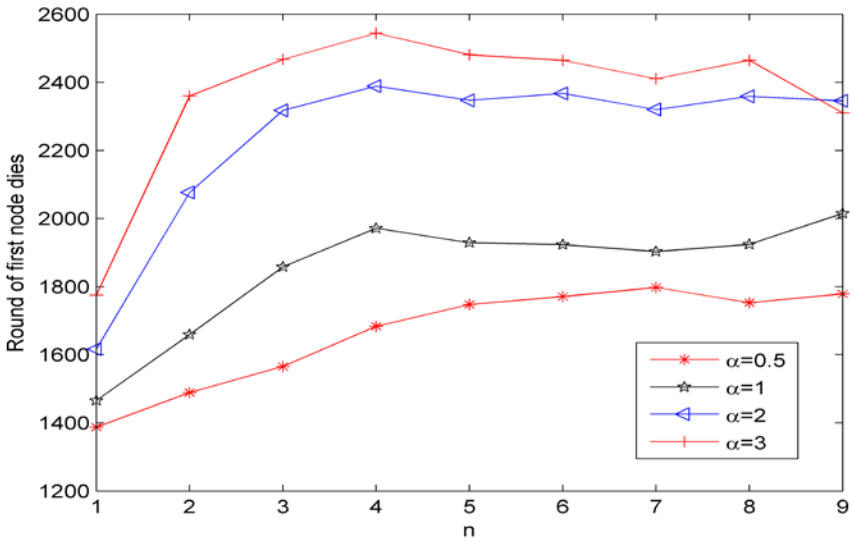

Figure 7. Round of First Node Dies for our WPCA for Different α when the Power Exponent n is Varying

In order to evaluate how the power exponent n in the weight function affects the outcome of WPCA, we change n from 1 to 9 and show the results in Figure 7. When n is small, the probability of energetic nodes is not fully enlarged while the nodes' probability with less energy is not sufficiently reduced. When n is too large, the probability of the nodes whose energy is above the average level is overly increased, thereby making much more than k_{opt} nodes are selected as cluster heads. This can also reduce the energy efficiency and result in a less network lifetime. From Figure 7, we can see that the optimal n is 4 for most cases in our simulation. In a word, by choosing an reasonable power exponent n, our WPCA protocol can effectively guarantee to elect the most proper cluster heads and prolong the network lifetime.

6. Conclusion

By reviewing the existing probabilistic clustering algorithms, we find that all the probabilistic methods have been designed on the basis of a weight function. Selecting different weight functions result in diverse clustering effect in terms of network lifetime. This paper proposes a non-linear power function to weight every node's probability according to their residual energy. On one hand, the nodes with most energy are encouraged to be chosen out; on the other hand, the nodes with least energy are suppressed. Besides, the rotation step in our algorithm is totally discarded. Simulation results show that our WPCA algorithm achieves an improved network lifetime compared with LEACH, SEP and DEEC. Although DEC sometimes outperforms WPCA, it is deterministic while our WPCA holds the distributed and probabilistic property. Moreover, by choosing different values of parameters λ and n, WPCA is adaptive to various network topologies and models.

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