

# Energy-Efficient Self-Organization for Wireless Sensor Networks: A Fully Distributed Approach

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**Abstract**—In this paper, we utilize clustering to organize wireless sensors into an energy-efficient hierarchy. We take a fully distributed approach to energy-efficient clustering and propose an Expellant Self-Organization (ESO) scheme that uses expellant election to achieve local energy efficiency. As a distributed scheme using only local information, ESO achieves comparable performance in terms of effective lifetime and Data/Energy Ratio compared with native LEACH that relies on other routing algorithm to access global information. An exponential data correlation model is also introduced to simulate variable extent of data aggregation effect.

## I. INTRODUCTION

A wireless sensor network (WSN) can be thought of as an *ad hoc* network consisting of sensors linked by a wireless medium to perform distributed sensing tasks. Sensor networks share many communication technologies with *ad hoc* networks, but there are some vital differences such as dense deployment and energy constraint [1], thus the protocols developed for traditional wireless *ad hoc* networks are not necessarily well suited to the unique features of WSN. When a sensor node may have to operate for a relatively long duration on a tiny battery, energy efficiency becomes a major concern.

A variety of “power-aware” routing protocols have been proposed to address this problem. In one school of thoughts [2]–[4], the traditional Shortest Path First strategy is replaced by Least Energy First routing, i.e., a multihop route is preferred to a single-hop one if only multiple short-distance relays cost less energy than a single long-distance transmission. For example, “Minimum Transmission Energy”(MTE) routing [3], [4] was proposed in place of traditional “minimum hops routing”. Another school of thoughts is that nodes are clustered so that a hierarchy is formed [5]–[7]. Based on the observations on cellular networks [8], it would be advisable to partition nodes into clusters for the reasons such as spatial reuse, less update cost, less routing information and less data transmission. LEACH (Low-Energy Adaptive Clustering Hierarchy) [9], an example of the latter school, can extend network lifetime by an order of magnitude compared with general-purpose multihop approaches. In conclusion, the characteristics of WSN prefer hierarchical structure with clusterheads.

However, the cluster formation in LEACH is based on global information. To access such information, other routing schemes are required. In this sense, LEACH is only a semi-distributed protocol for WSN. Another problem with LEACH

is the random head election that cannot guarantee that the desired number of cluster heads be elected or the elected heads evenly positioned. In this paper, we are concerned to optimize the cluster formation using only local information.

The paper is organized as follows. Section II introduces LEACH and the data correlation model that our research is based on. An Expellant Self-Organization (ESO) scheme is proposed in Section III and simulations are given in Section IV. Section V concludes this paper.

## II. MODELS

### A. LEACH

Our work is based on the hierarchy of LEACH, which uses a CDMA-TDMA hybrid communication scheme. Each cluster has its own Spread Spectrum code so that the interference between clusters is minimized. For intraccluster communications, TDMA slots are assigned for each member to minimize media contention. The operation of LEACH is divided into rounds. At the beginning of each round, cluster heads are elected and other nodes join them as members so that  $N$  nodes are partitioned into  $c$  clusters. When a cluster is formed, the cluster head creates and broadcasts a time schedule to its members. As shown in Fig.1, each member is assigned a time slot per frame to send its data to its cluster head, and then the cluster head performs data aggregation and sends the resulting data back to the base station. Compared with multihop routing schemes, LEACH shows an outstanding energy efficiency, which is referred to as clustering energy gain in the following.

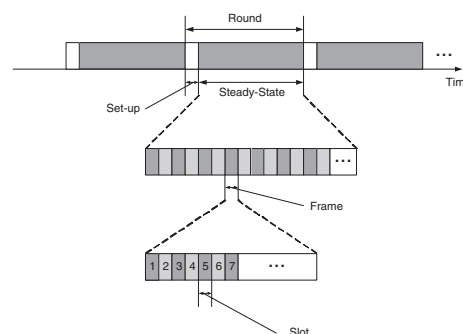


Fig. 1. Time line showing LEACH's frame structure.

However, there are two drawbacks in LEACH's cluster formation as below.

- a. **Dependence on global information** In LEACH, each node  $i$  elects itself to be a head at the beginning of round  $r+1$  (which starts at time  $t$ ) with probability  $P_i(t)$ . Reference [9] provides two ways to determine the self-electing probability  $P_i(t)$ . If all nodes are assumed to start with an equal amount of energy,  $P_i(t)$  is given by

$$P_i(t) = \begin{cases} \frac{c}{N - c * (r \bmod \frac{N}{c})} & : C_i(t) = 1 \\ 0 & : C_i(t) = 0 \end{cases}, \quad (1)$$

where  $c$  is the desired number of clusters and  $C_i(t)$  is the indicator function determining whether or not node  $i$  has been a head in the most recent  $(r \bmod (N/c))$  rounds. The more general estimate of  $P_i(t)$  is given by

$$P_i(t) = \min\left\{\frac{E_i(t)}{E_{total}(t)}c, 1\right\}, \quad (2)$$

where  $E_i(t)$  is the current energy (i.e. remaining battery capacity) of node  $i$  and

$$E_{total}(t) = \sum_{i=1}^N E_i(t). \quad (3)$$

Essentially,  $N$  in (1) and  $E_{total}$  in (2) are global information, which is only accessible via other routing schemes.

- b. **Random election** Although random decision generally strengthens the robustness by avoiding sticking to a single choice, too much randomness may shift the decision away from the optimal range. In LEACH's case, suppose (2) is used and all nodes have equal amount of energy, if  $N$  nodes want to elect  $c$  heads among them, then the self-electing probability for each node is

$$p = \frac{c}{N} \quad (4)$$

Then the probability of " $n$  heads are elected" is

$$Pr(n \text{ elected heads}) = \binom{N}{n} p^n (1-p)^{(N-n)} \quad (5)$$

The distribution of the number of elected heads is listed in Table I. Obviously, too few (Fig. 2(c)) and too many (Fig. 2(d)) elected heads would damage the energy efficiency. Moreover, in the case of "no elected head" whose probability listed in row 1, all the nodes have to communicate directly with the base station, in which case all the clustering energy gain is lost. When the number of elected heads is too few, for example, only one head is elected, the head may be exhausted by the tremendous data sent to it. In such cases, the energy efficiency is tremendously compromised.

Another problem introduced by the random head selection is that the positions are not taken into consideration. Obviously, the even layout of heads would favor energy efficiency (Fig. 2(a)). When heads are randomly selected as in LEACH, elected heads sometimes clump together as shown in Fig. 2(b), which leads to unnecessary energy waste.

TABLE I  
OUTCOME OF 100 NODES ELECTING 5 HEADS.

$n$ : number of elected heads	$Pr(n \text{ elected heads})$
0	0.0059
1	0.0312
2	0.0812
3	0.1396
4	0.1781
5	0.1800
6	0.1500
7	0.1060
8	0.0649
9	0.0349
$\geq 10$	0.0341

### B. Data Correlation Model

The data collected by neighboring sensors have a lot of redundancy, thus, [9] assumes perfect data correlation that all individual signals from members of the same cluster can be combined into a single representative signal. Nevertheless, this assumption cannot hold when the cluster size increases to some extent. Therefore, we develop a complementary exponential data correlation model based on the observations in distributed data compression [10], [11].

Considering the phenomenon of interest as a random process, the correlation between data collected by two sensors is generally a decreasing function of the distance  $r$  between them. After the data aggregation removes most of the redundancy, the residue can be assumed to be an increasing function of  $r$ . Based on the above observation, the data aggregation effect is modeled as below.

Suppose a node collects  $l$  bits and sends them back to its head at distance  $r$ , the head expends  $2lE_{DA}$  Joules to perform data aggregation on the  $2l$  bits (collected by itself and its member), where  $E_{DA}$  is set as  $5nJ/bit$  as in [9]. The resulting data is assumed of  $l(1+\eta)$  bits, where  $\eta$  is data aggregation residue ratio and assumed to be complementary exponential, namely,

$$\eta = 1 - e^{-\alpha r}, 0 < \alpha < 1. \quad (6)$$

$\alpha$  is a positive number whose value depends on specific phenomenon of interest. For example, the light, sound and temperature often show a strong correlation at short distance, and thus,  $\alpha$  will have smaller values for such data. Since  $\eta$  is a monotonic increasing function of  $r$ ,  $\eta$  varies from zero to one when  $r$  increases from zero to infinity. This model can approach the perfect-data-correlation assumption in [9] by decreasing  $\alpha$ , or approach the no-data-aggregation assumption in [3], [4] by increasing  $\alpha$ , thus, different scenarios can easily be set up by varying  $\alpha$ .

### III. EXPELLANT SELF-ORGANIZATION

Expellant Self-Organization (ESO) is designed to replace the cluster formation occurring at the beginning of each round in LEACH. As shown in Fig. 3, first, each node broadcasts its vital information at the maximum radio power level so that the knowledge is spread as wide as possible. The vital information may include nodes' energy, location, etc., but only energy information is needed by ESO. Then, each node counts

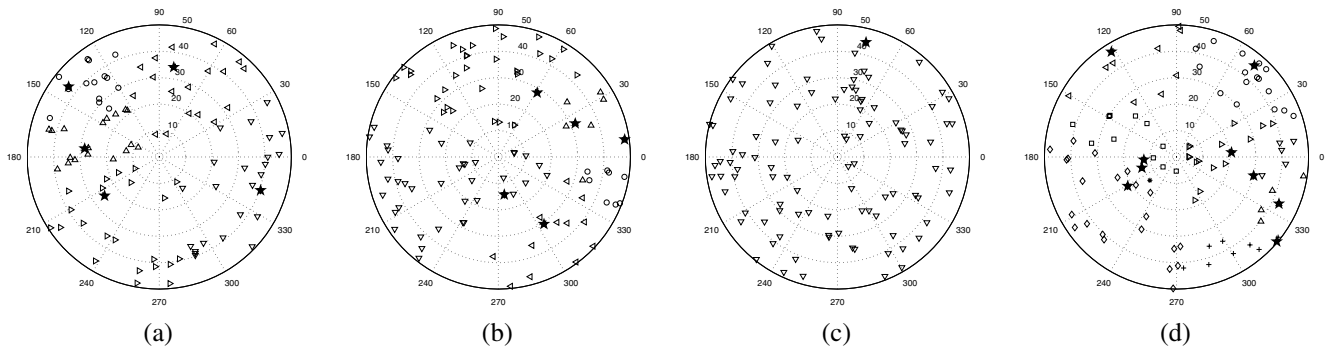


Fig. 2. 100 nodes elect 5 heads (Heads marked by pentagrams). (a) Five heads are elected and evenly distributed. (b) Five heads are elected and clump together. (c) Only one head is elected. (d) Nine heads are elected.

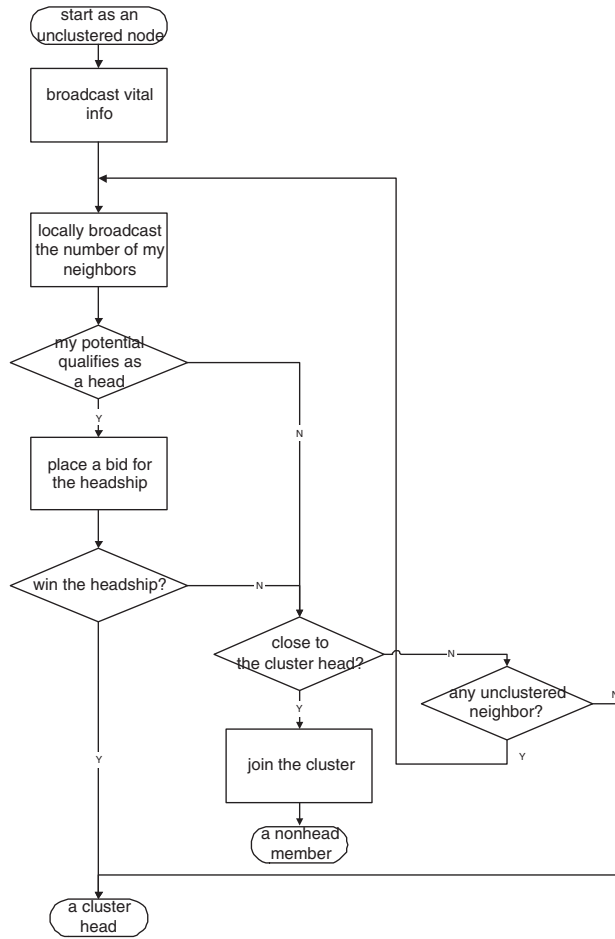


Fig. 3. Flow chart of a node in ESO.

its neighbors and broadcasts the number of its neighbors locally. “Local broadcast” here means broadcasting at an output power level corresponding to the cluster radius  $R_c$ , which is a predetermined system parameter. If a node’s headship potential *qualifies* as a head compared to its neighbors’, it will broadcast locally its claim to the headship, i.e., place a bid for the headship. “Neighbors” means the nearby nodes that are within distance  $R_c$ . Due to the possible contention for the headship, such bids could fail, which is indicated by the collision of “headship claims”. Using certain back-off strategy, the bidders will contend with each other until a

node with satisfactory potential wins. By doing so, the head-to-be eliminates other possible heads in its neighborhood, and in consequence, the elected heads are scattered so that the clusters are formed with desired size.

The headship potential is an important parameter that replaces the self-electing probability in native LEACH. As discussed in [9], the node’s energy is important to determine its potential, because the headship can be rotated among nodes by assigning more potential to the nodes with higher energy. In addition, we propose taking the number of neighbors into consideration, because the clustering energy gain is prominent only in the neighborhood of the head and thus it is energy-efficient to let the node with more neighbors win the headship.

The qualification conditions are set as below. For any node, let  $\mathcal{N}$  denote the set of its neighbors,  $E(i)$  and  $B(i)$  be the energy and the number of neighbors of the  $i^{th}$  neighbor respectively. The thresholds are set as the weighted combination of maximum and mean value of corresponding parameters as in (7) and (8) so that the thresholds vary adaptively according to the current distribution of parameters.

$$E_{Th} = \gamma_1 \max_{i \in \mathcal{N}} E(i) + (1 - \gamma_1) \text{mean}_{i \in \mathcal{N}} E(i) \quad (7)$$

$$B_{Th} = \gamma_2 \max_{i \in \mathcal{N}} B(i) + (1 - \gamma_2) \text{mean}_{i \in \mathcal{N}} B(i) \quad (8)$$

The weights  $\gamma_{1,2}$  are set as  $\gamma_{1,2} \in [0, 1]$  so that the thresholds would be between the maximum and mean values. These conditions can be relaxed by decreasing  $\gamma_{1,2}$ ,  $\gamma_{1,2} \in [0, 1]$ . Since there is no closed-form objective function, it is difficult to determine optimal  $\gamma$  analytically. In our experiments, the performance is not sensitive to the setting of  $\gamma$ . Thus, we choose a smaller value for  $\gamma_1$  and a larger value for  $\gamma_2$  as  $\gamma_1 = 0$ ,  $\gamma_2 = 0.8$ , because we want to emphasize the position condition in order to achieve energy efficiency and relax the energy condition in order to accept more nodes as bidders.

The nodes qualifying for both conditions are considered as Class A bidders, the nodes qualifying for only one of the conditions are Class B bidders, and the nodes failing both conditions will not place a bid. Class B bidders have delayed starting time compared to Class A so that the former will not bid until waiting long enough to ascertain there are no Class A bidders in their neighborhoods. Class B is set up to handle the rare exception that there are no Class A bidders in their

vicinities so that the extreme cases that no or too few heads are elected are avoided.

Once a node successfully sends out the “headship claim”, its neighbors will join it by sending “Request to join”. Since these requests can be eavesdropped by their neighbors, their neighbors can correct their numbers of unclustered neighbors correspondingly. Those nodes that are outside the neighborhood of existing cluster heads will not try to join any clusters. When such a node finds that the public channel is idle again, (which means there is no node in its neighborhood trying to join existing clusters), it can place a bid for the headship if it still qualifies as a cluster head. If a node finds no appropriate clusters to join and all its neighbors are already clustered, it shall claim to be a cluster head, though it has no existing members. Then another round of bid will begin until all nodes are clustered.

#### IV. SIMULATIONS

In this section, we compare the performance of ESO and LEACH using computer simulations. 100 nodes with 2J initial energy were evenly distributed in a circular region with diameter of 100 m, and the base station was located at (125m, 0). The communication energy consumption model is adopted from [9] with the same parameters. We ran 1000 simulations for each case and plotted received data, energy dissipation and the number of survival nodes.

##### A. Optimal $c$

In this case, the effect of  $c$  on energy efficiency was evaluated for perfect data correlation ( $\alpha$  in (6) is set as 0.001). Fig.4(a) shows the amount of data received at the base station per given amount of energy and (b) shows the number of survival nodes versus the amount of data received at the base station. It is noted that there exists a critical phase indicated by a plunging line in Fig.4(b), during which the survival nodes virtually send no data to the base station while they are still alive because these nodes still try in vain to organize themselves into clusters. Since some schemes can lengthen the actual lifetime by lengthening the useless critical phase, the actual lifetime is not a fair measurement of energy efficiency. In the following, we choose the effective lifetime whose end is marked by the critical phase.

Another good measurement of energy efficiency is the ratio of data transportation over energy consumption, termed as Data/Energy Ratio(DER), which is indicated by the slope in Fig.4(a). Higher slope implies the corresponding scheme can transport more data with given amount of energy dissipation. In the following, we use effective lifetime and DER to evaluate the energy efficiency.

Fig.4 clearly shows that both effective lifetime and DER are maximized at  $c = 5$ . Due to the randomness in the election, the performance does not degrade visibly when  $c$  is still close to 5.

##### B. ESO vs. LEACH

In this case, Expellant Self-Organization is compared to native LEACH for perfect data correlation ( $\alpha$  in (6) is set

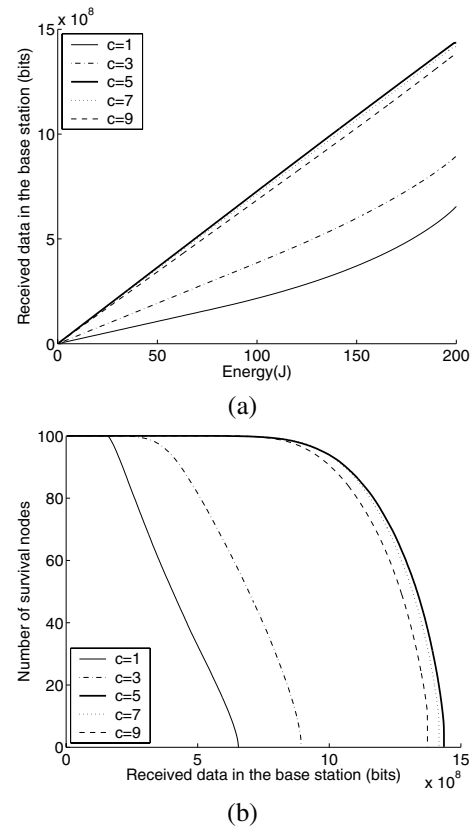


Fig. 4. Data of LEACH at varying  $c$ . (a) Amount of data received at the base station per given amount of energy. (c) Number of survival nodes per given amount of data received at the base station.

as 0.001). We ran 1000 simulations for each  $R_c$  and plotted the effective lifetime and DER. Fig.5 shows the performance of ESO is optimal at around  $R_c = 40m$  with  $DER \approx 7.62E3bits/J$  and effective lifetime around  $1.52E9 s$ . Compared with those of native LEACH at  $c = 5$ , ESO shows an approximately 6% improvement for DER and effective lifetime. Considering that ESO is a distributed scheme, such improvement demonstrates the energy efficiency of ESO, which is mainly due to the successful utilization of the MAC contention. The MAC contention is unwanted in that it increases latency and reduces throughput, though it is virtually unavoidable in wireless communications. In ESO, the contention is used to convey information about leadership potential of nodes, which is why ESO could waive aside the global information while keep clustering nearly optimal at no extra cost.

##### C. Data Aggregation Effect On Optimal $R_c$

In this case, the effect of data aggregation is evaluated. We ran 1000 simulations at different  $R_c$  with  $\alpha$  fixed at 0.05 and compare the effective lifetime and DER with those with  $\alpha = 0.001$ . Fig.6 shows that the performance of ESO is optimal at around  $R_c = 10$ , which is far from  $R_c = 40$  with  $\alpha = 0.001$ . The reason that the smaller clusters are formed is that the benefit range shrinks when the data correlation decreases. This demonstrate the effectivity of our data correlation model; we

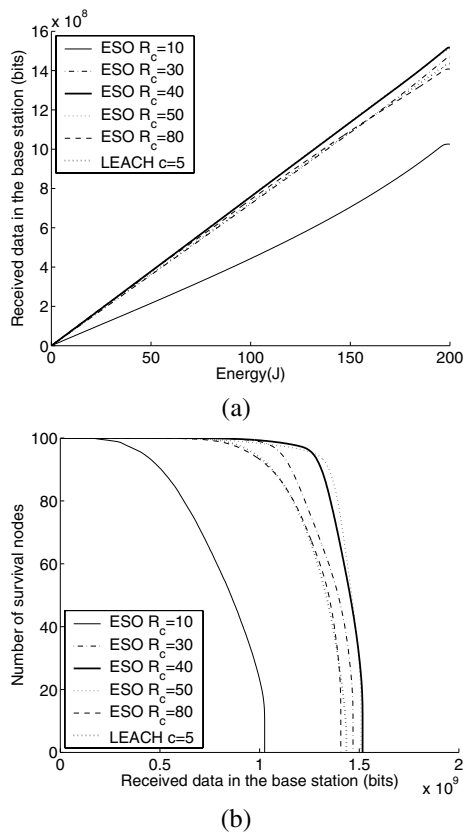


Fig. 5. ESO vs. LEACH. (a) Amount of data received at the base station per given amount of energy. (b) Number of survival nodes per given amount of data received at the base station.

can easily fit the simulation scenarios for the phenomena of interest by varying  $\alpha$ .

## V. CONCLUSION

The previous clustering researches often take a global approach, which is appropriate for global optimization. However, when a distributed clustering is desired, the already-answered questions such as “How many clusters should the nodes be partitioned into?” have to be translated into a distributed version, that is, “What’s the appropriate cluster size?”, because it is easier for a node to know its cluster size than the number of clusters in the whole network. We take a distributed approach to energy efficiency for WSN and propose Expellant Self-Organization that makes use of MAC contention to form clusters as needed. Although ESO uses only local information, it achieves comparable energy efficiency with native LEACH in terms of effective lifetime and Data/Energy Ratio.

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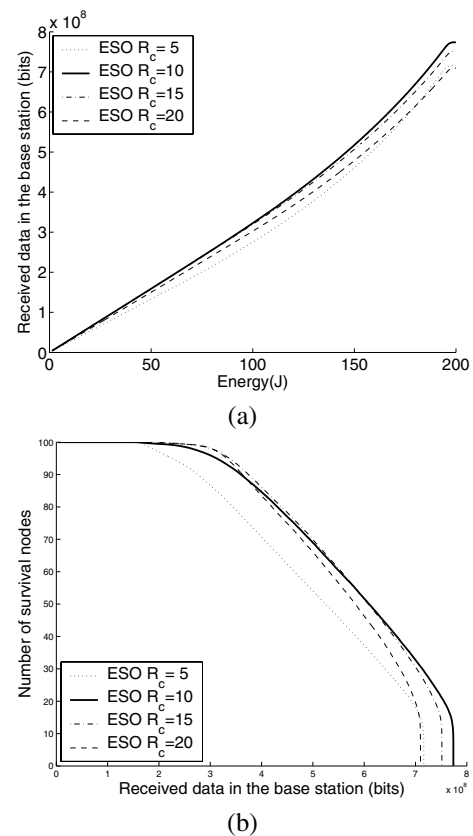


Fig. 6. ESO with  $\alpha = 0.05, 0.001$ . (a) Amount of data received at the base station per given amount of energy. (b) Number of survival nodes per given amount of data received at the base station.

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