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Balancing Energy Consumption in Heterogeneous Wireless Sensor Networks using Genetic Algorithm

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***Abstract*—In a heterogeneous Wireless Sensor Network (WSN), factors such as initial energy, data processing capability, etc. greatly influence the network lifespan. Despite the success of various clustering strategies of WSN, the numerous possible sensor clusters make searching for an optimal network structure an open challenge. In this paper, we propose a Genetic Algorithm based method that optimizes heterogeneous sensor node clustering. Compared with five state-of-the-art methods, our proposed method greatly extends the network life and the average improvement with respect to the second best performance based on the first-node-die and the last-node-die is 33.8% and 13%, respectively. The balanced energy consumption greatly improves the network life and allowed the sensor energy to deplete evenly. The computational efficiency of our method is comparable to the others and the overall average time across all experiments is 0.6 seconds with a standard deviation of 0.06.**

***Index Terms*—Wireless Sensor Networks, Genetic Algorithms, Clustering Methods, Energy Conservation**

I. Introduction

To improve network lifetime, clustering model has been used in Wireless Sensor Networks (WSNs) [1]. In a heterogeneous WSN, in addition to the network geospatial factors, e.g., distance to the base-station, and distance among nodes [2], factors such as initial energy, data processing capability, and ability to serve as cluster head greatly influence the network lifespan [3], [4]. Methods have been proposed to extend lifetime of a heterogeneous network. Stable Election Protocol (SEP) [5] used weighted probabilities to elect cluster heads based on the remaining energy in sensor nodes. Developed Distributed Energy-Efficient Clustering (DDEEC) [6] and Threshold Sensitive Stable Election Protocol (TSEP) [4] extended SEP by categorizing sensor nodes based on energy level and cluster heads were selected from those with higher energy. Similarly, Energy Efficient Heterogeneous Clustered scheme (EEHC) [7] and Efficient Three Level Energy algorithm (ETLE) [8] selected cluster heads based on probability proportional to the residual energy. In [9], energy-efficient multilevel heterogeneous routing (EEMHR) protocol was proposed, in which nodes were grouped into a hierarchy and the ratio of the number of alive nodes to the total number of nodes was used for the selection of cluster heads. In Hybrid Energy Efficient Reactive protocol (HEER) [10], the cluster head selection was based on the ratio of the residual energy of nodes and the average energy of the network.

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Searching for a balance among many factors is non-trivial, and many optimization methods have been applied to tackle the problem [11]. Genetic Algorithm (GA) provides an optimization method that, by defining an appropriate fitness function, identifies optimal or sub-optimal solutions to satisfy all constraints. GA has been used in the routing protocol of WSN [12], [13]. When GA is used, a key objective is to define an appropriate fitness function that encodes the network structure. However most of GA-based methods were developed for homogeneous WSNs, e.g., HCR [14], while a few were dealing with heterogeneous WSNs in which the difference between sensors in the initial energy is the dominate factor of heterogeneity. The Evolutionary based clustered Routing Protocol (ERP) [12] overcame the limitations of clustering-based GAs by uniting the cohesion and separation error, and proposed a fitness function based on these two factors.

Although most of the research concentrated on energy as the only heterogeneity factor, many types of heterogeneities exist [11], [15], e.g., communication capability and data processing power. In this paper, we propose a sensor clustering method for dynamically organizing heterogeneous WSN using GA. Our method provides a framework to integrate multiple heterogeneity and clustering factors, which employs remaining energy, expected energy expenditure, network locality, and distance to the base-station in search for an optimal, dynamic network structure for heterogeneous WSN. Heterogeneity factors are integrated as constraints to chromosomes, and a validation process is performed to ensure network integrity.

The contribution of this work is two-fold: First, expected energy expenditure of each sensor node is proposed to provide an estimation of the possible energy state in the next round if a network clustering structure is formed. This is significantly different from the widely used energy history (e.g., consumed energy and remaining energy) as a criterion for cluster head selection. Second, a GA-based optimization method is developed that encodes the network clustering structure with integrity validation and employs a fitness function of multiple aspects of the heterogeneous WSN.

In the rest of this paper, Section II formulated the clustering problem in heterogeneous WSNs and describes our method. Section III discusses our experimental results including a comparison study with five state-of-the-art methods and analysis of energy consumption. Section IV presents the conclusions.

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II. Self-Clustering method for Heterogeneous Network using Genetic Algorithm

A. Network Model and Clustering Factors

We adopt the first order radio model to describe sensor energy status [16]. The consumed energy E of a sensor node s is the summation of energy used to acquire l bits of data ($E_s^A(l)$), receive l' bits of data ($E_s^R(l')$), process l'' bits of data($E_s^P(l'')$), and transmit l'' bits of data over a distance d ($E_s^T(l'', d)$):

$$E_s = E_s^A(l) + E_s^R(l') + E_s^P(l'') + E_s^T(l'', d), \qquad (1)$$

where $E_s^R = E_i + l'E^*$, and E_i is the idle energy expenditure. $E_s^T = E_i + l''d^n$, and $n = 4$ for long distance transmission and $n = 2$ for short distance transmission, and E^* denotes the cost of beam forming approach for energy reduction.

To compute the expected consumed energy $\hat{E}$ of a non-CH sensor node s' and a CH sensor node s, we assume l bits of data are collected by each sensor node in a round. Let the number of sensors in a cluster headed by s be N_s; the expected consumed energy $\hat{E}$ for s and s' are computed as follows:

$$\hat{E}_{s'} = E + lD^2(s', s), \qquad (2)$$
$$\hat{E}_s = E + N_s l E^* + (N_s + 1) l D^4(s, B), \qquad (3)$$

where E is the constant energy consumption including the energy of data acquisition, processing and idle. Functions $D(s', s)$ and $D(s, B)$ use Euclidean distance to approximate the distances between sensor nodes inside the cluster and from the cluster head to the base-station B, respectively.

The local sensor density is proportional to the number of sensors within the δ-vicinity as follows:

$$G_s(\delta) \propto \|S_s\|, \text{ and } S_s = \{s_i; D(s, s_i) \leq \delta\} \qquad (4)$$

where S_s is the set of sensor nodes in the δ-vicinity of s and function $\|\cdot\|$ gives the set size.

B. Network Structuring using Genetic Algorithm

In our GA-based method, a binary chromosome is used to describe the network structure, in which ‘1’ represents a CH and ‘0’ represents a member node to a cluster. When a sensor becomes inactive, i.e., out of power, its corresponding gene value is set to ‘-1’, which exempts this sensor from further GA operations.

In each network transmission round, sensor node status data is transmitted to the base-station together with the data collected from the field. Such data is used by the GA to search for the optimal clusters and the computation is carried out by the base-station. After the cluster heads and member nodes are decided, the base-station broadcasts the assignments to the sensor nodes to prepare the next round of data acquisition.

The mapping a chromosome to sensor clusters is by minimizing the network communication distance $\mathbb{D}$ as follows:

$$\mathbb{D} = \sum_{i=1}^{C} \sum_{j=1}^{N_{s_i}} D(s_i, s_j) \qquad (5)$$

where C is the number of clusters in a network and N_{s_i} is the number of member nodes in a cluster headed by node s_i. In practice, minimizing $\mathbb{D}$ is equivalent to assigning sensor nodes to clusters following the nearest neighbor rule.

The fitness function integrates energy factors (i.e., Eq. (1)), spatial distances, and the local sensor density as follows:

$$f = \sum_s \frac{E_s(t)}{E_s(0)} + \frac{\tilde{E}}{\hat{E}} + \frac{1}{\hat{D}} + \frac{1}{N} \sum_{s'} G_{s'}(\delta), \qquad (6)$$

where $E_s(t)$ is the remaining energy of sensor node s at round t and $E_s(0)$ is the initial energy of sensor node s. $\tilde{E}$ is the total energy cost if the messages are transmitted directly from all sensor nodes to the base-station. $\hat{D}$ is the total distance between the CHs and the base-station B:

$$\hat{D} = \sum_{i=1}^{C} D(s_i, B) \qquad (7)$$

where each s_i is a sensor node that serves as a CH. Including sensor density favors the choice of CHs with more close neighbors.

C. Chromosome Validation and Evaluation

In a heterogeneous WSN, functions and capabilities of sensors vary. Some sensors are unable to serve as cluster head; whereas some are preferred to take the role due to their superior processing power and available energy. However, classical optimization method such as GA provides no integrated mechanism for ensuring alignment of different roles of the sensors. In addition, the random initialization and GA operations could introduce chromosomes that completely violate the current sensor properties. In our method, heterogeneity is presented as constraints and hence a validation process is needed before evaluating chromosomes’ fitness to ensure network integrity.

Fig. 1 shows the validation process. In GA optimization, a new chromosome represents the proposed structure for the WSN. Each gene defines the expected role of the corresponding sensor node, i.e., whether it serves as a cluster head or a member node. The process consults the ‘ability to serve as a CH’, and the ‘Sufficient Energy’ tables. The ‘ability to serve as a CH’ table is used to determine whether the node can serve as a cluster head (‘1’ represents serving as a cluster head and ‘0’ a member node). While, the ‘Sufficient Energy’ table is used to present the availability of nodes, i.e., ‘1’ denotes available nodes and ‘0’ denotes disabled nodes. The validation process determines if a chromosome is complied with the constraints and updated the bit accordingly. An example is shown in Fig. 1.

In GA optimization, crossover operation is performed with two randomly selected chromosomes decided by the crossover probability. When crossover is determined not to be conducted, the parent chromosomes are duplicated to the offspring without change. In practice, this probability is close to 1.

The mutation operation involves altering the value at a randomly selected gene within the chromosome. Similarly, a mutation probability is used. Different from the crossover probability, the mutation probability is usually fairly small. Essentially mutation operation could create completely new species, i.e., an arbitrary locus in the fitness landscape. Hence, it is a means to get out of a local optimum. Recall that when

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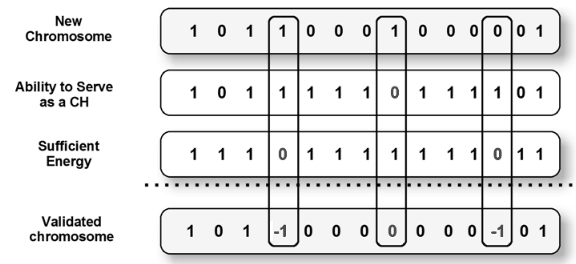

Fig. 1. The chromosome validation process is to ensure network integrity. Red bits mark the constraints and the changed bits.

a sensor node becomes inactive, its corresponding gene is set to -1 to exempt it from mutation operations.

After validation, Eq. (6) is used to evaluate the fitness of each chromosomes. An intermediate pool of chromosomes is created to hold the individuals created in a generation, and depending on the needs user can specify any intermediate population size that is greater than the initial population size.

The evolution terminates when one of the following criteria is satisfied: 1) the maximum number of generations is reached, or 2) the fitness converges. Upon completion of the GA evolution, the chromosome that gives the best fitness value is used to restructure the WSN.

III. Results and Discussion

The simulated WSN is in an area of 100 meters by 100 meters (m) with 50 sensors randomly placed in the field and the data packet size is 400 bits. The network parameters are listed in Table I. The heterogeneity includes different initial power, data processing efficiency, and capability of serving as cluster head. For the sensors with greater data processing efficiency, the energy used is 50% of that used by a regular sensor. 10% of sensor nodes possessed greater initial energy and data processing efficiency, and 10% of sensor nodes are unable to serve as cluster head. The heterogeneous sensors are chosen randomly in each experiment.

TABLE I
Network parameters.

Parameters		Values
Initial energy		$0.5J$ or $1.0J$
Idle state energy		$50nJ/bit$
Data aggregation energy		$5nJ/bit$
Amplification energy	$d \geq d_0$	$10pJ/bit/m^2$
(cluster head to base-station)	$d < d_0$	$0.0013pJ/bit/m^2$
Amplification energy	$d \geq d_1$	$E_{fs}/10 = E_{fs1}$
(sensor to cluster head)	$d < d_1$	$E_{mp}/10 = E_{mp1}$

The population size of our GA is 30 and the number of generations is 30. The crossover probability and mutation probability are 0.8 and 0.006, respectively. The δ-vicinity is 20 meters.

Table II compares the network life of our method with five state-of-the-art methods, which include HEER [10], TSEP [4], DDEEC [6], ETLE [8], and ERP [12]. The average number of rounds when first node dies (FND) and last node dies (LND) are reported; and 10 experiments are conducted for each analysis. Our method, denoted by GAHN, exhibits the longest average network life. The average improvement with respect to the second best performance based on FND and LND are 33.8% and 13%, respectively. Fig. 2 depicts the number of live nodes throughout the network life, which presents a progressive view. The dash line with solid dot shows the result of GAHN. The balanced energy consumption greatly improves the network life and allows the sensor energy to deplete evenly.

TABLE II
Network transmission rounds when first and last node dies.

Methods	ETLE	ERP	HEER	DDEEC	TSEP	GAHN
FND	1514	2010	1789	1100	1986	2690
LND	6904	9200	6150	8900	7640	10400

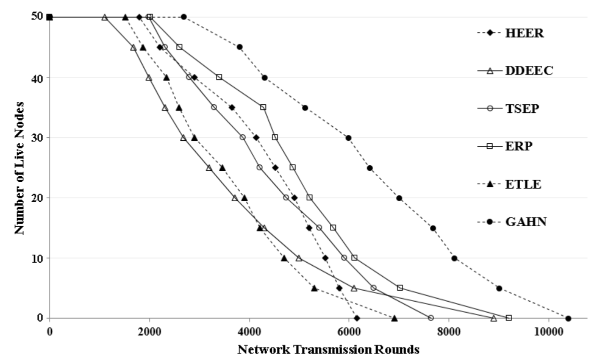

Fig. 2. Percentage of live nodes throughout network lifetime.

Fig. 3 illustrates an example of the remaining energy of sensors at four transmission rounds. At round 0, i.e., the initialization, 5 nodes (highlighted with green bars) are fueled with greater energy at $1J$. The red bars mark sensors unable to serve as cluster head. As transmission continued, the remaining energy of sensors gradually reduces mostly evenly.

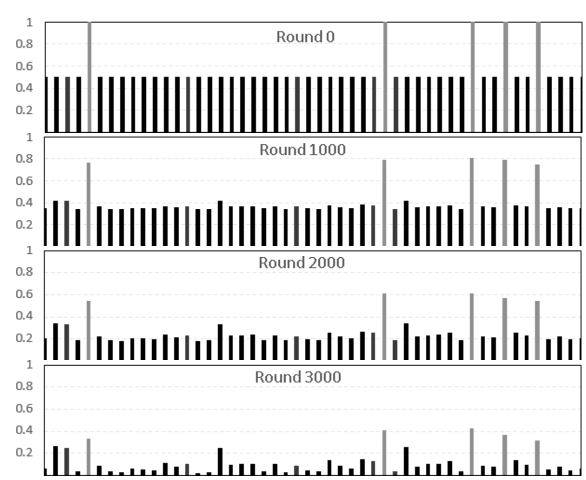

Fig. 3. The remaining energy of sensor nodes at certain transmission rounds.

Table III lists the average remaining energy of the low-initial-energy sensors and its standard deviation at various transmission rounds. Small STDs indicate balanced energy

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consumption among sensors. Due to unequal distances to the cluster head, the energy expenditure for the member nodes varied. It is inevitable that STDs continued to increase.

TABLE III
REMAINING ENERGY (J) AND ENERGY STANDARD DEVIATION (STD).

Rounds	500	1000	1500	2000	2500	3000
Mean	0.431	0.363	0.295	0.226	0.158	0.090
STD	0.010	0.020	0.031	0.042	0.052	0.062

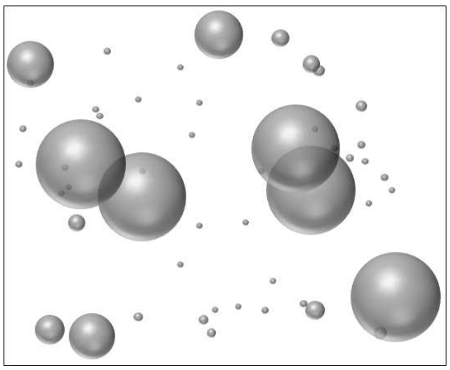

Fig. 4. Spatial and frequency view of sensor nodes serving as cluster head.

Fig. 4 illustrates the spatial and frequency view of sensor nodes serving as cluster head throughout the life of the network. The size of sphere is proportional to the number of times a sensor served as cluster head. It is clear that the ones with higher initial energy serve as cluster head most times. The placement of higher energy sensors is randomized but spatially uneven. Despite that the high-initial-energy sensors dominated the role of cluster head, their spatial disadvantage, i.e., closely located with each other, made some low-initial-energy sensors to act as cluster head to serve nearby sensors. The average number of clusters in all rounds of our 10 experiments is 6, among which 97% of times high-initial-energy nodes served as cluster head. The forming of clusters is greatly influenced by the spatial location of sensor nodes. The low-initial-energy nodes that serve as cluster head are usually far away from the high-initial-energy ones, which justifies their role as CH.

TABLE IV
AVERAGE TIME (IN SECONDS) FOR NETWORK STRUCTURING.

Methods	ETLE	ERP	HEER	DDEEC	TSEP	GAHN
50 sensors	0.42 (0.03)	0.60 (0.12)	0.43 (0.02)	0.39 (0.04)	0.45 (0.06)	0.54 (0.06)
100 sensors	0.53 (0.10)	0.71 (0.34)	0.51 (0.21)	0.55 (0.11)	0.61 (0.17)	0.63 (0.27)

Efficiency is an important factor in real-world applications. Our experiments are conducted in a computer with Intel core i5 2.6GHz CPU, 4GB memory, and Windows 7 operating system. The algorithms are implemented in C#. Table IV lists the average time used to structure clusters in each transmission round. The time reported is before the first node exhausts its energy. The number in parenthesis is the standard deviation. In addition to 50 sensors in the field, we also experiment with 100 randomly placed sensors with the other parameters remaining the same. The average time used by GAHN is comparable to the other methods. Note that the most time-consuming process in GAHN is evaluating fitness, which can be implemented with parallel programming to improve efficiency.

IV. CONCLUSION

In this paper, we propose a self-clustering method for heterogeneous network using Genetic Algorithm that optimizes the network life. Compared with five state-of-the-art methods, our proposed method greatly extends the network life and the average improvement respect to the second best performance based on the first-node- and the last-node-die are 33.8% and 13%, respectively. The average number of clusters in all rounds of our experiments is 6, among which 97% of times high-initial-energy nodes serve as cluster head. The overall average time across all experiments is 0.6 seconds with a standard deviation of 0.06.

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