

Queen-bee Algorithm for Energy Efficient Clusters in Wireless Sensor Networks

Z. Pooranian, A. Barati and A. Movaghar

Abstract—Wireless sensor networks include small nodes which have sensing ability; calculation and connection extend themselves everywhere soon. Such networks have source limitation on connection, calculation and energy consumption. So, since the nodes have limited energy in sensor networks, the optimized energy consumption in these networks is of more importance and has created many challenges. The previous works have shown that by organizing the network nodes in a number of clusters, the energy consumption could be reduced considerably. So the lifetime of the network would be increased. In this paper, we used the Queen-bee algorithm to create energy efficient clusters in wireless sensor networks. The Queen-bee (QB) is similar to nature in that the queen-bee plays a major role in reproduction process. The QB is simulated with J-sim simulator. The results of the simulation showed that the clustering by the QB algorithm decreases the energy consumption with regard to the other existing algorithms and increases the lifetime of the network.

Keywords—Queen-bee, sensor network, energy efficient, clustering.

I. INTRODUCTION

WIRELESS sensor networks (WSNs) consist of a large set of autonomous wireless sensing nodes, which is low-cost, low-power and multi-functional sensor nodes [1, 16]. Today, sensor networks find application in various areas ranging from environment monitoring to battlefield surveillance [12, 13, 14]. In addition to one or more sensors, for monitoring say temperature, pressure or motion, each sensor node typically consists of a wireless communication device, such as a radio transceiver, and a microcontroller, all powered by a battery [15]. Sensor nodes are usually powered by lightweight batteries, and replacing or recharging these batteries is often not feasible. Therefore, in many cases, the lifetime of a sensor network is over as soon as the battery power in critical node(s) is depleted [2, 3, 4, 5, 17]. So, offering methods in order to utilize the energy consumption which finally will lead to the increase in lifetime of the network is sensed very much. The previous researches have shown that by organizing the network nodes in clusters, the energy utilization will be increased. More energy utilization will lead to the increase of the network lifetime. In most of the researches the time passed till the death of the first or the last node of the network is called the lifetime of the network.

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For instance, Heinzelman et al. [6] describe the LEACH protocol, which is a hierarchical self-organized cluster-based approach for monitoring applications. The data collection area is randomly divided into several clusters, where the numbers of clusters are pre-determined. Based on time division multiple accesses (TDMA), the sensor nodes transmit data to the cluster heads, which aggregate and transmit the data to the base station. Bandyopadhyay and Coyle [7] describe a multi-level hierarchical clustering algorithm, where the parameters for minimum energy consumption are obtained using stochastic geometry. Hussain and Matin [8], [9] propose a hierarchical cluster-based routing (HCR) protocol where nodes self-organize into clusters and each cluster is managed by a set of associates called headset. Using round-robin technique, each associate acts as a cluster head (CH). The sensor nodes transmit data to their cluster heads, which transmit the aggregated data to the base station. Moreover, the energy-efficient clusters are retained for a longer period of time; the energy-efficient clusters are identified using heuristics-based approach. They improve the HCR protocol by using a Genetic Algorithm (GA) to determine the number of clusters, the cluster heads, the cluster members, and the transmission schedules [10].

In this research, we used the Queen-bee instead of the genetic algorithm for clustering. The Queen-bee has a lot of usages, which we could name the clustering and training the LVQ neural networks. The results of the simulation showed that the energy consumption of the nodes has been decreased by using this method and it led to the increase in the lifetime of the network. The rest of the paper is organized as follows: We review the GA-based intelligent hierarchical clusters in section 2. Then, we will investigate the Queen-bee algorithm in section 3. We will study the results of simulation in section 4 and finally in section 5, we will study the conclusion and provides a few directions for the future work.

II. INTELLIGENT HIERARCHICAL CLUSTERS

The HCR protocol is enhanced by using GA to create energy-efficient clusters for a given number of transmissions. The GA outcome identifies the suitable cluster heads for the network. The base station assigns member nodes to each cluster head using the minimum distance strategy. The base station broadcasts the complete network details to the sensor nodes. The broadcast message includes: the number of cluster heads, the members associated with each cluster head, and the number of transmissions for this configuration. All the sensor nodes receive these packets broadcasted by the base station and clusters are created accordingly; this completes the cluster

formation phase. Next comes the data transfer phase, which is identical to the HCR's data transfer phase. The WSN nodes are represented as bits of a chromosome. The head and member nodes are represented as 1s and 0s respectively. The fitness of a chromosome is determined by several parameters, such as node density and energy consumption. A population consists of several chromosomes and the best chromosome is used to generate the next population. For the initial population, a large number of random cluster heads are chosen. Based on the survival fitness, the population transforms into the future generation. A sensor node is represented as a bit that can be 0 or 1. A network of m nodes is represented by a chromosome of m bits. The fitness of a chromosome is designed to minimize the energy consumption and to extend the network life time. A few fitness parameters are as follows: a) D , the direct distance to sink; it is the sum of all distances from sensor nodes to the sink, b) C , the cluster distance is the sum of the distances from the nodes to the cluster head and the distance from the head to the sink, c) SD , standard deviation in cluster distances, d) E , transfer energy represents the energy consumed to transfer the aggregated message from the cluster to the sink, and e) T , the number of transmissions assigned by the base station. The fitness function is given as follows:

$$F = \sum_i \alpha_i(w_i, f_i), \forall f_i \in \{C, D, E, SD, T\}$$

The initial fitness parameters can be assigned arbitrary weights, w_i . Then, after every generation the best fit chromosome is evaluated and the weights for fitness parameters are updated accordingly [9].

III. QUEEN-BEE EVOLUTION ALGORITHM

The queen-bee evolution based on genetic (QEGA) is described as follows:

```
// t: time //
// n: population size //
// p: populations //
//  $\sigma$ : normal mutation rate //
//  $P_m$ : normal mutation probability //
//  $P'_m$ : strong mutation probability //
// Iq: a queen-bee //
// Im: selected bees //
01  $t \leftarrow 0$ 
02 initialize  $P(t)$ 
03 evaluate  $P(t)$ 
04 while (not termination-condition)
05 do
06  $t \leftarrow t+1$ 
07 select  $p(t)$  from  $P(t-1)$  (*)
08  $P(t) = \{Iq(t-1), Im(t-1)\}$ 
09 recombine  $P(t)$ 
10 do crossover
11 do mutation (*)
12 for  $i = 1$  to  $n$ 
13 if  $i \leq (\sigma \times n)$ 
14 do mutation with  $P_m$ 
15 else
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16 do mutation with  $P'_m$ 
17 end if
18 end for
19 evaluate  $P(t)$ 
20 end
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From the above algorithm scheme, we can find some differences between conventional genetic algorithm and QEGA. Compared with the conventional genetic algorithm, the queen-bee evolution algorithm (QEGA) has two major differences, which are marked by asterisks in QEGA. Firstly, the parents $P(t)$ in CGA are composed of the n individuals selected by a selecting algorithm such as roulette wheel selection, while parents $P(t)$ in QEGA consist of the $n/2$ couples of a queen-bee $Iq(t-1)$, where $q = \arg \max \{f_i(t-1), 1 \leq i \leq n\}$ and each selected bee $Im(t-1)$, where $1 \leq m \leq n/2$ is selected by a selection algorithm. Secondly, all individuals in conventional genetic algorithm are mutated with small mutation probability P_m , while in QEGA only a part of the individuals are mutated with normal mutation probability P_m and the others are mutated strong mutation probability P'_m . The ratio between P_m and P'_m is given as σ in QEGA. Generally, P_m is less than 0.1 and P'_m is greater than P_m .

Queen-bee evolution is similar to nature in that the queen-bee, the fittest individual in a generation, crossbreeds with the other bees selected as parents by a selection algorithm. The first feature of queen-bee evolution reinforces the exploitation of genetic algorithms. That is, offspring mainly depend on the crossover operation and the fittest individual. As a result, it also increases the probability of premature convergence. However, the second feature helps genetic algorithms search new space, i.e. it increases the exploration of genetic algorithms through strong mutation. These two features enable genetic algorithms to evolve quickly as well as to maintain good solutions. Finally, the queen-bee evolution makes it possible for genetic algorithms to quickly approach the global optimum as well as decreasing the probability of premature convergence [11].

IV. SIMULATION

The proposed algorithm of the Queen-bee was simulated in J-sim. J-sim has provided a complete protocol stack for the applications of the sensor networks. For the simulating parameters of the sensor network: We made use of 100 nodes and network area of 100×100 m² and base station has been located in 200m distance of network. The simulated parameters of QBE are as such: population size = 20; one-point crossover probability = 0.8; normal mutation ratio = 0.7; normal mutation probability = 0.01; strong mutation probability = 0.6. Fig. 1 shows a diagram that illustrates the changes in the number of active nodes against the number of the clusters. As it was expected, more action nodes in sensor network would result in more clusters and by increasing the number of clusters, the consumed energy of the nodes would decrease and so the lifetime of the network increases.

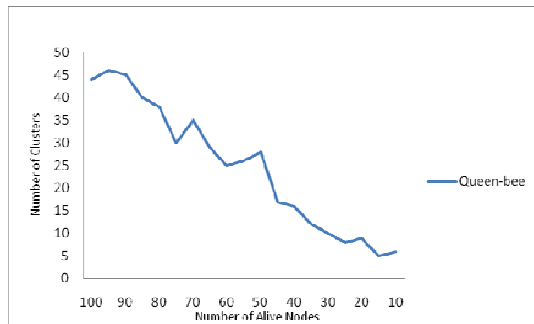


Fig. 1 Number of clusters with respect to number of alive nodes.

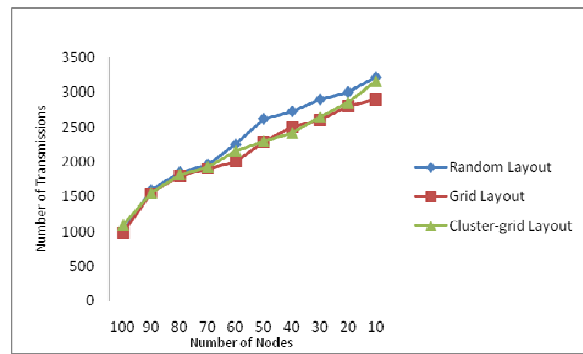


Fig. 3 Alive nodes with respect to transmissions.

In the simulation, three types of layouts are used: 1) random, 2) grid, and 3) cluster grid, as shown in Fig. 2. Fig. 2 (a) shows a sample random layout. Fig. 2 (b) shows the grid layout that creates the nodes at fixed distances. Finally, Fig. 2 (c) shows the cluster grid that is a combination of grid and random, where nodes are randomly created but there are fixed number of clusters.

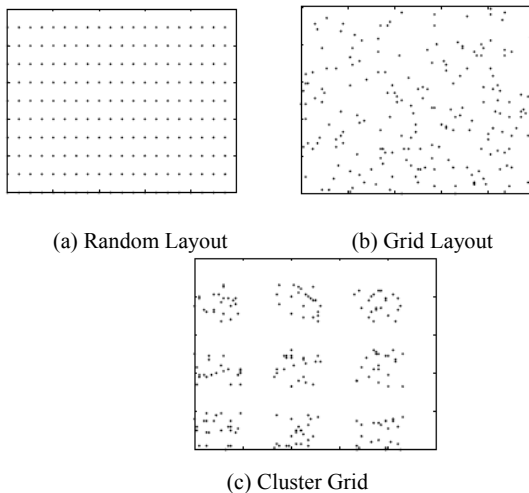


Fig. 2 Types of nodes layouts

Fig. 3 shows the number of alive nodes against the number of transmissions for grid and random and cluster grid layouts. The graphs show that the performance is independent of the network layout.

Fig. 4 compares GA and Queen-bee algorithms. In this graphs, the number of the alive nodes have been reported against the number of transmissions. As we could see, the number of the transmissions in the QB algorithm is more than that of GA. So, the lifetime of the network in the QB algorithm is much more than that of GA, since in the QB algorithm, in order to reproduce bees, only one mother is selected that is the Queen-bee and the Queen-bee with a number of the bee-population that are fathers reproduces many children by crossover operator, so the number of marriages in the Queen-bee algorithm is much less than this number in GA.

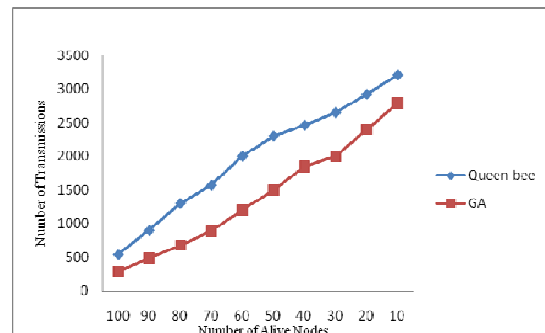


Fig. 4 Comparison between GA and Queen-bee.

Fig. 5 shows the remaining energy against the number of transmissions. The amount of the remaining energy is in fact the whole amount of energy that remains in the whole cluster in each transmission act. According to the graphs, it could be concluded that the amount of remaining energy in each transmission in Queen Algorithm is more than that of GA's. This indicates that the network which is created according to the Queen-bee algorithm has a longer life time as regards the genetic-based algorithm.

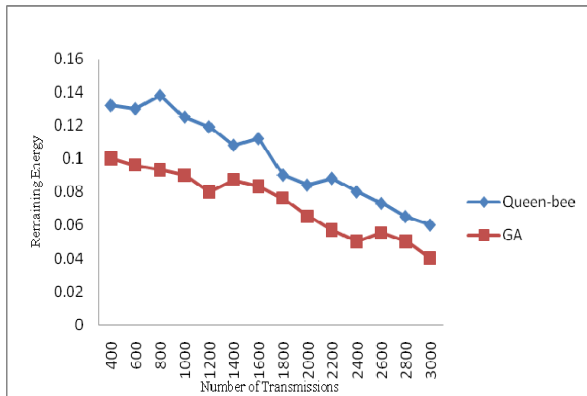


Fig. 5 Comparison between GA and Queen-bee as regards remaining energy.

V.CONCLUSION

The results of the simulation showed that the Queen-bee algorithm for clustering works better than the previous methods especially the genetic algorithm and increases the energy consumption and so the lifetime of the network. Since in this algorithm only one mother that is the Queen-bee is necessary and selected for the reproduction of bees and the Queen-bee reproduces many children with a number of the bee-population using the crossover operator, so the number of marriages in the Queen-bee algorithm are much less than that of the genetic algorithm which results increasing the rate of this algorithm as regards the genetic algorithm. The high rate of the algorithm results in the premature convergence. In the convergence phenomenon algorithm will converge to a local minimum of finding the optimum answer. In order to solve this problem, two mutation rates have been considered for the Queen-bee algorithm. One of them is the normal and the other is the strong mutation. So, the diversity in the children will be increased and the pre-mature divergence will be avoided.

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