Allocating Multiple Base Stations under General Power Consumption by the Particle Swarm Optimization

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Abstract - In this paper, a two-tiered wireless sensor networks consisting of small sensor nodes, application nodes and base-stations is considered. An algorithm based on particle swarm optimization (PSO) is proposed for multiple base stations under general power-consumption constraints. The proposed approach can search for nearly optimal BS locations in heterogeneous sensor networks, where application nodes may own different data transmission rates, initial energies and parameter values. Experimental results also show the good performance of the proposed PSO approach and the effects of the parameters on the results.

I. INTRODUCTION

In the past, many approaches were proposed to efficiently utilize energy in wireless networks. For example, appropriate transmission ways were designed to save energy for multi-hop communication in ad-hoc networks [16][10][5][19][7][6][20]. Good algorithms for allocation of base stations and sensors nodes were also proposed to reduce power consumption [12][15][16] [8][9].

Recently, a two-tiered architecture of wireless sensor networks has been proposed and become popular [1]. It is motivated by the latest advances in distributed signal processing and source coding and can offer a more flexible balance among reliability, redundancy and scalability of wireless sensor networks. A two-tiered wireless sensor network, as shown in Figure 1, consists of sensor nodes (SNs), application nodes (ANs), and one or several base stations (BSs).

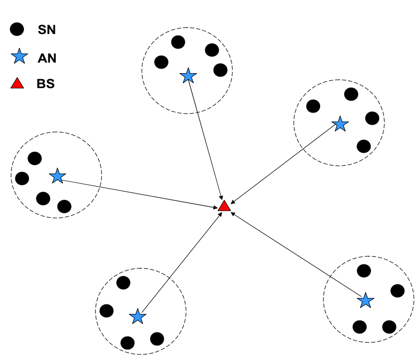

Figure 1: A two-tiered architecture of wireless sensor networks

Sensor nodes are usually small, low-cost and disposable, and do not communicate with other sensor nodes. They are usually deployed in clusters around interesting areas. Each cluster of sensor nodes is allocated with at least one application node. Application nodes possess longer-range transmission, higher-speed computation, and more energy than sensor nodes. The base station is usually assumed to have unlimited energy and powerful processing capability. Wireless sensor networks usually have some assumptions for SNs and ANs. For instance, each AN may be aware of its own location through receiving GPS signals [11] and its own energy.

A fundamental problem in wireless sensor networks is to maximize the system lifetime under some given constraints. Pan *et al*. proposed two algorithms to find the optimal locations of base stations in two-tiered wireless sensor networks [13]. Their approaches assumed the initial energy and the energy-consumption parameters were the same for all ANs. If any of the above parameters were not the same, their approaches could not work.

In this paper, an algorithm based on particle swarm optimization (PSO) is proposed to find the multiple base-station locations for general power-consumption constraints. The PSO technique was proposed by Eberhart and Kennedy in 1995 [2][3] and has been widely used in finding solutions for optimization problems. Some related researches about its improvement and applications has also been proposed [4][14][17][18]. It maintains several particles (each represents a solution) and simulates the behavior of bird flocking to find the final solutions. All the particles continuously move in the search space, tending to better solutions, until the termination criteria are met. After a lot of iterations, the optimal solution or an approximate optimal solution is expected to be found. The proposed approach can search for nearly optimal BS locations in heterogeneous sensor networks. Experimental results also show the performance of the proposed PSO approach on finding the BS locations and the effects of the parameters on the results.

II. REVIEW OF RELATED WORKS

As mentioned above, a fundamental problem in wireless sensor networks is to maximize the system lifetime under some given constraints. Pan *et al*. proposed two algorithms to find the optimal locations of base stations in two-tiered wireless sensor networks [13]. The first algorithm was used to find the optimal locations of base stations for homogenous ANs, and the second one was used for

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heterogeneous ANs. Homogenous ANs had the same data transmission rate and heterogeneous ANs might have different data transmission rates. In their paper, only the energy in ANs was considered. If a single SN ran out of energy, its corresponding AN might still have the capability to collect enough information. However, if an AN ran out of energy, the information in its coverage range would be completely lost, which was dangerous to the whole system.

Let d be the Euclidean distance from an AN to a BS, and r be the data transmission rate. Pan *et al*. adopted the following formula to calculate the energy consumption per unit time:

$$p(r,d) = r(\alpha_1 + \alpha_2 d^n)\ , \qquad (1)$$

where α_1 is a distance-independent parameter and α_2 is a distance-dependent parameter. The energy consumption thus relates to Euclidean distances and data transmission rates.

Pan *et al*. assumed each AN had the same α_1, α_2 and initial energy. For homogenous ANs, they showed that the center of the minimal circle covering all the ANs was the optimal BS location (with the maximum lifetime). They then tried to find by stacked planes the optimal BS location for heterogeneous ANs, which had different transmission rates.

III. REVIEW OF PARTICALE SWARM OPTIMIZATION

When the PSO technique is used to solve a problem, each possible solution in the search space is called a particle, which is similar to a bird mentioned above. All the particles are evaluated by a fitness function, with the values representing the goodness degrees of the solutions. The solution with the best fitness value for a particle can be regarded as the local optimal solution found so far and is stored as the *pBest* solution for the particle. The best one among all the *pBest* solutions is regarded as the global optimal solution found so far for the whole set of particles, and is called the *gBest* solution. In addition, each particle moves with a velocity, which will dynamically change according to *pBest* and *gBest*. After finding the two best values, a particle updates its velocity by the following equation:

$$V_{id}^{new} = w \times V_{id}^{old} + c_1 \times Rand_1() \times (pBest_{id} - x_{id}) + c_2 \times Rand_2() \times (gBest_d - x_{id})\ , \qquad (4)$$

where the terms are explained below.

1. V_{id}^{new} : the velocity of the i-th particle in the d-th dimension in the next iteration;
2. V_{id}^{old} : the velocity of the i-th particle in the d-th dimension in the current iteration;
3. $pBest_{id}$: the current *pBest* value of the i-th particle in the d-th dimension;
4. $gbest_d$: the current *gBest* value of the whole set of particles in the d-th dimension;
5. x_{id}: the current position of the i-th particle in the d-th dimension;
6. w: the inertial weight, generally set at 1 [17];
7. c_1: the acceleration constant for a particle to move to its *pBest*, generally set at 2 [3];
8. c_2: the acceleration constant for a particle to move to the *gBest*, generally set at 2 [3];
9. $Rand_1()$, $Rand_2()$: two random numbers between 0 to 1.

After the new velocity is found, the new position for a particle can then be obtained by the following formula:

$$x_{id}^{new} = x_{id}^{old} + V_{id}^{new} \qquad (5)$$

All the particles thus continuously move in the search space, tending to better solutions, until the termination criteria are met.

IV. A GENERAL PSO ALGORITHM FOR ALLOCATION OF MULTIPLE BASE STATIONS

The ANs produced by different manufacturers may own different data transmission rates, initial energies and parameter values. When different kinds of ANs exist in a wireless network, it is hard to find the optimal BS locations. In this section, the problem for allocation of base stations is considered. A heuristic algorithm based on PSO to search for the locations of multiple base stations under general constraints is thus proposed. An initial group of particles is first randomly generated, with each particle representing a set of possible base-station locations. Each particle is also allocated an initial velocity for changing its state. Let $e_j(0)$ be the initial energy, r_j be the data transmission rate, α_{j1} be the distance-independent parameter, and α_{j2} be the distance-dependent parameter of the j-th AN. The lifetime $l_{i(k)j}$ of an application node AN_j communicating with the k-th location in the i-th particle is calculated by the following formula:

$$l_{i(k)j} = e_j(0) / r_j(\alpha_{j1} + \alpha_{j2} d_{i(k)j}^n)\ , \qquad (6)$$

where $d_{i(k)j}^n$ is the n-order Euclidian distance from the j-th AN to the k-th location in the i-th particle. Assume there are M base stations to be allocated. The lifetime l_{ij} of AN_j for the i-th particle is calculated by the following formula:

$$l_{ij} = \underset{k=1}{\overset{M}{Max}}\{l_{i(k)j}\} \qquad (7)$$

The fitness function used for evaluating each particle is thus shown below:

$$fitness(i) = \underset{j=1}{\overset{N}{Min}}\{l_{ij}\}, \qquad (8)$$

where N is the number of ANs. That is, each particle takes the minimal lifetime of all ANs as its fitness value. A larger fitness value denotes a longer lifetime of the whole system, meaning the corresponding base station locations are better. The fitness value of each particle is then compared with that of its corresponding *pBest*. If the fitness value of the i-th particle is larger than that of $pBest_i$, $pBest_i$ is replaced with the i-th particle. The best $pBest_i$ among all the particles is chosen as the *gBest*. Besides, each particle has a velocity, which is used to change the current position. All particles thus continuously move in the search space. When the termination conditions are achieved, the final *gBest* will be output as the locations of the multiple base stations. The proposed algorithm is stated below.

The proposed PSO algorithm for allocation of multiple base stations:

Input: A set of N ANs, each AN_j with its location (x_j, y_j), data transmission rate r_j, initial energy $e_j(0)$, parameter α_{j1}, and parameter α_{j2}.

Output: M base-station locations that will cause a nearly maximal lifetime for the system.

Step 1: Initialize the fitness values of all *pBest*s and the *gBest* to zero.

Step 2: Randomly generate a group of n particles, each particle representing a possible solution of M base-station locations. Locations may be two-dimensional or three-dimensional, depending on the problems to be solved.

Step 3: Randomly generate an initial velocity for each particle.

Step 4: Calculate the lifetime $l_{i(k)j}$ of the j-th AN communicating with the k-th base station in the i-th particle by the following formula:

$$l_{i(k)j} = e_j(0) \big/ r_j(\alpha_{j1} + \alpha_{j2} d^n_{i(k)j}),$$

where $e_j(0)$ is the initial energy, r_j is the data transmission rate, α_{j1} is a distance-independent parameter, α_{j2} is a distance-dependent parameter of the j-th AN, and $d^n_{i(k)j}$ is the n-order Euclidean distance from the k-th base station of the i-th particle to the j-th AN.

Step 5: Calculate the maximal lifetime l_{ij} of the j-th AN for the i-th particle by the following formula:

$$l_{ij} = \underset{k=1}{\overset{M}{Max}} \{l_{i(k)j}\}.$$

Step 6: Calculate the lifetime of the whole sensor system for the i-th particle as its fitness value ($fitness_i$) by the following formula:

$$fitness(i) = \underset{j=1}{\overset{N}{Min}}\, l_{ij},$$

where N is number of ANs and i = 1 to n.

Step 7: Set $pBest_i$ as the current i-th particle if the value of *fitness(i)* is larger than the current fitness value of $pBest_i$.

Step 8: Set *gBest* as the best *pBest* among all the particles. That is, let:

fitness of $pBest_q = max_{i=1}^{n}$ fitness of $pBest_i$, and set $gBest = pBest_q$.

Step 9: Update the velocity of the i-th particle as:

$$V^{new}_{i(k)d} = w \times V^{old}_{i(k)d} + c_1 \times Rand_1() \times (pBest_{i(k)d} - x_{i(k)d}) + c_2 \times Rand_2() \times (gBest_{kd} - x_{i(k)d}),$$

where $V^{new}_{i(k)d}$ is the new velocity of the k-th base station at the d-th dimension for the i-th particle, is the current velocity of the k-th base station at the d-th dimension for the i-th particle, w is the inertial weight, c_1 is the acceleration constant for particles moving to *pBest*, c_2 is the acceleration constant for particles moving to *gBest*, $x_{i(k)d}$ is the current position of the k-th base station at the d-th dimension for the i-th particle, $pBest_{i(k)d}$ is the value of the k-th base station of $pBest_i$ at the d-th dimension, and $gBest_{kd}$ is the value of the k-th base station of *gBest* at the d-th dimension, $Rand_1()$ and $Rand_2()$ are two random numbers among 0 to 1.

Step 10: Update the position of the i-th particle as:

$$x^{new}_{i(k)d} = x^{old}_{i(k)d} + V^{new}_{i(k)d},$$

where $x^{new}_{i(k)d}$ and $x^{old}_{i(k)d}$ are respectively the new position and the current position of the k-th base station at the d-th dimension for the i-th particle.

Step 11: Repeat Steps 4 to 10 until the termination conditions are satisfied.

In Step 11, the termination conditions may be predefined execution time, a fixed number of iterations or when the particles have converged to a certain threshold.

V. EXPERIMENTAL RESULTS

Experiments were made to show the performance of the proposed PSO algorithm on finding the optimal positions of base stations. They were performed in C language on an AMD PC with a 2.0GHz processor and 1G main memory and running the Microsoft Window XP operating system. The simulation was done in a two-dimensional real-number space of 100*100. That is, the ranges for both x and y axes were between 0 to 100. The data transmission rate was limited between 1 to 10 and the range of initial energy was limited between 10000000 to 99999999. The data of all ANs, each with its own location, data transmission rate and initial energy, were randomly generated. Each experiment was made with 100 runs for average.

Experiments were first made to show the convergence of the proposed PSO algorithm for two base stations when the acceleration constant (c_1) for a particle moving to its *pBest* was set at 2, the acceleration constant (c_2) for a particle moving to its *gBest* was set at 2, the inertial weight (w) was set at 0.6, the distance- independent parameter (α_{j1}) was set at zero, and the distance-dependent parameter (α_{j2}) was set at one. The experimental results of the resulting lifetime along with different iterations for 50 ANs and 5 particles in each iteration are shown in Figure 2.

It is easily seen from Figure 2 that the proposed PSO algorithm could converge very fast (below 100 iterations). Next, experiments were made to show the effects of different parameters on the lifetime. The influence of the acceleration constant (c_1) for a particle moving to its *pBest* on the proposed algorithm was first considered. The process was terminated at 300 iterations. When w = 1 and c_2 = 2, the nearly optimal lifetimes for 50ANs and 5 particles along with different acceleration constants (c_1) are shown in Figure 3.

Figure 2: The lifetime for 50 ANs and 5 particles

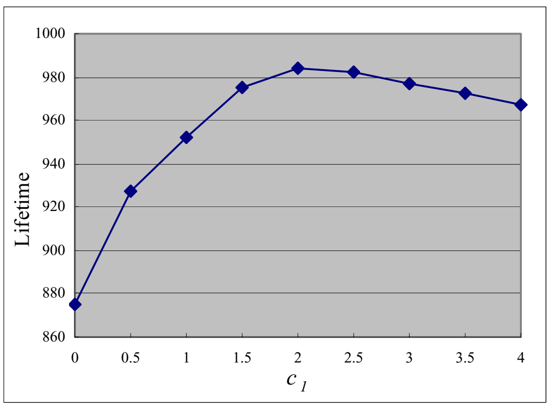

Figure 3: The lifetimes along with different acceleration constants (c_1)

It can be observed from Figure 3 that the lifetime first increased and then decreased along with the increase of the acceleration constant (c_1). When the value of the acceleration constant (c_1) was small, the velocity update of each particle was also small, causing the convergence speed slow. The proposed PSO algorithm might thus not get the optimal solution after the predefined number of iterations. On the contrary, when the value of the acceleration constant (c_1) was large, the velocity change would be large as well, causing the particles to move fast. It was then hard to converge. In the experiments, the optimal c_1 value was about 2. Next, experiments were made to show the effects of the acceleration constant (c_2) for a particle moving to its *gBest* on the proposed algorithm. When w = 1 and c_1 = 2, the experimental results are shown in Figure 4.

It can be observed from Figure 4 that the lifetime first increased and then decreased along with the increase of the acceleration constant (c_2). The reason was the same as above. In the experiments, the optimal c_2 value was about 2. Next, experiments were made to show the effects of the inertial weight (w) on the proposed algorithm. When c_1 = 2 and c_2 = 2, the experimental results are shown in Figure 5.

It can be observed from Figure 5 that the lifetime first increased and then decreased along with the inertial weight (w). This was because when the value of the inertial weight was large, the particles would move fast due to the multiple of the old velocity. It was then hard to converge. In the experiments, the optimal w value was about 0.6.

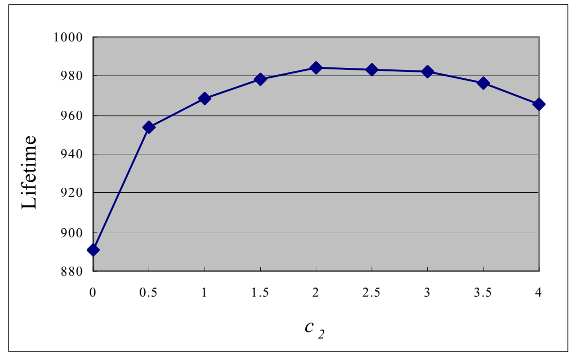

Figure 4: The lifetimes along with different acceleration constants (c_2)

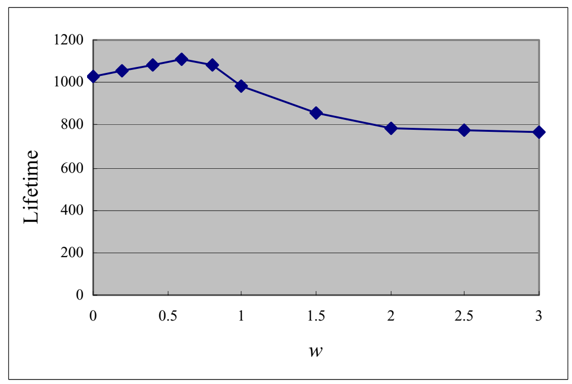

Figure 5: The lifetimes along with different inertial weights (w)

Experiments were then made to show the effects of the distance-independent parameter (α_1) on the lifetime. In the experiments, all ANs had the same value of the distance-independent parameter. The experimental results are shown in Figure 6.

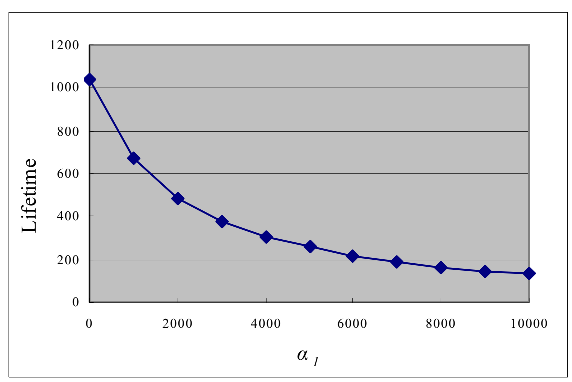

Figure 6: The lifetimes along with different values of the distance-independent parameter (α_1)

It can be observed from Figure 6 that the lifetime decreased along with the increase of the value of the distance-independent parameter (α_1). It was consistent with the formula of energy consumption. Next, experiments were made to show the effects of the distance-dependent parameter (α_2) on the lifetime. The experimental results are shown in Figure 7.

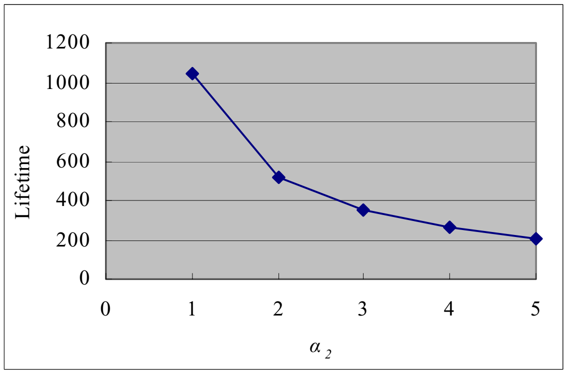

Figure 7: The lifetimes along with different values of the distance-dependent parameter (α_2)

It can be observed from Figure 7 that the lifetime decreased along with the increase of the distance-dependent parameter (α_2). It was also consistent with the formula of energy consumption. Besides, the relation between the lifetime and the value of the distance-dependent parameter presented an approximately inverse proportion. Next, experiments were made to show the relation between lifetimes and numbers of ANs. The experimental results are shown in Figure 8.

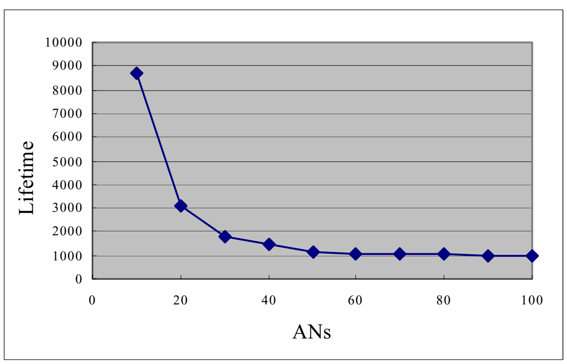

Figure 8: The lifetimes along with different numbers of ANs

It can be seen from Figure 8 that the lifetime decreased along with the increase of the number of ANs. It was reasonable since the probability for at least one AN in the system to fail would increase when the number of ANs grew up.

Experiments were then made to show the relation between lifetimes and numbers of particles for 50 ANs and 300 iterations. The internal weight was set at 1. The experimental results are shown in Figure 9. It can be seen from Figure 9 that the lifetime increased along with the increase of numbers of particles.

Next, experiments were made to show the relation between lifetimes and numbers of base stations. The experimental results are shown in Figure 10. It can be seen from Figure 10 that the lifetime increased along with the increase of the number of base stations. This is because the distance from an AN to a desired base station would become shorter for a larger number of base stations.

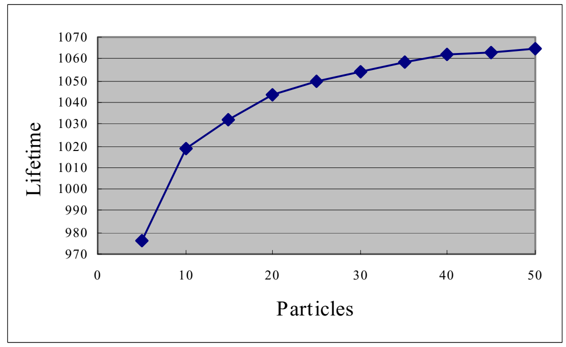

Figure 9: The lifetimes along with different numbers of particles

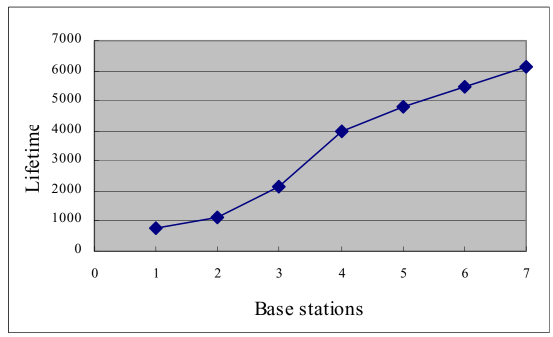

Figure 10: The lifetimes along with different numbers of base station

Note that no optimal solutions can be found in a finite amount of time since the problem is NP-hard. For a comparison, an exhaustive search using grids was used to find nearly optimal solutions. The approach found the lifetime of the system when a BS was allocated at any cross-point of the grids. The cross-point with the maximum lifetime was then output as the solution. A lifetime comparison of the PSO approach and the exhaustive search are shown in Table 1.

TABLE 1: A LIFETIME COMPARISON OF THE PSO APPROACH AND THE EXHAUSTIVE GRID SEARCH

Method	Lifetime
The proposed PSO algorithm	1123.3463
The exhaustive grid search (grid size = 1)	1122.1773

It can be observed from Table 1 that the lifetime obtained by our proposed PSO algorithm was better than those by the exhaustive grid search. The lifetime by the proposed PSO algorithm was 1123.3463 and was 1122.1773 for the exhaustive search when the grid size was set at 1. The execution time by the two approaches is shown in Table 2.

TABLE 2: A COMPARISON OF EXECUTION TIME BY THE TWO APPROACHES

Method	Time (sec.)
The proposed PSO algorithm	0.07
The exhaustive grid search (grid size = 1)	3983.515

It can be seen from Table 2 that the exhaustive grid search spent much more execution time than the proposed PSO algorithm.

VI. CONCLUSION AND FUTURE WORKS

In this paper, a two-tiered wireless sensor networks has been considered and an algorithm based on particle swarm optimization (PSO) has been proposed for finding the multiple base stations. The proposed algorithm first randomly generates an initial group of particles, with each particle representing a possible solution of multiple base-station locations. Each particle is also allocated a velocity for changing its state. System lifetime is used as the fitness function to evaluate each particle. Both the local optimal value *pBest* and the global optimal value *gBest* are then used to guide the search direction. When the termination conditions are achieved, the final *gBest* will be output as the location of the multiple base stations. Experiments have also been made to show the performance of the proposed PSO approach and the effects of the parameters on the results. In summary, the proposed algorithm can help find good BS locations to reduce power consumption and maximize network lifetime in two-tiered wireless sensor networks. In the future, we will attempt to extend the proposed approach to solving more complicated problems in wireless sensor networks.

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