An Ant Colony Optimization Algorithm based on Scheduling Preference for Maximizing Working Time of Wireless Sensor Networks

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ABSTRACT

Abstract—With the proliferation of wireless sensor networks (WSN), the issues about how to schedule all the sensors in order to maximize the system's working time have been in the spotlight. Inspired by the promising performance of ant colony optimization (ACO) in solving combinational optimization problem, we attempt to apply it in prolonging the life time of WSN. In this paper, we propose an improved version of ACO algorithm to get solutions about selecting exact sensors to accomplish the covering task in a reasonable way to preserve more energy to maintain longer active time. The methodology is based on maximizing the disjoint subsets of sensors, in other words, in every time interval, choosing which sensor to sustain active state must be rational in certain extent. With the aid of pheromone and heuristic information, a better solution can be constructed in which pheromone denotes the previous scheduling experience, while heuristic information reflects the desirable device assignment. Orderly sensor selection is designed to construct an advisable subset for coverage task. The proposed method has been successfully applied in solving limited energy assignment problem no matter in homogenous or heterogeneous WSNs. Simulation experiments have shown it has a good performance in addressing relevant issues.

Categories and Subject Descriptors

• **Mathematics of computing~Evolutionary algorithms** • *Hard ware~Sensor applications and deployments*

General Terms

Algorithms, Performance, Design, Experimentation

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Keywords

Ant colony optimization algorithm; Wireless Sensors Network (WSN); maximize working time; schedule.

1. INTRODUCTION

With the rapid development and a wide range of application of embedding chips, Wireless Sensors Network has been applied in some aspects in technological and daily life. Sensors are tiny embedding devices which are commonly comprised of sensing component, signal transformer, transmitter and sources of energy supplying. These tiny embedding devices can detect surrounding environment, and gather quantified state changes of monitored objects, then transform changes to electrical signals and provide a corresponding output, transmit it to the control center (decision-making center) [17]. Owing to its practical properties, WSN has been widely applied in real-time monitoring field [1], [3], [8]-[9], [22]-[23],[25]-[26], [28] , such as smart home management [3], [26], natural disease prevention and control [28], environmental security tracking [4], [5], and some other domains [8],[25]. For instance, in security field, based on data gathered from sensors, we can judge whether there are some dangerous things will happen [9].

Since the main energy source of sensors is non-replaceable battery, in the same environment, the quality of performance of WSN mainly depends on the working time of systems. With this momentum, studies about how to use the fixed energy and prolong the working time of the whole system have been one of the most significant cases which scientists are committing them to studying. Recent days, some novel approaches have been brought up [2], [5], [7], [10]-[14], [16], [20]-[21], [27], [29], [32]-[33]. Among them, scheduling devices efficiently, choosing a minimal subset of sensors to achieve the coverage mission while the rest of sensors turn to sleep state to save energy, has shown a satisfying performance [10]-[12], [34]. Finally, in order to achieve longer working time, we need a function-well method to schedule active sensors, and to make the disjoint subsets of sensors which can accomplish covering job at its own as much as possible. With available usage counts of sensors changing, schedule scheme will updated simultaneously. It is a headache problem because sensors scheduling in the previous time interval may lay influence on choice making in the latter time interval. Therefore, how to maximize disjoint minimal subsets of sensors in the whole proceeding flow has been prone to a non-deterministic polynomial (NP) complete problem and exhaustive search is impossible.

Furthermore, depending on the types of sensors and different coverage scopes of devices, WSN can be categorized as homogeneous and heterogeneous wireless sensors network. In application reality, due to the complexity of the task, multiple sensors (e.g., chemical, pressure, humidity, thermal and fluid velocity sensor) are generally required to cooperate to achieve tasks. Diversity of sensors makes the solving of such issues become thornier. It is indispensable that taking different coverage radii of different sensors into consideration while scheduling sensors. Existing work on WSN typically assumes all sensors in system are identical, and uses Boolean Detect Model to express the relationship between the sensor and the target point [34]. Therefore some methods exist to progress the problem in homogeneous wireless sensor networks, researches on heterogeneous wireless sensor network have progressed at a slow pace. In this paper, equal attentions will be attached on these two kinds of networks. In the meantime, another model, Probability Detect Model is considered [6] which recently have been used by many papers [10], [13]. In the new model, a target point being covered by a sensor is measured with probability which do comply more with the application reality and turn the topologies between sensors and target points into mathematically formal representation.

However, how to schedule sensors efficiently is still a thorny problem. Recent studies have shown that the inherent characteristic of stochastic algorithms makes it essential in solving such problems in terms of influences of experimental results imposed by scheduling sequence. Particle swarm optimization (PSO) [13], genetic algorithm (GA) [34] and ant colony optimization (ACO) algorithms [10]-[11], [32]-[33], etc., have been applied in handling such a headache challenge. Among them, ACO has shown to be promising. Although existing work on this has progressed a lot, there still are some issues to be solved, e.g., basically, which factors put constraints on system working time, whether some favorable scheduling preference are waiting to be discovered, and how to construct a optimal solution though applying the ACO algorithm.

Ant colony algorithm was developed by Marco Dorigo [18]-[20], inspired by foraging behaviors of ants. Based on heuristic information and pheromone, an approximately optimal solution of the problem can be constructed. ACO algorithm has inherent advantages in terms of combinational optimization problem and variable-length coding. In order to solve different practical problems and reflect characteristics of specific issues, the key is how to choose heuristic information, initialize and update pheromone, and then optimize the conventional algorithm for the better performance. The existing methods for utilizing ACO algorithm to solve the Efficient Energy Coverage problem of WSNs focus on the issues of constructing heuristic information, pheromone and evaluation criterion [10], [11]. Nevertheless, scheduling order has been omitted, which is indispensable in scheduling cases. Therefore, this paper comprehensively analyzes how to improve performance of conventional ACO algorithm by introducing a novel scheduling sequence and changing the solution constructing space of an ant. As the well-known Cannikin Law say, how much of a bucket filled with water, does not depend on the highest piece of wood on the sides of casks, but rather depends on the shortest piece on the sides of casks. Hence, more attention should be put on the shortest piece of wood in the scheduling algorithm. In this paper, we try to find the key factors that are constraints for working time of the whole system. It is quite clear that the target points which are covered by few sensors become the shortest piece of wood. Therefore, all targets points will be sorted according to coverage ratio. The lower coverage ratio a target point have, the higher its priority level of scheduling preference is which the sensor node is selected to meet its coverage need.

In order to schedule sensors in a more reasonable and efficient way, system working time are divided into several minor time intervals. In the existing methods on how to construct an optimal schedule [10], [11], ACO algorithm is applied in constructing an optimal schedule scheme in the current time interval until no subset of sensors which could accomplish sensing task can be found, and then the past time intervals are the total working time of the whole system. In fact, there are defects in the above approach. It is well known that sensors scheduling in the previous time interval will affect schedule in the latter time interval. A least reasonable schedule in the previous time interval will shorten the total working time of the system. Therefore, we change solution constructing space of an ant. An ant constructs an integrated schedule about the whole working flow, though stigmergy between ants, some better solution for the whole schedule can be constructed.

The rest of this paper is organized as follows. Part Two explains some precondition definitions, for instance, problem definition, explanations about Probability Detect Model and priority level of scheduling preference. Part Three displays the details about the approach proposed in this paper. Simulation results are presented in Part Four to evaluate the effectiveness of the proposed approach. Part Five concludes the whole paper.

2. PRELIMINARY

In this section, we will have a deep introduction about some definitions about problem properties and computational formula in the proposed algorithm. Then we'll have a brief introduction about ant colony optimization.

2.1 Problem definition

In a common wireless sensor network, these are some target points in the monitored area. Some sensors are deployed to detect the changing states of the target points. On the ground of the places of sensors, WSN could be divided into unstructured WSN and structured one. In the structured WSN, all places of sensors are designed based on the places of target points in advance according to a particular topological algorithm. However, attempts to find a suitable placement are time-consuming and headache issues. At the same time, there are still some places where are full with dangerous or harmful objects out of reach. As a consequence, in this paper, assumed that wireless sensors network is unstructured, sensors are densely placed in the monitored area. It means the positions of sensors are random and there is no need to take complicated topological structure into consideration that is still unsolved. Apparently, unstructured WSN makes the formation for solution to the problem in a more clear way.

In the unstructured WSN, sensors are always redundant for all target points. In order to achieve the monitoring task, there is no need to activate all sensors. Choose a minimal and optimal subset of sensors which can accomplish the coverage task to be scheduled to be working state until some of them are energy drained or a better combination occurs while the remained sensor nodes turn to be sleeping mode. In the existing methods [30], the scheduled subset of sensors tends to continue working until some of them are energy drained that the subset of sensors can't achieve the coverage task. In a certain extent, there is much irrationality in the above approaches. With the decay of available usage counts of sensors, the previous scheduled subset may become little reasonable for the current time interval. Therefore, a new model is adopted by recent researches in which system time is divided into several minor time intervals, then according to a scheduling algorithm an optimal subset of sensors is scheduled for the current time interval and energy distribution of sensors. There are several assumption in the proposed algorithm, e.g. Sensors have fixed usage counts; active sensors consume once from available usage counts in a time interval. In every time interval, energy distribution of sensors is different, then an optimal of sensors scheduling for the current time interval are changing. When a new time interval starts, sensors should be scheduled again. As a prerequisite, the working subset of sensors must fulfill the coverage task. All things we need to do are maximizing the number of subsets of sensors to prolong working time of the whole system.

In the general case, considerating the working time of wireless sensors network, there are two issues need to be focused on. One is the sensing coverage issue and other is network connectivity. With the development of electronic technology, these above issues can be performed by sensors simultaneously. Coverage means active sensors can detect changes of states about all target points. The sensing coverage issue can be measured by the sensing radius of sensors and the distance between the sensor node and the target point. While the connectivity among devices demands all sensors form a well-communicating network and sensors can transmit information gathered to the control center. If the communication range r_c of devices is more twice than the sensing coverage radius r_s, it has been well proven that full coverage in target area infers well-connected communication between devices [4]. In this paper, this restriction is assumed to be satisfied on the ground that it is has become a technological requirement with progress in sensor technology.

In the problem scenario, formally, there are some target points p_i(i=1,2,3⋯N_p, N_p is the number of target points) to be monitored the occurrence of events in the target area A. Some sensors s_j (j=1,2,3 ⋯ N_s, N_s is the number of sensors) are deployed to monitor the changes of states about target points.

2.2 Probability detect model

In Boolean Detect Model, sensor nodes are deemed to have a coverage radius; when Euclidean distance between the sensor node and the target point is more-or-equal than the covering radius of sensor, sensor can't detect anything about the target point, while the distance is less than the coverage radius, the sensor node can detect changes about the objective node. When dealing with heterogeneous sensors which different types of sensor nodes may occur, Boolean Detect Model are appeared with some defects and become unsuitable to handle cases about different coverage radii. In this paper, Probability Detect Model is considered [6] which recently have been adopted by many papers [13]. Probability Detect Model measures coverage problem with probability, every kind of sensors has two types of coverage radii, r_s and r_u, when Euclidean distance between the sensor node and the target point is less than r_s, the probability of the target point be detected is almost equal to 1, while distance is more than r_u, the probability is almost 0, when distance is within the range between r_s and r_u, the probability increases exponentially along with distance decreasing.

Mathematically, the probability that a sensor j detect the target point i can be written as follows:

$$p_{ij} = \begin{cases} 0, & if\ d_{ij} > r_u \\ e^{-a(d_{ij}-r_u)^m}, & if\ r_s < d_{ij} \le r_u \\ 1, & if\ d_{ij} \le r_s \end{cases} \quad (1)$$

Where d_{ij} is symbolized the Euclidean distance between the senor j and the target point i.

A target point can be detected by many sensors with probability being more than zero. Nevertheless, being covered means the probability by which the target point is detected is more than a fixed parameter ε which is user-specified. Mathematically, the definition can be formalized as follows:

$$p_i = 1 - \prod_{s_t \subseteq s} (1 - p_{ij}) \ge \varepsilon \quad (2)$$

Where S is the set of all sensors, $s_t \subseteq s$ is the set of sensors that is scheduled in the current time interval. In every time interval, this condition as above must be met by every target point.

Therefore, in every time interval, sensors are either active states or dormant states. The problem we are aimed to handle is turned to a binary-code programming, that is, for a specific sensor, whether to choose it to achieve the coverage task.

On the ground that every target point must meet the above demand about coverage quantified with probability, target points which are covered by few sensors will be constraints to the working time of systems. Once sensors are energy drained, they will have no available usage counts to be active then become unavailable for scheduling. Unreasonable scheduling sequence may make these sensors become too fewer sensors to cover it to meet the demand about coverage. Therefore, we define the coverage priority level of scheduling preference for every target point according to the Cannikin Law. Defining the coverage priority level on the ground of a numeric variable computed as follows:

$$x_i = \sum_{j=1}^{N_s} e_j p_{ij} \quad (3)$$

Where e_j is the remained usage counts of sensor j can continue working, p_{ij} is the probability that sensor j detect the target point i and N_s is the number of all sensors. Therefore, x_i is a value which can reflect the being coverage ratio of the target point i. The smaller the value of x_i is, the higher the priority level of scheduling preference is which a sensor is selected to cover it.

2.3 The conventional ACO algorithm

In this subsection, we will have a brief introduction about ant colony optimization algorithm. ACO is a member of swarm intelligence algorithms, and is a kind of stochastic algorithms.

Inspired by the foraging behavior of ants, the ACO algorithm was initially proposed by Marco Dorigo [18]-[20]. An ant seeks to a path between its colony and the source of food. When the ant constructs a complete path, it deposits pheromone in the past edges. The next ant can construct better solution depend on pheromone on the paths and some random factors. After many ants completing the construction of paths, a shortest path between the source of food and the ant colony can be found through stigmergy between ants. Pheromones represent empirical experiences from those past individuals, while heuristic information that are random factors in the algorithm represent the desirability of exploring more possible paths and reflects the stoaschtic characteristics simultaneously. ACO first applied in solving the traveling salesman problem (TSP) [18]. A salesman wanders in a map with many cities to construct a shortest circuit which pasts all cities only once. Though the proceeding procedure of solving the TSP problem, we can have a clear understanding about ACO algorithm.

Algorithm 1: ACO algorithm for Traveling Salesman Problem

```
Input: information about cities
Output: the shortest circuit between cities

Let t=0
Set parameters: N_k, N_c, ρ
Initialize(d_ij , P_ij)
While t< N_c do
 // a new colony starts selection
    for each ant k=1,⋯,n_k
    //a new solution for ant k starts
      do
        Add link(i, j) to path x^k(t) based on equation (4)
      until a circuit between all cities accomplish
    if f^k(t)<f_best f^k(t)->f_best x^k(t)->x_best
  update τ_ij using equation (5)
t=t+1
Return the path x_best with the length f_best as the solution
```

Figure 1. Pseudocode flow of solving TSP with conventional ACO algorithm

Where N_c denotes the number of the colonies and N_k is the number of ants in each colony. $f^k(t)$ is the length and $x^k(t)$ is the path of the circuit constructed by the ant k in the colony t. x_{best} is the integrated path and f_{best} is the length of the shortest circuit.

When an ant chooses which edge to be joined into the path, selection is based on the heuristic information and the pheromone. Roulette Wheel Selection is usually applied in selection process. The probability of the ant on the city i choosing the city j to be the next city to reach is computed as follow:

$$p_{ij}^k(t) = \begin{cases} \dfrac{\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)}{\sum\limits_{u \in \mathrm{N}_i^k(t)} \tau_{iu}^{\alpha}(t)\eta_{iu}^{\beta}(t)} & if\ j \in \mathrm{N}_i^k(t) \\ 0 & if\ j \notin \mathrm{N}_i^k(t) \end{cases} \qquad (4)$$

Where $\tau_{ij}(t)$ is the pheromone and $\eta_{ij}(t)$ is the heuristic information on the link between i and j. α and β are parameters specified for the problem to balance the weight of pheromone and heuristic information, $\mathrm{N}_i^k(t)$ is the collection of the remained cities which have a link with city i but haven't been visited for the ant k in the colony t. When all ants in a colony have accomplished the construction of paths, pheromone will be updated, updating formula like this:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij} \qquad (5)$$

$$\Delta\tau_{ij} = \sum_{k=1}^{\mathrm{N}_k} \frac{1}{f^k(t)} \qquad (6)$$

Where $f^k(t)$ is the distance of circuit constructed by ant k, and ρ is the decay ratio of pheromone. At the beginning of the algorithm, pheromone in each edge usually is initialized with an identical little random number or in some other ways.

In this scenario, heuristic information is set to the reciprocal of the distance of path constructed by the ant which is due to that a short path is expected to be found.

For a specified practical problem, It's critical that how to construct the pheromone and heuristic information.

3. MODEL DESCRIPTION

As introduced in the Part One, these are some factors to be constraints to working time of the whole system. For target points which are covered by few sensors, undoubtedly, they become the shortest pieces among influences for working time of the network. Therefore, more attentions must be put on those target points to avoid unreasonable schedule makes them couldn't be covered by enough sensors in the early time to shorten working time of the whole network.

To achieve a rational schedule and a maximal working time, according to the Cannikin Law theory, at the beginning of scheduling, coverage ratios of all target points will be computed and sorted in ascending order to find the shortest board. Sensors should be scheduled firstly to meet the coverage demand of target points which have a small coverage ratio computed as the formula (3). For every target point, a set of candidate sensors will be maintained, and a sensor will be selected from the candidate set to meet coverage task of the target point. Selection is made on the basis of probability which is computed as follows:

$$p_{ij}^s(t) = \begin{cases} \dfrac{\tau_{ij}(t)\eta_{ij}(t)}{\sum\limits_{u \in \mathrm{N}_i^s(t)} \tau_{iu}(t)\eta_{iu}(t)} & if\ j \in \mathrm{N}_i^s(t) \\ 0 & if\ j \notin \mathrm{N}_i^s(t) \end{cases} \qquad (7)$$

Where $\tau_{ij}(t)$ denotes the pheromone and $\eta_{ij}(t)$ denotes the heuristic information for sensor j is chose to cover the target point i. $\mathrm{N}_i^s(t)$ is the candidate set of sensors that remains several available usage times and can cover the target point i in the time interval t for the solution constructed by the ant s.

In this paper, pheromone τ_{ij} is set to the tendency that the target point i is mainly covered by the sensor j. We firstly initialize all pheromone with an identical value. After a colony of ants completing the construction of solutions, values of pheromone will be updated. The updating formula could be formalized like follows:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij} \quad (8)$$

Pheromone evaporates with time elapsing and ρ is the decay ratio of pheromone.

$$\Delta\tau_{ij} = \sum_{s=1}^{n_k} \frac{n_{ij}}{n_s} \quad (9)$$

Where n_s is the total working time of the schedule constructed by the ant s, and η_{ij} is the number of times for sensor j is selected to meet the coverage task of target point i in all time intervals of the current solution constructed by the ant s. n_k is the number of ants in the current colony.

For a reason that a sensor which has more residual times for using and could cover more target points is preferable to be selected, the heuristic information for sensor j to cover the target point i is computed like this:

$$\eta_{ij}(t) = e_j(t) \cdot c_j \quad (10)$$

Where $e_j(t)$ is the residual times for using in the current time interval t and c_j is the number of target points that sensor j can cover. In different time interval, the usage counts for sensor j are changing all the time. Thus, when a new time interval starts, the value of $\eta_{ij}(t)$ need be updated.

After computing the choosing probability for all sensors, a 0.9-roulette wheel selection strategy is adopted to select a sensor from the candidate set of sensors. The 0.9-roulette wheel selection is an improved version from roulette wheel selection strategy. A random number p between 0 and 1 is produced, if p is less than 0.9, the sensor in candidate set which has the biggest choosing probability will be chose directly. If p is more or equal than 0.9, roulette wheel selection strategy will be applied to select a sensor from the candidate set. Obviously, the improved version speeds the running of the algorithm and reserves the stochastic characteristics.

The selected sensor doesn't only cover the current target point, but also cover other target points under coverage. Along with the sorted sequence of target points, sensors will be selected until all target points have reached the demand about coverage, otherwise, the above procedures will be repeated, then a sub-schedule for the current time interval completes. Available usage counts of sensors in the current sub-schedule will decrease, then the rank of all target points will updated. The above things are done over and over again until there isn't a set of sensors can accomplish the coverage task for all target points. The past working time intervals are the active time for the whole system in the solution constructed by the ant. Figure 2 has shown this process. Then, construction of solution by the current ant ends, and the next ant starts constructing new solution.

With multiple updating of pheromone, under the guide with richer experiences, a better scheduling scheme can be found.

In this paper, the selecting rule of conventional ACO is still observed. When wandering in the solution graph, choosing a direction to construct the solution simultaneously.

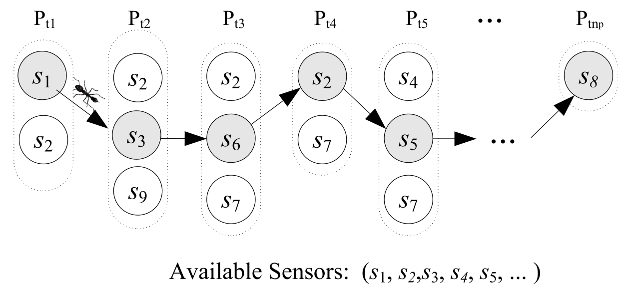

Fig 2. A simplified process of solution construction

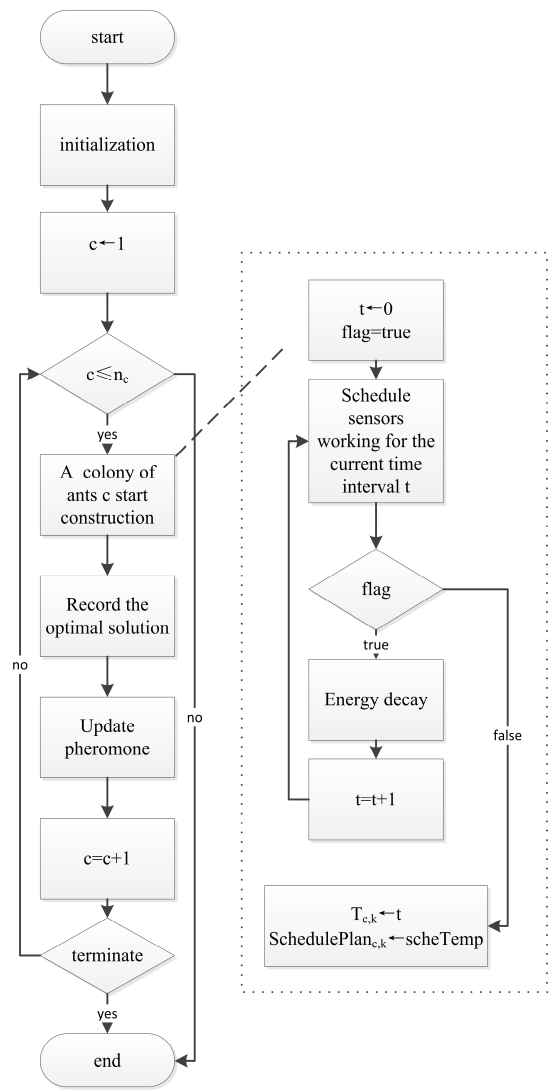

Fig. 3 The flow chart of the new proposed method

Every ant in the colony constructs an integrated solution independently. In other words, the constructing space for solutions by an ant is an integrated scheduling scheme for the whole network. Therefore, it is more possible to construct a better solution for the whole scheduling than an ant just constructs a partial solution.

In the Figure 3, an integrated proceeding flow for the new proposed approach will be shown.

4. SIMULATION

In this section, we present some experimental results to verify performance of the proposed approach. Since many methods have been proposed for maximizing the working time of wireless sensors network, a comparison between the new approach and the approach in [10] will be shown. Both of them apply the ACO to search a function-well scheduling scheme to prolong working time of WSN. For the new proposed approach, two improved aspects have been introduced, then, efficiency in application reality is verified in the homogeneous and heterogeneous WSN. The key point of comparison lies not only in the performance but the computational complexity.

4.1 Experimental conditions

We carried out two simulations to verify the performance of the proposed approach. In the first simulation, we compare working time of the network with the algorithm proposed in [10] applied in the homogeneous network. There are six different scenarios in first simulation, all scenarios are set in a background which sensors and target points are deposed at random in a 10m*10m square area. Table 1 shows the number of sensors and target points in different scenarios. There is only one type of sensors that we set parameters as follows: r_s=1.5m, r_u=6m, a=0.5 and m=0.5. All sensors have an initial using time of 10, if a sensor always keeps working state, it can sustain working ten time intervals. In all scenarios, we set identically for the number of ants, the number of colonies and the parameter ε and ρ as follows: NA=50, NC=200, ε=0.97, ρ=0.5. In every scenario, the algorithm runs thirty times for the same map. The settings about parameters are same as in previous ACB-SA algorithm in [10].

In the second simulation, experiments are conducted in heterogeneous WSNs. All sensors are belonged to different categories and have different coverage radii. In experiments, coverage radii are randomly generated. r_s ranges between 1m and 3m, and r_u ranges between 4m and 6m. This simulation was conducted in an extreme condition that sensors are densely deployed in the target area. The number of sensors and target points are set to 100 and 50. All other parameters are identical as above. Particularly, possibility of a sensor being chosen is computed as formula (7). The parameter α and β in conventional ACO are set to be equal to 1.

All experiments are carried out on the PC with Intel(R) Core(TM) i3-4150 CPU at 3.50GHz and RAM of 8 GB.

Table 1.The number setting in every scenario

scenario	**Number of sensors**	**Number of target points**
S1	100	10
S2	150	10
S3	200	10
S4	100	30
S5	150	30
S6	200	30

4.2 Performance comparison

Conducted the two simulations, a comparison about the average working time will show as follows as Table.2.

Table 2.experimental results

Homogenous case			
	New method	ACB-SA	t-test
S1	71.8	68.1	18.13591
S2	126.7	124.5	8.02814
S3	126.2	123.1	13.99126
S4	64.1	61.0	11.49643
S5	79.6	72.7	24.22337
S6	145.2	139.7	14.74179
Heterogeneous case			
Ss1	66.3	64.8	5.56976

The first and second column of numbers is the average working time of the two algorithms. From the Table 2, significant differences can be shown, compared with the approach in [10], in every scenario, the average working time achieved by the new approach is significantly longer than that achieved by the ACB-SA. Hence, the new proposed approach has a promising performance in scheduling the sensors to achieve longer working time. The efficiency not only works well in the homogeneous WSNs, but also in the heterogeneous WSNs.

4.3 Computational complexity analysis

A promising algorithm has many requirements from kinds of aspects. Other than achieving good performance, in reality, fewer time and space consume are needed to be take into consideration. In this part, we focus on the comparation of computational complexity between approach in [10] and the new proposed approach to illustrate the promising performance of the new proposed approach in a further aspect.

In the ACB-AS, a round of ACO algorithm is aimed to select an optimal schedule in a time interval. Therefore, its computational complexity can be measured as (*# of colonies*) ·(*# of ants*) · (*# of target points*). In the new proposed approach, an ant finish an integrated schedule scheme includes schedule in every time interval. Similarly, its computational complexity can be calculated as (*# of colonies*) · (*# of ants*) · (*# of target points*). Apparently, these two algorithms has same order of magnitude in the case of computational complexity. However, the new proposed algorithm has a more promising performance than the existing approaches.

5. CONCLUSION

In this paper, we propose a novel approach to solve the Efficient Energy Coverage problem by applying an improved ACO. Proved by several experiments, the approach has a better performance than the existing one in [10]. Applied two improvements in two aspects, working time of WSNs have been extended in a relatively large extent. First of all, difference between target points has been taken into consideration. Target points which restrict the whole lifecycle have been taken as a priority of scheduling preference.

Then, a round of ACO algorithm is applied in constructing an optimal solution not only for a time interval, but a whole solution for the network. Introduced by this strategy, it is more possible to construct an optimal solution for the whole scheduling.

The construction of pheromone and heuristic information are also adjusted to make them more instructional for constructing solutions.

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