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Ant Colony Optimization for Enhancing Scheduling Reliability in Wireless Sensor Networks

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Abstract—**In the application of wireless sensor networks (WSNs), energy efficiency is always an important topic for extending the network lifetime. Scheduling the operation modes of sensors can reduce the energy wasted by redundant sensors, but frequent alterations of sensors' modes and different data transmission routes influence the reliability of the WSN. In this paper, a novel algorithm for maximizing the reliable working lifetime of a WSN is proposed. The considered problem restricts the minimum working period of the sensors before changing their operation modes. In order to extend the working lifetime of a reliable WSN, the proposed algorithm adopts the ant colony optimization (ACO) for finding the maximum number of reliable working periods of sensors. The performance of the proposed algorithm has been tested on various WSNs and compared with the state-of-the-art algorithms. The results show that the proposed algorithm can enhance the scheduling reliability of WSNs.**

Keywords- ant colony optimization; communications; coverage; lifetime maximization; routing; wireless sensor networks

I. Introduction

A wireless sensor network (WSN) [1]-[3] is composed of a large number of sensors, which are responsible for collecting information via sensing and transmitting the data to the sink via wireless communication. Each sensor is a relatively simple device with limited sensing and transmission ranges, and restricted data storage and processing ability. The sensors cooperate to accomplish a task in the WSN. Based on the sensing tasks of the sensors in the network, a WSN can be used to monitor humidity, temperature, pressure, and detect intrusions. Different from the other wireless networks, the feature of WSNs is that sensors are battery-powered and generally difficult to be recharged. Therefore, the energy should be used efficiently so that the WSN can operate normally in a long time.

Scheduling the operation modes of sensors is an effective method for energy conservation in a WSN [4]-[8]. Generally, there are sensors that can be turned to the sleep mode while the other sensors are active for work. It has been reported that the energy consumption of a sensor in the sleep mode is much smaller than that of an active sensor [7]. Scheduling redundant sensors to sleep can save the energy of the sensors and the sleeping sensors can wake up to be active when necessary.

According to the number of times for changing a sensor from the sleep mode to the work mode, there are two types of sensor scheduling implementations. The first is that the sensors can be changed from the sleep mode to the work mode only once, forming disjoint cover sets [9]-[11]. In this problem, the set of sensors ceases to operate when any one of the sensors in the set runs out of energy. In the second type of the sensor scheduling implementation, there is no constraint on the mode transition times of the sensors. The sensors can be active in different working periods and are not required to form disjoint sets. Reports have shown that the second scheduling implementation can extend the lifetime of a WSN better than the disjoint cover sets [12][13]. In this paper, the sensor scheduling implementation is based on the second type.

When a WSN is in normal operation, the scheduling of sensors' operation modes must comply with the requirements of coverage and connectivity of the active sensors to the sink. On the other hand, the sensed data must be sent to the sink. Because long distance radio transmission is energy consuming and the transmission ranges of sensors are limited, multi-hop transmission is widely used in WSNs. The resulting routing tree for transmitting data is termed a connected cover tree. If any active sensor runs out of energy or the predefined scheduling time interval is reached, the sensors change to sleep while another group of sensors is activated and forms a new connected cover tree. If no connected cover tree can be built any more, the lifetime of the WSN ends.

The length of each working time period has direct impact on the number of data transmission routing trees in the lifetime of the network and thus influences the reliability of the WSN. Some monitoring tasks require that each working period of the same group of sensors should not be shorter than a predefined value. Otherwise, the collected data will not be accurate enough for data analysis so that the WSN cannot fulfill its task. In that case, the reliable working lifetime of the WSN equals to the sum of the working periods, each of which is no shorter than the required minimum time.

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Many protocols and algorithms have been proposed for finding the scheme that can maximize the lifetime of WSNs. Zhao and Gurusamy [12] considered a connected target coverage problem and proposed an approximation algorithm and a communication weighted greedy cover (CWGC) algorithm for maximizing the network lifetime. Pyun and Cho [14] proposed a sensor-scheduling algorithm for multiple-target coverage and considered both the transmitting energy for collected data and overlapped targets. There are various methods for extending the lifetime of WSNs, but the work for maximizing the reliable working lifetime of a WSN remains unexplored.

In this paper, a novel algorithm for maximizing the reliable working lifetime of WSNs is proposed. We term the considered problem a scheduling time interval restricted WSN optimization problem, because the working period between two consecutive scheduling is restricted. The motivation of our work is to find the maximum number of the reliable working periods for scheduling the sensors to fulfill the monitoring task. Based on the optimal scheduling scheme, the WSN can work reliably in the longest time. The proposed algorithm adopts the ant colony optimization (ACO) [16]-[17] metaheuristic search framework for addressing the problem. In the literature, various heuristic algorithms have been proposed. Heuristic algorithms always give a feasible but not the optimal solution for the problem. For enhancing the solution quality for the problem, a metaheuristic algorithm has more chances to find much better solutions in an acceptable time.

In the proposed ACO_{rwsn} algorithm, the solutions are constructed not only based on the energy consumption of sensors' sensing and data communication, but also on the pheromone information that presents the historical attractions for using the sensors to cover the targets. The performance of the proposed algorithm has been tested on various WSNs and compared with the state-of-the-art algorithms. We also test the performance of the heuristic version of the ACO_{rwsn} algorithm. The results show that not only the ACO_{rwsn} algorithm but also its heuristic version can obtain more reliable working periods than the state-of-the-art algorithms.

The remainder of this paper is organized as follows. Section II presents the energy consumption model and the problem definition. Section III describes the detailed implementation of the proposed algorithm. A series of experiments are conducted and the results are analyzed in Section IV. Section V concludes our research.

II. ENERGY CONSUMPTION AND PROBLEM DEFINITION

The energy of sensors in a WSN is mostly used in sensing and data communication. In this section, we first introduce the energy consumption model by sensing and communication. Then the method for measuring the lifetime of a sensor is presented. At last, the definition of the optimization problem is described.

A. Energy Consumption by Sensing

Sensors in a WSN monitor a group of targets or an area by using their sensing components. Each sensor has a sensing range R_i, which covers a certain area. In the application of coverage problems, active sensors in a WSN must keep the targets under surveillance. The sensing range of a sensor has a direct impact on its energy consumption by sensing. The energy consumed by a sensor s_i for collecting a data bit of information is denoted as e_i^{sen}.

B. Energy Consumption by Communication

The sensed data must be transmitted to the sink. Each active sensor has a route to the sink and all the active sensors form a data transmission routing tree. Similar to sensing, the energy consumed by a sensor s_i for transmitting per data bit to another sensor s_j is closely related to the distance between the two sensors. The energy consumption can be measured as

$$e_{ij}^{\text{tran}} = \begin{cases} e_{\text{tran}} + bd_{ij}^{v}, & \text{if } i \neq j \text{ and } d_{ij} \leq r^{\text{tran}} \\ Inf, & \text{otherwise} \end{cases}, \tag{1}$$

where e_{tran}, b, and v are constants that depend on the transmission medium properties, d_{ij} stands for the Euclidean distance between sensors s_i and s_j when sensor s_j is the receiver of the data. In a WSN, sensors communicate via wireless signals. Wireless signals are restricted by a maximum transmission range r^{tran} ($r^{\text{tran}} = 2R$ in this paper). If the distance between any two sensors is larger than r^{tran}, the two sensors cannot communicate directly.

When a sensor s_j receives data from the other sensor s_i, the energy consumed for receiving per data bit is a constant denoted by e_i^{rec}.

It can be noted that the energy consumption by communication depends on the distance between any two communication sensors and the amount of data to be sent or received. According to (1), long distance radio transmission is energy-consuming. Therefore, multi-hop transmission has been widely used in WSNs and it has been proven to be more energy-efficient than one-hop transmission.

C. Estimation of the Lifetime of a Group of Sensors

In each working period of a group of active sensors, some active sensors (sensing sensors) work for covering targets, i.e. both sensing and data communication, whereas the other active sensors (relaying sensors) only facilitate data communication. The maximum lifetime of the group of sensors can be determined by the time when at least one sensor runs out of energy. Suppose the residue energy for each sensor s_i is E_i, the estimated lifetime of a sensing sensor s_i in the group g is

$$t_i^g = \frac{E_i}{c_i^{\text{sen}} e_i^{\text{sen}} + \sum_{j \in \Omega_i} c_{ji} e_i^{\text{rec}} + (c_i^{\text{sen}} + \sum_{j \in \Omega_i} c_{ji}) e_{il}^{\text{tran}}} \tag{2}$$

and the estimated lifetime of a relaying sensor s_i in the group is computed as

$$t_i^g = \frac{E_i}{\sum_{j \in \Omega_i} c_{ji} e_i^{\text{rec}} + \sum_{j \in \Omega_i} c_{ji} e_{il}^{\text{tran}}}, \tag{3}$$

where c_i^{sen} is the data generation rate of sensor s_i, c_{ij} denotes the data rate passed from sensor s_i to sensor s_j, Ω_i is the set of sensors that transmit data to s_i, and s_l is the receiver of the data sent by s_i.

D. *Definition of the Optimization Problem*

When a large number of sensors are deployed, part of the sensors can already fulfill the surveillance task and the other sensors can be changed into a sleep mode. Many examples have shown that scheduling the operation mode of sensors between working and sleeping after a period of time can extend the lifetime of the network better than just keeping the sensors working until their energy is exhausted. In each working period, data traffic is transmitted in a routing tree from the source sensor to the sink. Although reducing the time interval for scheduling the working mode of the sensors may increase the lifetime of the network, the network will become unstable for the frequent changing of the routing trees. Moreover, in some applications each working period for the sensors are restricted by a lower bound. It needs enough time to complete the monitoring and analysis task before starting a new working period. Suppose the time interval for each working period of active sensors is no smaller than σ .

In a scheduling time interval restricted WSN, a proper scheduling of sensors not only enhances the reliability of the network, but also extend its lifetime. The objective of the considered optimization problem is to maximize the reliable working lifetime of a WSN by finding the maximum number of reliable scheduling periods of sensors. In each period, the active sensors form a connected cover tree that can completely cover the targets and can operate reliably in the predefined time σ .

After the reliable working period of sensors, the residual energy may still be able to completely cover the targets until the targets cannot be completely covered any more. The total lifetime of those unreliable scheduling periods forms an unreliable working period of the network. For the scheduling plans that have the same number of reliable working periods, the length of the unreliable working period is used to measure which scheduling plan is better.

III. Implementation of the Proposed Algorithm

The proposed algorithm, termed ACO_{rwsn}, is a metaheuristic algorithm that is based on the ACO framework. In this section, we will describe the implementation of the algorithm.

A. *ACO Framework*

In the algorithm, each ant is a metaphor for a constructive process for selecting sensors to form connected cover trees. During the ants' solution construction, the possibility for selecting a sensor is measured by its pheromone value and a heuristic value. The pheromone value represents the historical searching experience of the ants, whereas the heuristic value reflects the desirability based on the current situation. The search framework of the ACO algorithm is illustrated in Fig. 1. We use *iter* to denote the number of iterations for running the algorithm. In each iteration, a group of *m* ants are dispatched to

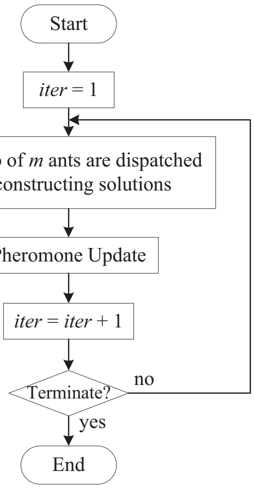

Figure 1. Framework of a basic ACO algorithm.

construct their solutions based on the pheromone and heuristic values. Pheromone values are updated according to the solution quality.

B. *An Ant' Solution Construction Behavior in ACO_{rwsn}*

In ACO_{rwsn}, the ants are independent solution construction process. They cooperate to search for better solutions via the indirect guidance of the pheromones. In this part, we will describe the behavior of an ant for constructing a solution step by step.

Step 1) Initialization

Before an ant starts to construct a solution, some parameters are initialized. We use an index 0 to denote the sink. Because the sink is not energy limited, its energy is always infinite (*Inf*). All the sensors 1 to N have their initial energy E_i, $i = 1, 2,\ldots, N$. Initially, all sensors have their initial energy level $E_i^{(k)} \leftarrow E_i,\ i = 1,2,\ldots,N$. The index k of the working period is initially set as 1 and the number N_{r} of the reliable working period is 0. In the following parts, we use the terminology 'node' in the graph theory to represent both the sensors and the sink.

Step 2) Construct a Complete Connected Cover Tree

Step 2-1) At the beginning, all sensors are in the sleep mode so that the set $\boldsymbol{V}$ of active sensors is empty ($\boldsymbol{V} \leftarrow \varnothing$). The set $\boldsymbol{C}$ of active sensors that perform the sensing operation is also empty ($\boldsymbol{C} \leftarrow \varnothing$). The targets are not covered therefore the uncovered targets set $\boldsymbol{D}$ is composed of all the targets. The weight w_{ij} for each edge between the nodes i and j in the graph is computed as

$$w_{ij} = \begin{cases} e_{ij}^{\text{tran}} / E_i^{(k)}, & \text{if } E_i^{(k)} > 0 \text{ and } E_j^{(k)} > 0 \text{ and } e_{ij}^{\text{tran}} \neq Inf \\ Inf, & \text{otherwise} \end{cases} , \quad (4)$$

where $i = 1,2,\ldots,N$, $j = 0,1,\ldots,N$. The value of the edge weight represents the estimated cost for using the edge for transmitting data from node i to node j. If the energy consumption by transmission e_{ij}^{tran} is small and the residual energy $E_i^{(k)}$ of the sender node i is large, the edge is more desirable. Note that if any one of the node is out of energy or they are not directly connected, the cost is regarded as infinite. Because the sink is the receiver of the data, the edge costs from the sink to the other sensors are not considered, simply denoting by $w_{0j} = Inf$, $j = 1,2,\ldots,N$. The initial traffic on each edge is zero.

Based on the edge weights, the minimum weight cost tree (MWCT) is built. The MWCT is a shortest path tree that connects all living sensors to the sink. It can be computed by algorithms such as the Dijkstra's algorithm.

Step 2-2) In the previous sub-step, the estimated minimum cost path for each living sensor to send data to the sink is obtained. In this sub-step, the sensors are selected one by one to fulfill the complete cover to all the targets while using the best route to transmit the data. Before completely covering all the targets, the following process is performed repeatedly.

1) For all living sensors j with $j \notin \boldsymbol{C}$, the heuristic value for selecting the sensor j is computed as

$$\eta_j = Cov_j \,/\, wp_j \,, \tag{5}$$

where Cov_j is the number of uncovered targets that are covered by the sensor j, wp_j is the total weight of the estimated minimum cost path from sensor j to the sink.

The desirability for selecting the sensor i is based on the heuristic value and the pheromone value as

$$\mu_j = \eta_j \cdot \tau_{ij}^{(k)} \,, \tag{6}$$

where $\tau_{ij}^{(k)}$ denotes the pheromone that is assigned to the connection for selecting a sensor i after selecting a sensor j in the kth working period.

2) According to (7), the ant has a probability q_0 to select the sensor j ($j \notin \boldsymbol{C}$) that has the maximum desirability, or a probability ($1 - q_0$) to perform a roulette wheel selection.

$$j = \begin{cases} \arg\max_{j \notin \boldsymbol{C}} \{\mu_j\}, & \text{if } q_1 < q_0 \\ J, & \text{otherwise} \end{cases}, \tag{7}$$

where q_1 is a uniform random value in [0,1). In the roulette wheel selection, suppose the candidate sensors are $b_1, b_2, \ldots, b_{|\overline{\boldsymbol{C}}|}$, the sensor b_s is selected if

$$\begin{cases} q_2 < p_1, & \text{if } s = 1 \\ \sum_{i=1}^{s-1} p_i \le q_2 < \sum_{i=1}^{s} p_i, & \text{if } s = 2,\ldots,|\overline{\boldsymbol{C}}| \end{cases}, \tag{8}$$

where q_2 is a uniform random value in [0,1) and

$$p_i = \frac{\mu_{b_i}}{\sum_{s \notin \boldsymbol{C}} \mu_s}, \quad i = 1,2,\ldots,|\overline{\boldsymbol{C}}|\,. \tag{9}$$

The first equation in (7) is also known as an exploitation search because the ant greedily selects the most desirable sensor, whereas the second equation is for exploring a different sensor by introducing a probability in selection. Such a construction method maintains diversity between the ants' search and avoids early searching stagnation.

3) After the next sensor j is selected by the ant, the sensor is added into $\boldsymbol{C}$ and $\boldsymbol{V}$. The targets covered by the sensor j are marked as covered.

4) A local pheromone update is performed by updating the pheromone value on the connection for selecting a sensor i after selecting a sensor j in the kth working period as

$$\tau_{ij}^{(k)} \leftarrow (1-\rho) \cdot \tau_{ij}^{(k)} + \rho \cdot I \,, \tag{10}$$

where ρ is a parameter in (0,1), I stands for one unit time. Because $\tau_{ij}^{(k)} > I$, the local pheromone update is used for evaporating the pheromone value on the selected connection so as to influence the other ants' selection for the same connection.

5) The sensors on the estimated minimum cost path from sensor j to the sink are traversed. Suppose the path is $<b_0, b_1, \ldots, b_n>$, where $b_0 = j$, $b_n = 0$. If they are not in the set $\boldsymbol{V}$, then add them in the set. Because the sensor j is responsible for sensing, the traffic is added on the edges on the path from sensor j to the sink. The updated traffic per time unit through the sensor b_i on the edge $< b_i, b_{i+1} >$ is presented by

$$traffic_{b_i} \leftarrow traffic_{b_i} + (e^{\text{new}} + e_{b_i b_{i+1}}^{\text{tran}}) \cdot c_j^{\text{sen}} \,, \tag{11}$$

If $i = 0$, $e^{\text{new}} = e_j^{\text{sen}}$. If $i = 1,2,\ldots,n-1$, $e^{\text{new}} = e_{b_i}^{\text{rec}}$. The weights $w_{b_i b_{i+1}}$ are also modified by

$$w_{b_i b_{i+1}} \leftarrow \left(1 + \frac{(e^{\text{new}} + e_{b_i b_{i+1}}^{\text{tran}}) \cdot c_j^{\text{sen}} \cdot \sigma}{E_{b_i}^{(k)}}\right) \cdot w_{b_i b_{i+1}} \,, \tag{12}$$

The numerator in the equation stands for the total energy needed in the whole reliable working period. The larger the proportion of the needed energy to the residual energy of the sensor, the cost of the edge is larger.

6) Based on the new edge weights, compute the MWCT again and update the wp_j for all living sensors j with $j \notin \boldsymbol{C}$. Isolated sensors are removed without consideration.

Step 2-3) After all the targets are covered and the data transmission routes are determined, compute the residual lifetime of all the active sensors $j \in \boldsymbol{V}$ by

$$life_j = E_j^{(k)} \,/\, traffic_j \,, \tag{13}$$

The minimum lifetime $\min_{j\in V}(life_j)$ of the sensors is the lifetime of the group of the active sensor in the kth working period. If the lifetime of the group is smaller than σ, the working period is not a reliable working period. Otherwise, the number N_r of the reliable working period adds one. The length of the kth working period is set as $t^{(k)} = \min(\min_{j\in V}(life_j), \sigma)$.

The residual energy of each active sensor $j \in V$ after the kth working period is updated by

$$E_j^{(k+1)} = E_j^{(k)} - traffic_j \cdot t^{(k)}, \tag{14}$$

The residual energies of the other sensors are not changed, i.e. $E_s^{(k+1)} = E_s^{(k)}$, $\forall s \notin V$.

Step 3) Complete Cover Detection

This step is used to evaluate whether the sensors still have enough energy to completely cover the targets. If the sensors cannot completely cover the targets, the ant finishes constructing the solution and stops. Otherwise, set $k \leftarrow k+1$ and go to Step 2) to construct a new tree.

C. Pheromone Mechanism

In the proposed ACO_{rwsn} algorithm, pheromones are assigned to each connection for selecting a sensor i after selecting a sensor j in the kth working period. The pheromone value for each connection is initially set as

$$\tau_{ij}^{(k)} \leftarrow \begin{cases} t^{(k)}, & \text{if } l_{ij} \in \Theta_k \\ I, & \text{otherwise} \end{cases}, \tag{15}$$

where Θ_k denotes the connection set which is composed of the connections selected in the kth working period. The initial value of $t^{(k)}$ can be obtained by any traditional heuristic algorithm such as CWGC or the greedy heuristic version of ACO_{rwsn} by setting $q_0 = 1$. It should be noted that the initial pheromone value on the selected connection is larger than that on an unselected connection, i.e. $t^{(k)} > I$.

During the construction process of the ants, the pheromones on the selection connections are reduced by the local pheromone update. After the m ants finish constructing their solutions, the m solutions are evaluated and compared with the best-so-far solution. The best-so-far solution is replaced if a better solution is found. The pheromone values of the selection connections $\tau_{ij}^{(k)}$ in the best-so-far solution are increased by the global pheromone update process as

$$\tau_{ij}^{(k)} \leftarrow (1-\alpha)\cdot\tau_{ij}^{(k)} + \alpha \cdot t_{\text{bsf}}^{(k)}, \tag{16}$$

where α is a parameter in (0,1), $t_{\text{bsf}}^{(k)}$ is the length of the kth working period in the best-so-far solution, $k = 1,2,\ldots,\Psi_{\text{bsf}}$. During the search of the algorithm, the reliable working periods tend to appear in the first few working periods. Therefore, we use Ψ_{bsf} to record the last appearance of the reliable working periods in all the periods. The global pheromone update is performed only to the first Ψ_{bsf} working periods. The pheromone values added to the connections depend on their previous pheromone values and the lengths of the corresponding working period. Before the termination of the algorithm, a new group of m ants will be dispatched and they search for better solutions.

IV. Experiments

We use a series of WSNs to test the performance of the proposed algorithm. All sensors are placed in a $100\text{m}\times100\text{m}$ area with the sink in the middle. The initial energy of each sensor is set to be 20 J. The parameters of energy consumption are set as $e_i^{\text{sen}} = e_i^{\text{rec}} = 150$ nJ/bit, e_{tran} = 50 nJ/bit, b = 100 pJ/bit/m^4, v = 4. The data rate generated by each sensing sensor i is c_i^{sen} = 10 kbps. The default setting of the proposed algorithm is m=5, $\alpha = 0.2$, $\rho = 0.2$, and $q_0 = 0.9$. Totally 90 ants are used for running the algorithm. In this paper, point coverage applications are considered.

The proposed ACO_{rwsn} algorithm is compared with a basic minimum set cover-shortest path tree (MSC-SPT) algorithm, the CWGC algorithm in [12], and the greedy heuristic version (HEU) of ACO_{rwsn} by choosing only the node with the largest value in (5) as the next node. The MSC_SPT algorithm repeatedly selects the sensor that covers the largest number of uncovered targets until the selected sensors can completely cover the targets. The sensed data are transmitted via the shortest path with the minimum communication energy consumption. Each complete cover group is formed in the above way until no more complete cover groups can be formed. The CWGC algorithm computes a MWCT before constructing each complete cover group. It greedily chooses the sensor with the largest profit as (5) and then uses a function to update the path weights of the upstream nodes in MWCT. In the heuristic version of the proposed algorithm, the edge weights are updated and a new MWCT is computed before selecting a new sensor. In this way, the sensors selected later can use the new minimum cost path to transmit its sensed data.

The sensors in the point coverage applications have the same sensing radius as R = 20m and $\sigma = 100\text{s}$. Fig. 2 shows the results of the four algorithms for solving the WSN cases with different number of sensors. The number of targets is 20. Fig. 2(a) shows the average number of reliable working periods obtained by the four algorithms in the cases that the number of sensors is from 50 to 130. The solutions achieved by the proposed ACO_{rwsn} algorithm are the best among the four algorithms. The heuristic version of ACO_{rwsn} is in the second place. Fig. 2(b) presents the proportions of the results of ACO_{rwsn} to those of MSC-SPT, CWGC, and HEU. The results of ACO_{rwsn} are almost twice of those by MSC-SPT. ACO_{rwsn} improves the results of CWGC and HEU by approximately 35% and 15% respectively.

Fig. 3 shows the influence of the number of targets to the performance of the algorithms. The number of sensors in the cases is 100. As the number of targets increases, the number of reliable working periods for the four algorithms reduces. The advantage of the proposed ACO_{rwsn} is still obvious.

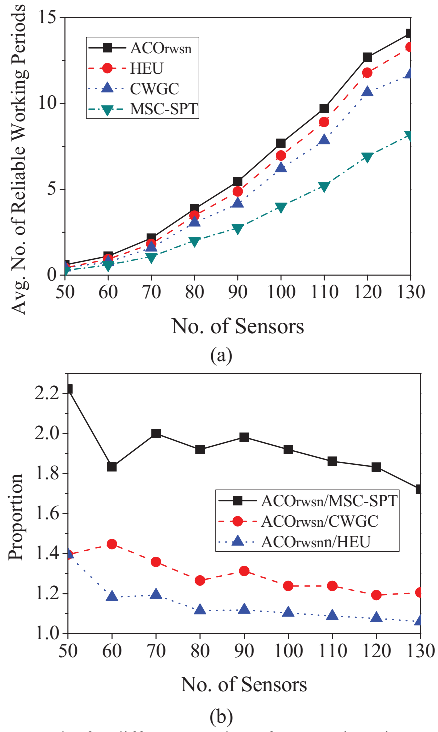

Figure 2. Results for different number of sensors in point coverage. (a) Average number of reliable working periods. (b) Proportions.

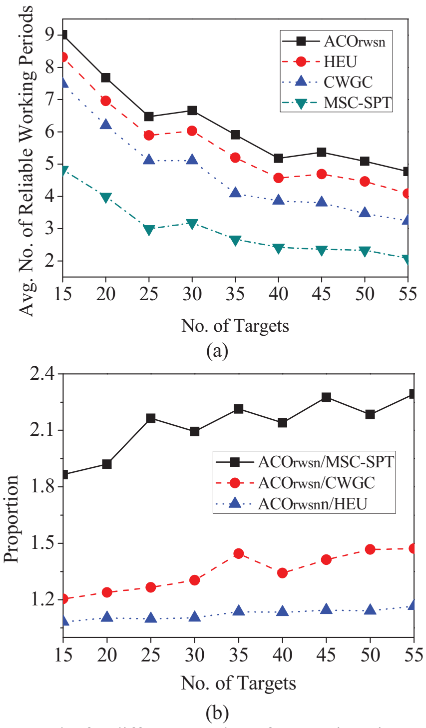

Figure 3. Results for different number of targets in point coverage. (a) Average number of reliable working periods. (b) Proportions.

V. CONCLUSION

In this paper, a scheduling time interval restricted WSN optimization problem is considered. The objective of the problem is to maximize the reliable working lifetime of the WSN. Although there are various methods for extending the lifetime of WSNs in the literature, the work for considering the reliable working lifetime of WSNs is new. This paper proposes a novel ACO_{rwsn} algorithm for addressing the problem. The algorithm adopts the ACO metaheuristic searching framework for finding the maximum number of reliable working periods of sensors. By comparing the performance of the algorithm with the state-of-the-art algorithms for WSNs, the proposed algorithm can enhance the reliable working lifetime of the network.

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