Ant colony optimization with greedy migration mechanism for node deployment in wireless sensor networks

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Node deployment is one of the most crucial issues in wireless sensor networks because it determines the deployment cost, the detection capability of the networks, and even the network lifetimes. To solve such a problem is an intricate task with realistic deployment factors such as deployment cost, connectivity guarantee, load balancing and channel collisions. In this paper, we consider the problem of grid-based coverage with low-cost and connectivity-guarantee (GCLC), and propose a novel deployment approach, ACO-Greedy, to settle this question. This approach is based on the ant colony optimization with greedy migration mechanism, which can quickly complete the full coverage, and markedly decrease the deployment cost. In addition, ACO-Greedy can dynamically adjust the sensing/communication radius to alleviate the energy hole problem and prolong the network lifetime. The simulation results reveal that our developed approach can not only decrease the deployment cost remarkably, but also effectively balance power consumption among sensor nodes and prolong the network lifetime in grid-based WSNs.

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1. Introduction

Wireless sensor networks (WSNs) have gained worldwide attention in recent few years, particularly with the development in Micro-Electro-Mechanical Systems (MEMS) technology and wireless communication technology. A WSN consists of a large number of sensors, which have the ability of sensing, computing and communicating, observing and reacting to relative events and phenomena in a specific region (Akyildiz et al., 2002; Akkaya and Younis, 2005; Sohraby et al., 2007). WSNs can be employed in wide applications in both military and civilian scenarios, including environmental monitoring, security surveillance, health care, home entertainment, building control, traffic management, object tracking, etc. (Muhammad et al., 2011; Daniel and Luiz Afonso, 2010). Due to various advantages such as ease of deployment, extended transmission range, and self-organization, WSNs have been replacing the traditional networks (Chin-Ling and I-Hsien, 2010).

The design of WSNs is a complicated task which has substantial impact on the quality, efficiency and cost of various applications. The deployment issue is a fundamental problem for WSNs, in that it determines the performances of the networks, including the deployment cost, the detection capability, and the lifetime. As such node deployment has newly attracted the attention of the research community. As sensor nodes are equipped with low-energy batteries whose charge cannot be replaced after deployment, energy conservation is a major concern in WSNs, while the rate of energy depletion primarily relies on the nature of node deployment (Subir et al., 2011).

Generally, the main goal of node deployment is to realize coverage and connectivity. WSN coverage can be classified based on different applications or metrics. Generally, it falls into three types (Misra et al., 2011): (1) area coverage, such as (Tao et al., 2006; Cheng et al., 2007); (2) point coverage, such as (Ai and Abouzeid, 2006; Cai et al., 2007); and (3) barrier coverage, such as (Kumar et al., 2007; Ram et al., 2007). For point coverage, it is usually divided into two categories, i.e., continued-points-based coverage and grid-based coverage. In addition, network connectivity is indispensable for node deployment, because it determines the realizability of communication among the wireless sensor nodes, the node and base station, base station and the clients, the clients and the servers (Zhang and Liu, 2012).

In general, sensor nodes act as both data originator and data forwarder. Moreover, data transmission follows a many-to-one communication pattern. For this reason, sensor nodes close to the sink have larger energy consumption because they are burdened with heavier relay traffic. Sensor nodes in these areas tend to die early when they deplete their energy and result to what is called energy hole (Cheng and Ruzena, 2004). If this appears, no more data can be delivered to the sink, a considerable amount of energy is wasted, and the network lifetime ends prematurely (Wu et al., 2008; Rabun et al., 2011). Therefore, the energy hole problem
should be taken into account for WSN designing, including node deployment.

In this paper, we consider and solve the problem of grid-based coverage with low-cost and connectivity-guarantee (GCLC). The objective of this problem is to design an algorithm which makes the needed region be covered by the deployed nodes. Besides, being defined by the total number of the deployed node in the network, the system cost is required as small as possible, as well as all the deployed nodes are connected through one or multiple hops. In this paper, a novel deployment approach, named ACO-Greedy, is proposed to solve the problem of GCLC. The goal of our approach is to avoid energy hole, decrease deployment cost, raise coverage speed, and finally better resolve the GCLC problem. ACO-Greedy is based on the ant colony optimization (ACO), but improves ACO by adding a new character, ants’ greedy migration. ACO is a well-known intelligent algorithm where complex collective behavior emerges from the behavior of ants. As one of the most successful swarm intelligence algorithms, it is very effective for solving NP-hard combinatorial optimization problems, such as traveling salesman problem (TSP) (Dorigo and Gambardella, 1997), and Quadratic Assignment Problem (QAP) (Gambardella et al., 1999). The problem of GCLC is also an applicable combinatorial optimization problem, thus ACO can be suitable for solving this problem.

The main contributions of our work are summarized as follows: (1) ACO is adopted and performed successfully for settling the GCLC problem in WSNs. (2) Based on non-uniform node distribution idea, we designed a non-uniform sensing/communication radius scheme, by which the energy hole problem is markedly alleviated and the network lifetime is distinctly prolonged. (3) By the high efficient scheme of object point selection in ACO, the heuristic value and the pheromone updating rule are reasonably defined, by which the total number of deployed sensors is decreased. (4) In ACO, it is the first time that the greedy migration scheme is proposed, thus it contributes to quickly completing the full coverage, as well as markedly decreasing the deployment cost.

The rest of the paper is organized as follows. In Section 2, literature review is elaborated. Section 3 presents the basic idea of our approach. The proposed novel algorithm is described in detail in Section 4. In Section 5, the performances of our approach are evaluated and analyzed by simulation results. Finally, the paper is concluded in Section 6.

2. Related work

Owing to various advantages, such as simplicity, flexibility, extendibility and implementability, the grid-based deployment has been widely used in WSNs to achieve significant improvements in terms of the network coverage and connectivity (Moro and Monti, 2011; Fadi and Hossam, 2013). Moreover, the grid deployment becomes necessary if sensor nodes are expensive and their operation is significantly affected by their positions. Hence, it has a broad range of applications, such as aircraft health monitoring, pollution flux monitoring, forest fire detection, and red wood trees monitoring (Fadi and Hossam, 2013). In the literature, the coverage of the grid-based WSNs has been extensively studied and several approaches have been designed to solve some experienced problems.

For grid-based coverage in WSNs, it has been proved to be NP-complete for deploying a network to k-cover points with minimum number of sensor nodes in Wei-Chieh et al. (2007). Moreover, it is also shown in Wei-Chieh et al. (2011) that the problem of deploying the minimum number of sensors on grid points to construct a WSN fully covering critical square grid cells is NP-complete.

An integer programming model has been developed to solve the sensor deployment problem of cost minimization under coverage constraints in Chakrabarty et al. (2002), then the framework of identifying codes is used to determine sensor placement for unique target location. A resource-bounded optimization framework has been presented for grid coverage in Dhillon and Chakrabarty (2003), and it is targeted at an average coverage as well as at maximizing the coverage of the most vulnerable grid points, but the storage and computing costs are too much on account of the large number of grid arrays.

Based on simulated annealing (SA) (Frank and Chiou, 2005), the grid-based node placement problem is formulated as a combinatorial optimization problem in WSNs, but the position of the sink and the connectivity problem have not been taken into account. Genetic algorithm (GA) has been used to determine optimal sensor placement for coverage (Habit, 2007; Yong and Xin, 2006). In Yong and Xin (2006), GA has been presented for grid-based node deployment, and a heuristic approach is presented to decode the chromosome, but the node communication problem has not been taken into consideration. ACO is also used for grid-based sensor deployment (Li et al., 2010), whose goal is to achieve full coverage with the minimal number of sensors, but it possesses large searching range, results in lots of inferior solutions and slow convergence. Besides, ACO with three classes of ant transitions is proposed in Liu (2012), where the coverage cost is obviously decreased compared with that in Li et al. (2010), while the deployment cost can be further improved. In addition, ACO based scheduling algorithm (Joon-Woo and Ju-Jang, 2012) and ACO with three types of pheromones (Joon-Woo et al., 2011) are proposed to solve the efficient-energy coverage problem in WSNs. However, the problem of energy hole has not been taken into account.

A virtual tree topology is constructed based on grid-based WSNs, and two node-placement methods, distance-based and density-based deployment schemes are proposed in Chih-Yung and Hsu-Ruey (2008) to balance the power consumption throughout the network, but this cannot achieve the deployment goal of the minimal number of sensor nodes. A multi-objective deployment method (Andreas et al., 2009) is presented for WSN deployment and power assignment, which is decomposed into a set of scalar sub-problems that are sorted according to their objective preference and tackled in parallel by using neighborhood information and evolutionary operators. The deployment issue in a planar grid region was formulated as a combinatorial optimization problem in Wu et al. (2007), where an approximate solution was proposed based on GA. The problem of sensors deployment was solved by devising the corresponding heuristic method. In He et al. (2010), an optimal deterministic deployment approach of sensor nodes is proposed by using the maximum multi-overlapping domains of target point s and the genetic algorithm. The genetic algorithm is used to find the least number of nodes to cover the target set and the optimal positions of these nodes from the candidate node positions. Literature (Guo et al., 2012) proposes a target coverage method based on grid scan. The best grid is chosen to place the next sensor. Meanwhile, a probabilistic sensing model is introduced, and the least sensing probability with which a node can sense a target is used to measure the whole coverage level. The deployment of indeterministic space with obstacles is researched in Zhang et al. (2010), where sensor’s detection models and coverage quality evaluation are set up, and the watershed algorithm is employed to choose the deploying sub-area. However, there is no consideration for the energy hole problem among the above literature.

According to our survey, each of the above methods has certain limitations and the problem of GCLC in WSNs has not been completely solved by the mathematic optimization methodology. Our proposed algorithm, ACO-Greedy, and the other ACO-based
algorithms, EasiDesign (Li et al., 2010) and ACO-TCAT (Liu, 2012), have some resemblances, but ACO-Greedy differs from the others in the following main aspects: (1) greedy migration mechanism is proposed in ACO-greedy, which further decreases the coverage cost compared with the other algorithms; (2) energy hole problem is considered and corresponding measure is taken in ACO-greedy, while this problem is not taken into consideration in other algorithms; (3) the goals of our algorithm are to achieve low coverage cost and realize load balancing. In some cases, ACO-Greedy would sacrifice a slight coverage cost for a large improvement of load balancing.

3. Basic idea

3.1. System model

In this work, we made some simple, common and realistic assumptions regarding the network:

(1) There is a sink, i.e., base station randomly located in the grid-based sensing field. Sensor nodes and the sink are all stationary after deployment.
(2) All the sensor nodes are with the same initial energy, while an unlimited amount of energy is set for the sink.
(3) All the sensor nodes can use power control to vary the amount of transmission power which depends on the distance to the receiver.
(4) Links are symmetric, i.e. any sensor node can compute the approximate distance to another node based on the received signal strength.
(5) Periodic data gathering is performed for WSNs in which each sensor node generates and sends the same amount of data per unit time to the sink via multihop relay transmission.
(6) For simplicity, the value of sensing radius is equal to that of communication radius for a specific sensor node, although they are not equal in some scenarios.
(7) The simplified model shown in Heinzelman et al. (2002) for energy dissipation is adopted. The energy spent for transmission of a l-bit packet over distance d is

\[ E_{tx}(l, d) = \begin{cases} lE_{elec} + l\gamma d^2, & d < d_0 \\ lE_{elec} + l\alpha d^2, & d \geq d_0 \end{cases} \]  

The energy spent for receiving a l-bit packet is

\[ E_{rx}(l) = lE_{elec} \]  

(8) The signal propagation model, which describes the path loss in the monitored environment, is used as follows (Rodrigues et al., 2007):

\[ P_r = K_0 - 10\gamma \log(d) - \mu d \]  

(3)

(9) The detection rate of a target with distance d to a sensor is given in the following way (Chakrabarty et al., 2002):

\[ P(d) = \begin{cases} 1, & if \ d \leq R_r \\ 0, & otherwise \end{cases} \]  

(4)

3.2. Basic idea

In the binary WSN model, the sensing field comprises discrete grid points on which sensors can be deployed and can detect the points of interest (PoIs) within the sensing radius. The goal of the GCLC problem is to search for a solution, i.e., a set of as small number of points as possible from the candidate grid points, so that a node is deployed on each grid point of the set. Finally, all the PoIs can be covered by the deployed nodes. Each member of the set is named a point of solution (PoS). Furthermore, every PoS should be connected to the sink by one hop or multiple hops. As an example, a WSN model and a solution to the problem of GCLC is shown in Fig. 1, where the black dots represent PoIs and the red ones represent PoSs. Here the green stars are the sink and the shadows represent the sensing/communication range of the nodes.

Our approach, ACO-Greedy, is based on the basic ACO. In the beginning the ant is on the sink which is located randomly in the network. The ant moves from a grid point to another step by step and a node is deployed on each grid point visited by the ant. The set of all grid points visited by the ant is a solution of the GCLC problem. In other words, each grid point visited by the ant is a PoS. By continuous ant transitions, all the deployed nodes can be connected together and the connectivity of the system is guaranteed.

4. Algorithm description

4.1. Object-point selection strategy

Each ant chooses the next point with a probability according to the pheromone intensity and the heuristic desirability. For the t-th iteration, the transition probability of the ant from point i to point j is...
is as follows:

\[ p_{ij}(t) = \frac{[r_{ij}(t)]^\alpha [h_{ij}(t)]^\beta}{\sum_{r \in S_{ij}^{\text{candidate}}} [r_{ij}(t)]^\alpha [h_{ij}(t)]^\beta} \]  
(5)

where the variable \( r_{ij}(t) \) is the pheromone intensity on edge \((i, j)\), the variable \( h_{ij}(t) \) is the heuristic value of the route from point \(i\) to point \(j\). The parameters \( \alpha \) and \( \beta \) are the constants, which determine the relative influence of the pheromone and the heuristic on the decision of the ant. For node \(i\), \( S_{ij}^{\text{candidate}}\) is the set of candidate points, located within the communication radius of node \(i\). In order to decrease the total number of deployed nodes, we choose the point that can cover relatively more Pols as a PoS. This idea is similar to that in Li et al. (2010) and Liu (2012).

**Definition 1. (ECP):** ECP (Effective Candidate Point) is defined as such a point on which the sensor node can cover at least one uncovered PoI.

In formula (5), the heuristic value of the route from point \(i\) to point \(j\), i.e.\( h_{ij}(t) \), is defined as

\[ h_{ij}(t) = \text{summation} \ (j) + 1 \]  
(6)

where the function summation \((j)\) is the summation of the ECPs within the communication radius of point \(j\). It is mirrored that \( h_{ij}(t) \) denotes the approximate number of potential ECPs, and this helps the PoS to cover more uncovered Pols.

After the ant finishes a tour, the pheromone intensity on every edge \((i, j)\) is updated according to

\[ r_{ij}(t + 1) = (1 - \rho) r_{ij}(t) + \Delta r_{ij}(t) \]  
(7)

where \( \rho \in (0, 1) \) is the pheromone evaporation parameter, and the added amount of pheromone \( \Delta r_{ij}(t) \) is given by

\[ \Delta r_{ij}(t) = \frac{Q}{\text{total} \ (t)} \]  
(8)

where the function total \((t)\) is the number of total PoSs in the solution, \(Q\) is a constant and \(Q > 0\). The function total \((t)\) in formula (8) contains the global optimization. Obviously, the added amount of pheromone has the potential capability of using less total nodes.

By above knowledge, both the heuristic definition and the pheromone updating rules can save deployment cost and raise efficiency of object point selection for ACO.

**4.2. Pheromone constraining strategy**

In order to prohibit algorithm stagnation or premature convergence in different scales of networks, the pheromone constraining process (Li et al., 2010) is adopted to constrain the pheromone value within the imposed limits, namely, \( r_{\min} \leq r_{ij} \leq r_{\max} \).

However, the pheromone value is not constrained in every iteration, but periodically. When the period \( T_c \), counted in specific iterations, is achieved, the pheromone is adjusted to the value within the limits. The period \( T_c \) differs in different scales of networks. In small-scale networks, the ant is likely to be attracted by the earlier paths, thus a relatively small value is assigned to \( T_c \) to constrain the pheromone value with high frequency. In contrast, the ant is not likely to be attracted by the earlier paths in large-scale networks, hence a relatively large value is given to \( T_c \) to constrain the pheromone value with low frequency.

**4.3. Non-uniform sensing/communication radius design**

Non-uniform node distribution is proved to be an effective method for alleviating energy hole in WSNs (Wu et al., 2008). In order to solve the problem of energy hole, we use non-uniform node deployment to place more nodes to the areas with heavier traffic, thus create different node densities in different areas. Specifically, we narrow the communication radius and/or sensing radius of the nodes that are close to the sink. In other words, in these areas, the communication region where the ACO candidate points are located is smaller, while the situation is reversed in the areas far from the sink. This is different from other approaches for the GCLC problem in grid-based WSNs, including EasiDesign (Li et al., 2010) and ACO-TCAT (Liu, 2012).

The sensing/communication radius is designed as follows. Let suppose \( R_{\max} \) is the maximum sensing/communication radius which is known and predefined. The sensing/communication radius of node \(i\), designed as a function with respect to its distance to the sink, is calculated by

\[ R_i = \left[ 1 - \frac{d_{\max} - d(i, \text{sink})}{\mu(d_{\max} - d_{\min})} \right] R_{\max} \]  
(9)

where \( d_{\max} \) and \( d_{\min} \) respectively represents the maximum and minimum distance between sensor nodes and the base station, \( d(i, \text{sink}) \) denotes the distance between node \(i\) and the sink, \( \mu \) is a predefined constant, which determines the minimal sensing/communication radius and can be adjusted according to the real environment. For instance, if \( \mu = 2 \), the sensing/communication radius of node \(i\) varies from \( R_{\max}/2 \) to \( R_{\max} \). Although the parameter \( \mu \) can be adjusted according to experiments, the minimal sensing/communication radius should not be too small for the purpose of avoiding packet collisions among nodes in realistic networks.

By setting non-uniform sensing/communication radius, the nearer the area is to the sink, the higher its node density is. By creating different node densities in different areas, i.e. adding more nodes to the areas with heavier traffic, the problem of energy hole can be markedly mitigated. Though the number of sensors is increased in the areas close to the sink, it is well worth it in that the extent of energy hole can be alleviated and the network lifetime can be prolonged.

**4.4. Ants' greedy migration scheme**

**Definition 2. (PoO):** In ACO, if the ant transfers from point \(i\) to point \(j\) according to the probability of formula (5), point \(i\) is defined as a PoO (Point of Origination).

**Definition 3. (PoD):** In ACO, if the ant transfers from point \(i\) to point \(j\) according to the probability of formula (5), point \(j\) is defined as a PoD (Point of Destination).

Generally, if ACO is used for the GCLC problem, such as EasiDesign, the ant performs continuous transitions with each step within the communication radius. In other words, on the path of the ant, the next PoO must be the latest PoD. Obviously, this method has great limitations, because an ECP or more may not be within the communication region of the latest PoD. Even if there is an ECP in the region, it may not cover more uncovered Pols. In other words, there will exist many sensors that cover little Pols. Accordingly, there will be too much deployment cost by traditional methods. Hence, in order to increase coverage efficiency and save deployment cost, the PoO selection mode should be improved.

In this paper, we present the strategy, greedy migrations of ants, to select better PoOs for high coverage efficiency and low deployment cost.

**Definition 4. (OPO):** Among all the PoSs, the point that possesses at least one ECP within its own communication radius is defined as an OPO (Ordinary Point of Origination).
**Definition 5. (SPO):** Among all the PoSs, the point that possesses the largest number of ECPs within its own communication radius is defined as a SPO (Superior Point of Origination).

With strength from **Definition 4**, there are multiple OPOs in many cases. Besides, known from **Definition 4**, if multiple PoSs possess the largest number of ECPs within the communication radius, there also exist multiple SPOs. In ACO-Greedy, on the path of the ant, the next PoO is not necessarily the latest PoD, while only the current SPO can be selected as the current PoO. If the current PoD is not a current SPO, the ant must migrate to a random current SPO which has the most ECPs. This is the reason that this strategy is named greedy migration.

As mentioned above, a SPO has the largest number of ECPs within the communication radius, thus more of uncovered PoIs are located on the area near to the SPO. By migrating to the SPO, the priority is given to tackling the deployment problem of this area with minimum nodes. For this reason, ants’ greedy migration helps to rapidly complete the full coverage, and significantly decrease the deployment cost. This is the most significant characteristic of our approach that makes it different from other algorithms for the GCLC problem, including EasiDesign. Moreover, on the basis of this, the connectivity of the system is guaranteed by continuous ant transitions with each step going back to one PoS which belongs to a connected system.

**Figure 2** is the comparison of different deployment approaches to the problem of GCLC. In (a), the method of ordinary ACO, the visiting route of the ant has been translated into “sink–A–B–C–D–E–F–G–H–I–J”, and there are totally 10 sensors deployed for this scene. However, in (b), the method of ACO-Greedy, when the ant arrives at point E, it could find that this point possesses very few ECPs. Thus, the ant does not regard point E as the current PoO, but migrates to the SPO of point B, which includes much more ECPs, and regards it as the current PoO. Then, it transfers from point B to point J and point I in turn. In the same scene, the visiting route of the ant has been translated into “sink–A–B–C–D–E–B–J–I” and only totally 7 sensors are deployed. It is mirrored from (a) that point F, point G and point H have little contribution for covering PoIs. Just due to the inexistence of sensors on the three points, the total number of deployed sensors is decreased in ACO-Greedy. In other words, the coverage efficiency is increased while the deployment cost is decreased.

Here, it is important to note that the greedy migration scheme in ACO-Greedy is different from the transition method in ACO-TCAT (Liu, 2012). It is just an ordinary migration scheme in ACO-TCAT (Liu, 2012), where the ant randomly chooses OPO as its PoO. However, the ant chooses a SPO as its PoO in ACO-Greedy. A SPO possesses the largest number of ECPs within its communication range, so generally more ECPs are distributed around the SPO, and the greedy migration scheme makes the ant quickly transfer to this area. This helps the algorithm to get rid of blindness in searching solutions and decrease the deployment cost as much as possible. For example, there are three OPOs, i.e. point A, point B, and point D, in **Figure 3**, where the ECPs are marked with blue cross-stars within the relative communication range. It is shown from the figure that point A, point B, and point D possesses one ECP, three ECPs, and one ECP respectively. Obviously, point B is the SPO. In ACO-TCAT (Liu, 2012), the ant randomly transfers to one OPO, including point A and point D, which is shown in **Figure 3(a)**, which could need more visiting steps and more deployment cost. Instead, the ant only transfers to point B, which is shown in **Figure 3(b)**. Apparently this migration scheme is better than the former.

**4.5. Algorithmic flow**

The algorithmic flow of ACO-Greedy is shown in **Algorithm 1**.

**Algorithm 1. ACO-Greedy**

```
Initialize all the parameters;
while (the maximum iterating times C max does not met) do
  for (each ant) do
    while (the set of uncovered PoIs is not empty) do
      for (each PoS) do
        computes the number of ECPs within the corresponding region;
        achieves the current SPOs;
      end for
    end while
  end for
end while
```

Fig. 2. The comparison of different deployment approaches. (a) ACO with no migration and (b) ACO with greedy migration.
if (the current PoD is not a SPO) then
migrates to a random SPO and regards it as the current PoO;
end if
computes the transition probabilities of all the candidate points;
transfers to one of the candidate points in terms of formula (5);
updates the set of PoSs;
updates the set of uncovered PoIs;
updates the set of ECPs;
end while
end for
compute each total number of sensors deployed by ants;
update the best solution;
update the pheromone intensity on every edge visited by ants;
end while
return the best solution;

5. Performance evaluation

5.1. Basic description

In this section, we assess the performance of grid-based deployments in terms of deployment cost, load balancing, and network lifetime. In each case we validate our approach under Visual C++ 6.0. Then, we discuss properties of different methods on the basis of some numerical results which have been validated through extensive simulations, as well.

EasiDesign (Li et al., 2010), ACO-TCAT (Liu, 2012) and ACO-Greedy share some similarities, including ACO-based, grid-based, and searching low cost of coverage, etc. Hence, we compare the three algorithms in terms to different performances. To keep the test simple, we only consider the plane environment with no obstacles.

As described previously, the goals of our algorithm are to achieve low coverage cost and realize load balancing. In other words, this is a multi-objective problem, which is generally NP-hard. It would be undesirable to observe a single performance by a unidirectional view. For this reason, the improvement of a specific performance is not emphasized.

The experiment was done with a square-shape network with totally 9 × 9 or 17 × 17 grid points. For the network with 9 × 9 grid points, the number of PoIs is set to 30 and 60 respectively, while for the network with 17 × 17 grid points, the number of PoIs is set to 90 and 180 respectively.

For simplicity, the communication radius is equal to the sensing radius. The communication radius in EasiDesign and ACO-TCAT is set to 2 grids, while varies from 1 grid to 3 grids in ACO-greedy. The initial energy of each sensor is set to 100 J. Other parameters are set as follows: $\alpha = 1.0, \beta = 3.0, \rho = 0.2, C_{max} = 150$. The above parameters are achieved by many experiments which make different algorithms have relatively good performances.

5.2. The average coverage cost

The average coverage cost of different approaches are compared in Fig. 4, where the value of the horizontal axis shows the position of the sink, denoted as $(x, y)$. From this figure, one can obviously witness that it needs more deployed nodes in EasiDesign compared with that in the other two algorithms. This is attributed to the migration schemes in ACO-TCAT and ACO-Greedy, both of which narrowed the searching space obviously. In most cases, the coverage cost in ACO-Greedy is larger than that in ACO-TCAT. This is due to the greedy migration scheme in ACO-Greedy, which could significantly decrease the number of the deployed nodes.

5.3. Comparison of energy consumption

Figure 5 compares the performance of different approaches in terms of residual energy after 25 rounds of data transmission. For simply, we select the first deployed 10 nodes, which are generally near the sink and bear huge responsibilities. It is mirrored from this figure that the residual energy values of different nodes in EasiDesign and ACO-TCAT vary significantly, while they vary relatively smoothly in ACO-Greedy. Therefore, compared with other algorithms, ACO-Greedy bears more ability...
of balancing workload of each node and avoiding energy hole. This is mainly owing to the non-uniform sensing/communication radius design, which results in uneven node deployment.

5.4. Comparison of the ratio of surviving nodes

In order to study the appearance time of the energy hole and the degree of the load balancing, different approaches with respect to the ratio of surviving nodes are compared in Fig. 6. By the same energy consumption model as above, it is mirrored from this figure that the first node dies later in ACO-Greedy than that in the other algorithms. In other words, ACO-Greedy is less likely to be subject to energy hole associated with the others. This is mainly due to the non-uniform node deployment scheme of our approach, which is described above. Compared with other algorithms, it can be revealed from Figs. 5 and 6 that the ability of load balancing can be improved markedly in ACO-Greedy.

6. Conclusion

In this paper, the problem of GCLC in WSNs was considered, and a novel deployment approach called ACO-Greedy was proposed to solve this problem. The goals of this algorithm are to use
the possible least number of sensors to cover the predefined PoIs and maintain communication connectivity in a real environment. In addition, energy hole must be controlled as much as possible. For this objective, the non-uniform sensing/communication radius scheme is presented to alleviate the energy hole problem and prolong the network lifetime. Moreover, the greedy migration scheme is proposed to quickly complete the full coverage and further decrease the coverage cost. It is witnessed from theoretical analysis and simulation results that our approach can not only maintain network connectivity and balance power consumption, but also decrease the deployment cost.

We will investigate some other issues with respect to the deployment algorithm in the future, including the extent of signal interference, the relationship between the communication range and the packet collision, the simulation methodology, etc.

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