Hindawi Publishing Corporation
Journal of Sensors
Volume 2016, Article ID 7057490, 12 pages
http://dx.doi.org/10.1155/2016/7057490

Research Article

Optimization-Based Artificial Bee Colony Algorithm for Data Collection in Large-Scale Mobile Wireless Sensor Networks

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Received 21 October 2015; Revised 27 January 2016; Accepted 17 February 2016

Academic Editor: Matthew J. Whelan

Data collection is a fundamental operation in various mobile wireless sensor networks (MWSN) applications. The energy of nodes around the Sink can be untimely depleted owing to the fact that sensor nodes must transmit vast amounts of data, readily forming a bottleneck in energy consumption; mobile wireless sensor networks have been designed to address this issue. In this study, we focused on a large-scale and intensive MWSN which allows a certain amount of data latency by investigating mobile Sink balance from three aspects: data collection maximization, mobile path length minimization, and network reliability optimization. We also derived a corresponding formula to represent the MWSN and proved that it represents an NP-hard problem. Traditional data collection methods only focus on increasing the amount data collection or reducing the overall network energy consumption, which is why we designed the proposed heuristic algorithm to jointly consider cluster head selection, the routing path from ordinary nodes to the cluster head node, and mobile Sink path planning optimization. The proposed data collection algorithm for mobile Sinks is, in effect, based on artificial bee colony. Simulation results show that, in comparison with other algorithms, the proposed algorithm can effectively reduce data transmission, save energy, improve network data collection efficiency and reliability, and extend the network lifetime.

1. Introduction

In recent years, there has been considerable advancement in research and development of wireless sensor networks, which are now commonly used in military, intelligent medical, and environmental monitoring fields [1]. Data collection is one of the key technologies applied in wireless sensor networks and as such has garnered particular attention from a large number of experts and scholars [2]. In traditional data collection program design, all nodes are fixed in position to collect data before being forwarded to the Sink through routing protocol [3]. Currently, the most challenging unsolved problems with this process include (1) the energy hole problem, where data streams follow a "many-for-one" mode which subjects nodes near the Sink to greater traffic load, resulting in premature energy depletion and the creation of an "energy hole" around the Sink; (2) the communication overhead problem, where, because the self-energy of sensor nodes is limited, there is control overhead regardless of the routing protocol algorithm and thus an inherent need to control the energy consumption of network nodes; and (3) the communication constraint problem, where the data from some certain nodes cannot be transmitted and thus necessitates control strategies for communication reliability, when the network is not connected.

Previous researchers have addressed the above problems by means of node mobility. The mobile node acts as a data collector, migrating through the network in accordance with defined routes to conduct data collection in the monitoring area. By taking advantage of mobile node features, the connectivity, coverage, and energy distribution of mobile wireless sensor networks (MWSN) can be deployed dynamically or adjusted according to real-time conditions so as to fill in routing voids in the network and blind zones in the sensor. Existing MWSN can be roughly divided into three categories: (1) those in which the Sink node moves and the common node stands; (2) those in which the Sink node stands and the common node moves; and (3) those in which both the Sink node and common nodes move. Wireless sensor networks with mobile Sinks are simple and practical and can significantly increase the life cycle of the network, so they are currently most popular with researchers out of the three categories. Because the nodes around the Sink transmit much more data than others, however, and are associated with large energy consumption, the Sink's moving path must be designed very carefully to ensure that the network has a sufficiently lengthy life cycle.

Previous researchers also have proposed a series of data collection algorithms based on solutions for mobile Sinks [4–8], which have partially solved the three problems mentioned above. It is difficult for these existing methods, however, to successfully account for data collection maximization, mobile path length minimization, and network reliability optimization simultaneously. In this study, we focused on a large-scale and intensive MWSN that allows for a certain amount of data latency, and through which partial nodes are selected as a cluster head node; the Sink dynamically selects its moving path so that, prior to its next data collection, the next hop destination is calculated and selected according to the prevailing network environment parameters and moving strategy. The traveling salesman problem (TSP) of artificial bee colony optimization is simultaneously employed to obtain the shortest path to each cluster head node while the other nodes transmit data to the nearest cluster head node for temporary storage via multihop routing. When the mobile Sink has reached the cluster head node, the cluster head node transmits the previously stored data to the mobile Sink. Based on this data collection program, we present a heuristic algorithm that jointly considers cluster head selection, the routing path from ordinary nodes to the cluster head node, and mobile Sink path planning to form a mobile Sink data collection algorithm based on the artificial bee colony. The proposed algorithm can effectively reduce data transmission and energy consumption, improve network data collection efficiency and network reliability, and extend the network's lifetime.

Verified through extensive analysis, this paper presents an efficient and reliable data collection mechanism, a MWSN data collection program based on the artificial bee colony algorithm. The main contributions of this paper can be summarized as follows:

(1) The mobile Sink data collection process, cluster head selection problems, routing path from ordinary nodes to the cluster head node, and mobile Sink path optimization, when considered synthetically, form an NP-hard problem.

(2) The path optimization of the mobile Sink can be formulated as a traveling salesman problem; then the artificial bee colony algorithm can be used to seek the features of the optimal solution and the shortest path of the mobile Sink so as to improve network data collection efficiency.

(3) Extensive numerical results are provided below which demonstrate the usage and efficiency of the proposed data collection algorithm.

(4) We also evaluated the performance of the proposed algorithm by comparing it with random walk and ant colony data collection algorithms.

The remainder of this paper is organized as follows: Section 2 analyzes the application scenario model and discusses other relevant studies on mobile WSN. Section 3 explains the maximization of data collection, the shortest moving path of the mobile Sink, and the NP-hard problem of network reliability optimization. Section 4 describes the basic principles of the artificial bee colony algorithm and presents the applied mathematical models and optimization steps for MWSN data collection. Section 5 provides the parameter setting and simulation results which validate the performance of the proposed algorithm, and Section 6 concludes the paper.

2. Application Scenario Analysis and Related Works

2.1. Application Scenario Analysis. Mobile Sinks can significantly reduce network energy consumption and avoid the energy hole caused by multihop transmission so that data collection is unaffected even if there is no data path between nodes. Mobile Sinks have particularly obvious advantages in sparse or unconnected networks [9]. Nevertheless, because the speed of the moving Sink node cannot be compared to the speed of wireless transmission, there is a delay from generation to transmission of sensor data. Figure 1 shows an example of a typical MWSN data collection process, where first the monitoring area is clustered and then the sensor node transmits the collected data to the cluster head node via routing for buffer memory and the mobile Sink only needs to visit the cluster head nodes to realize data collection, so the moving path is truncated, data transmission latency is reduced, and the network data collection efficiency and reliability are improved compared to a network without a mobile Sink.

In this study, we assumed the following characteristic application scenarios.

(1) Common sensor nodes are unmovable and the same as the model, with the exact same initial energy. Sensor nodes receive and transmit data consecutively and the cache point has enough RAM to store the necessary data.

(2) The Sink node has plenty of battery power, high storage capacity, and an appropriate degree of mobility. The communication distance of the Sink node is the same as that of an ordinary node.

(3) The Sink node can move freely regardless of restrictions of real road conditions toward the moving path of the nodes, assuming the ground in the monitoring area is flat.

(4) The intensive network allows some data transmission latency, and all nodes can be connected in a single- or multihop manner.

(5) All member nodes transmit data to their respective cluster head nodes along the shortest possible path.

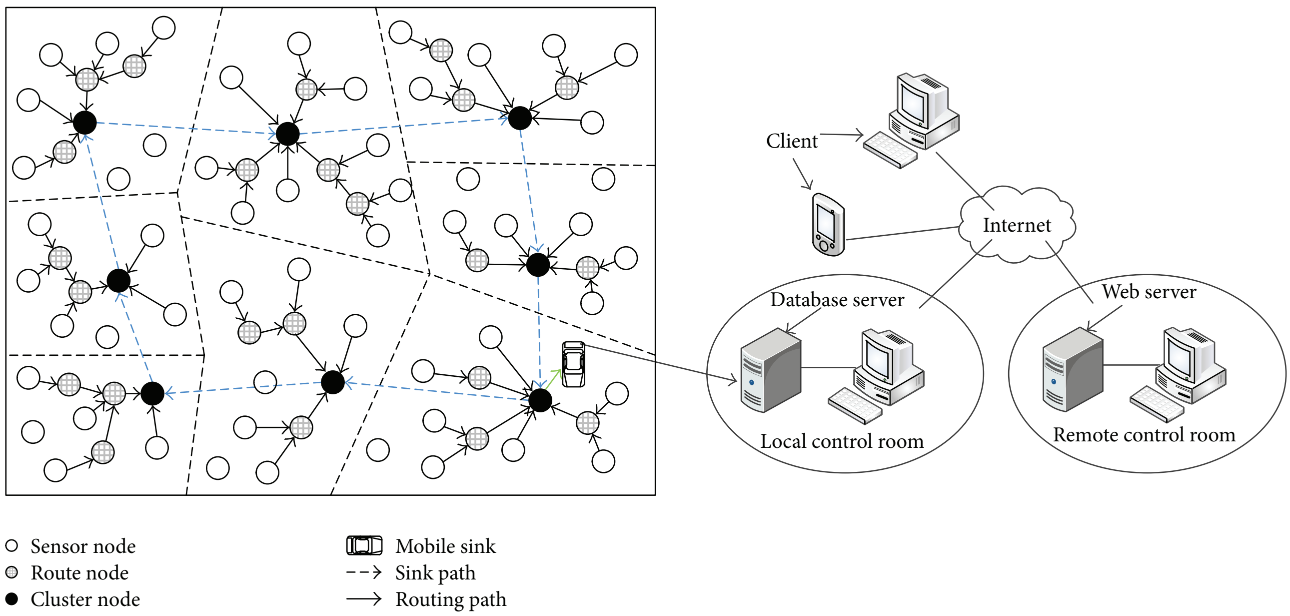


Figure 1: MWSN data collection.

2.2. Related Works. Currently, WSN data collection methods in terms of mobile Sinks can be divided into two categories: clustering schemes and mobile data collection. Clustering schemes represent a simple and effective approach to routing messages to the data Sink in a MWSN. Velmani and Kaarthick [10], for example, proposed the velocity energy-efficient and link-aware cluster-tree (VELCT) scheme for WSN data collection which effectively mitigates problems with coverage distance, mobility, delay, traffic, tree intensity, and end-to-end connection. Zhu et al. [11] proposed the tree-cluster-based data gathering algorithm (TCBDGA) for WSN with mobile Sinks and introduced a novel weight-based tree-construction method; TCBDGA can significantly balance the load of the entire network, reduce its energy consumption, alleviate the hotspot problem, and prolong the network's lifetime. Bai et al. [12] divided the entire sensor field into small patches to gather correlated data from each patch and proposed the estimation technique based on the marginal value theorem (EMVT), which maintains the fidelity of the interested data with relatively fewer collected sensor observations.

Compared to clustering scheme data collection, introducing mobility for data collection benefits the network with balanced energy consumption. Li et al. [13], for example, studied the ubiquitous data collection problem of mobile users in WSN and proposed a novel approach to collecting network-wide data which ensures low data collection delay and real-time data acquisition for the mobile user. In another study, the authors established a theoretical model where sensor nodes are uniformly distributed in a circular area; when the mobile Sink along the radius is shorter than the monitoring area radius the circle, results are optimal [14]. Zhao et al. [15] proposed a three-tier network architecture for MWSN which includes a distributed load-balancing algorithm that improves data collection efficiency and lengthens network lifetime. Liu et al. [16] studied the relationship between MADC (mobility-assisted data collection) during the network life cycle and data collection efficiency and analyzed the impact of a single node versus multiple Sinks' node network in terms of data collection efficiency and network lifetime. In another study, researchers investigated the selection problem of the aggregation node on the fixed straight track selection problem, where the Sink periodically moves along a straight track for data collection and obtains the shortest path to each cluster head node, while other nodes transmit data to the nearest cluster head node for temporary storage via multihop routing; when the mobile Sink has reached the cluster head node, the cluster head node transmits the previously stored data to the mobile Sink [17]. He et al. [18] formulated a traveling salesman problem with neighborhoods (TSPN) and, due to its NP-hardness, proposed a combine skip substitute (CSS) scheme which was proven efficient through extensive simulation.

As opposed to the above approaches, we would assert that the problems of cluster head selection, the routing path from ordinary nodes to the cluster head node, and mobile Sink path planning optimization should be considered synthetically and regarded as an NP-hard problem. Mobile Sink path optimization can likewise be considered as a traveling salesman problem; then the artificial bee colony algorithm can be used to seek optimal solution features and search the shortest path of the mobile Sink so as to improve network data collection efficiency.

3. Problem Description

The primary objective of this study was to develop a WSN mobile Sink path optimization selection mechanism based on the artificial bee colony algorithm which solves problems related to data acquisition quantity, energy consumption, network reliability, and a few other technical indicators. This included three specific optimization objectives:

(1) maximize system data acquisition quantity;

(2) ensure the shortest moving path of the mobile Sink while collecting data;

(3) minimize the overall system power consumption and optimize network reliability based on maximized data acquisition.

In order to minimize the maximum energy consumption of each sensor node as well as the total energy consumption in the next round, the optimal location of Sink's next hop can be calculated under linear constraints. The target function (see formula (1) for an example) takes minimizing the maximum energy consumption of a single sensor node. X_{ij} represents the amount of information that node i passes to node j ($j \in N(i)$) in a round of data collection, Restrictive Constraint (2) balances each node's information, and the output information of node i is equal to the input information plus the information produced by node i. E_r (resp., E_t) represents the energy consumption of a sensor node for receiving (sending) a data packet. Condition (3) ensures that the energy consumption of node i is less than αRE_i ($0 < \alpha \leq 1$), and Condition (4) ensures that the Sink has at most $K_{\max}$ viable positions. Constraint (5) ensures that node i with the Sink only can send information at a viable position. The restrictions on the target function and Constraint (6) minimize the maximum energy consumption of each node in each round of data collection [19]. See the following:

$$\text{minimize} \quad E_{\max} \tag{1}$$

$$\sum_{j \in N(i)} x_{ij} - \sum_{k \in N(i)} x_{ki} = T, \quad i \in V \tag{2}$$

$$E_t \sum_{j \in N(i)} x_{ij} + E_r \sum_{k \in N(i)} x_{ki} \leq \alpha RE_i, \quad i \in V \tag{3}$$

$$\sum_{l \in V_f} y_l \leq K_{\max} \tag{4}$$

$$\sum_{l \in V_s} x_{ik} \leq T \left| V_s \right| y_k, \quad k \in V_f \tag{5}$$

$$E_t \sum_{j \in N(i)} x_{ij} + E_r \sum_{k \in N(i)} x_{ki} \leq E_{\max}, \quad i \in V \tag{6}$$

$$\begin{aligned} & x_{ij} \geq 0, \quad i \in V_s, \ j \in V; \\ & y_k \in \{0, 1\}, \quad k \in V_f. \end{aligned} \tag{7}$$

During the data collection process, the mobile Sink can find as many cluster head nodes and the shortest traversal path it needs. Moreover, it can also find the shortest route from the common sensor node to its own path. In effect, MWSN data collection is an NP-hard problem. The function combination, TSP path planning optimization, and other problems have been addressed successfully when formulated as NP-hard problems.

As mentioned above, the artificial bee colony algorithm is an intelligent, efficient, simple, and easily implemented optimization algorithm characterized by fast speed and distributed computing. Here, we propose that the artificial bee colony algorithm lends energy-saving and enhanced reliability effects to MWSN data collection, as it optimizes the path of the mobile Sink, reduces energy consumption, improves network data collection efficiency and consistency, and prolongs network lifetime.

4. Artificial Bee Colony (ABC) Algorithm and Data Collection

4.1. ABC Algorithm. In a 2005 study, inspired by the foraging behavior found in bee colonies, Zhang et al. [20] proposed an innovative heuristic method called the artificial bee colony (ABC) algorithm. In the ABC algorithm, there are three "bee" groups in the "colony": onlookers, scouts, and employed bees, where each bee represents a position in the search space; the ABC algorithm employs populations of bees to identify the optimal path. A bee waiting on the "dance" area to choose a food source is an onlooker, a bee randomly searching is a scout, and a bee going to a previously visited food source is an employed bee. The positions of food sources represent possible solutions to the optimization problem, and the amount of "nectar" of a food source corresponds to the quality (fitness) of the associated solution. The first half of the colony consists of employed bees and the second half consists of onlooker bees.

The ABC algorithm can be split into four main steps [21].

(1) Initialization. Assume that population size is SN, where N is the first generated food source of initial population $X_i = \{X_{i1}, X_{i2}, \ldots, X_{iD}\}$ ($i = 1, 2, \ldots, N$), with D being the vector dimension of the optimization problem. The random initial population is then

$$X_i = X_{\min} + \text{rand}(0, 1) \cdot \left(X_{\max} - X_{\min} \right). \tag{8}$$

(2) Population Updating. The initial positions of food sources are randomly generated and each employed bee was assigned to a food source; then every employed bee determines a new neighboring food source of its currently associated food source via (9) and then computes the nectar amount of the new food source for each iteration. If the nectar amount of the new food source is higher than the previous one, the employed bee moves to the new food source; if not, it continues with the old one:

$$V_{ij} = X_{ij} + \text{rand}(-1, 1) \cdot \left(X_{ij} - X_{kj} \right), \tag{9}$$

where $k \in \{1, 2, 3, \ldots, SN\}$, $j \in \{1, 2, 3, \ldots, D\}$, and rand$(-1, 1)$ is the numerical value between randomly produced $(-1, 1)$, which controls the producing range of X_{ij} neighborhood. The neighborhood scope gradually decreases as the search approaches the optimum solution.

(3) Bee Source Selection. In this stage, the employed bees move according to the income rate (calculated according to fitness

```
Initialize the routing table
While TRUE do
  Listen for packets;
  If Receive Broad_Msg{0, 0, 0}
    Be selected as a cluster;
    Send Broad_Msg{1, SNA, 0} //SNA is the network address of current node
  Else If Receive Broad_Msg{1, srcNetwAddr, hop}
    Lookup routing table with destination srcNetwAddr;
    If no corresponding route item
      Add new item to the routing table {Destination = srcNetwAddr, Metric = hop + 1}
      Broadcast Broad_Msg{1, srcNetwAddr, hop + 1}
    Else If Metric > hop + 1
      Update route item with new metric Metric = hop + 1
      Broadcast Broad_Msg{1, srcNetwAddr, hop = 1}
    Else
      Ignore current broadcast message
    End If
  End If
```

Algorithm 1: Cluster selection algorithm.

value) of their sources. Food sources with high income rates are more likely to be selected, according to the following equation:

$$P_i = \frac{\text{fit}(X_i)}{\sum_{n=1}^{SN} \text{fit}(X_n)}, \tag{10}$$

where $\text{fit}(X_n)$ is the fitness value of the solution $n(n)$ proportional to the nectar amount of the food source $n \in \{1, 2, 3, \ldots, SN\}$. Fitness is calculated as follows:

$$\text{fit}(X_n) = \begin{cases} \dfrac{1}{f(X_n)}, & f(X_n) \geq 0 \\ 1 + \text{abs}(f(X_n)), & f(X_n) < 0, \end{cases} \tag{11}$$

where $f(X_n)$ is the objective function value of bee source X_n. The followed bees search in the neighborhood of the sources, which improves the local exploitative ability of the algorithm.

(4) Population Elimination. Suppose a certain solution gains no obvious improvement after continuous limit cycling updates; it is then assumed to be caught into local optimum and is abandoned; then the corresponding onlooker bees turn into scouting bees and randomly produce a new solution to replace the eliminated solution by

$$X_{ij} = X_{\min j} + \text{rand}(0, 1)\left(X_{\max j} - X_{\min j}\right). \tag{12}$$

The new solution obtained by calculation replaces the old and the optimum solution is output accordingly. $j \in \{1, 2, 3, \ldots, D\}$, $\text{rand}(0, 1)$ is the numerical value between randomly produced $(-1, 1)$, and $X_{\max}$ and $X_{\min}$ are the maximum and minimum values [22].

The ABC algorithm is a new type of intelligent population optimization which shows the following advantages: (1) the bee population algorithm is convergent to the whole and at relatively quick convergence speed; (2) the application range of the algorithm is quite wide; (3) it requires relatively few parameters to be set compared to other optimum algorithms; and (4) it is based upon population, so it is easily realized and processed.

4.2. ABC Algorithm in Data Collection Applications. Considering that the mobile Sink energy source, storage source, and algorithm source are not restricted, the Sink completes the complicated centralized optimum algorithm in data collection communication protocol; said communication protocol can be divided into two stages: the initialization phase and data collection phase.

The initialization phase comes first, through which entire network topology information is obtained, cluster head nodes are selected, and member nodes join each cluster head and node. The mobile Sink runs three respective stages to complete this task. First, it gradually broadcasts Broad_Msg{0, 0, 0} of Type 0 and all the nodes receiving information are automatically chosen as cluster heads. Cluster heads broadcast Broad_Msg information of Type 1; then other member nodes continue broadcasting this information to establish several shortest path trees which take the cluster head as the root. In Broad_Msg of Type 1, srcNetwAddr is the address of the tree's root node, and hops move to the current route tree root cluster head (see Algorithm 1 for a diagram). By the end of this process, all nodes have obtained the shortest hop information from the cluster head; then they send related information to the corresponding cluster head; in the next stage, the latter send the shortest hop information to the mobile Sink. During this first stage, cluster nodes also record the first time they enter and last time they leave the communication scope of the mobile Sink.

In the next stage, again, the cluster head and node send the shortest hop information and communication time information collected in the above stage to the mobile Sink. According to this information, the mobile Sink calculates the communication time assigned to each cluster head. This numeration of communication time and data collection is expected to be completed by the mobile Sink with strong calculating and storage ability in the offline mode.

In the third stage, the mobile Sink broadcasts the above calculation results to the entire network, creating a series of matching relationship lists between member nodes and cluster heads. Each node receiving this broadcasting information obtains its objective cluster head information and then eliminates items related to itself in the broadcast information and continues broadcasting, thus completing the optimum cluster head selection process for the entire network.

Next comes the data collection phase. After initialization, all network nodes continuously collect data and send it to their objective cluster head along the route tree as established. Each cluster head caches itself and the sensory information of other member nodes before the arrival of the mobile Sink. Similar to mobile route planning issues of the ABC algorithm as it optimizes the traveling salesman problem, the Sink dynamically selects its mobile route; in other words, before it collects the next round's data, it calculates and chooses the next hop's objective position according to current network environment parameters and mobile strategy to obtain the shortest route to each cluster head and node.

As mentioned above, new cluster heads have higher priority in terms of communication with the mobile Sink. In order to maintain balance in the amount of information exchanged among member nodes, the cluster head is selected through a roulette wheel method. Again, the Sink selects its mobile route dynamically by calculating and selecting the next hop's objective position before collecting the next round of data according to the current network environment parameters and mobile strategy; it uses the ABC algorithm to solve the traveling salesman problem to find the shortest route to each cluster head from which it receives data (Figure 2).

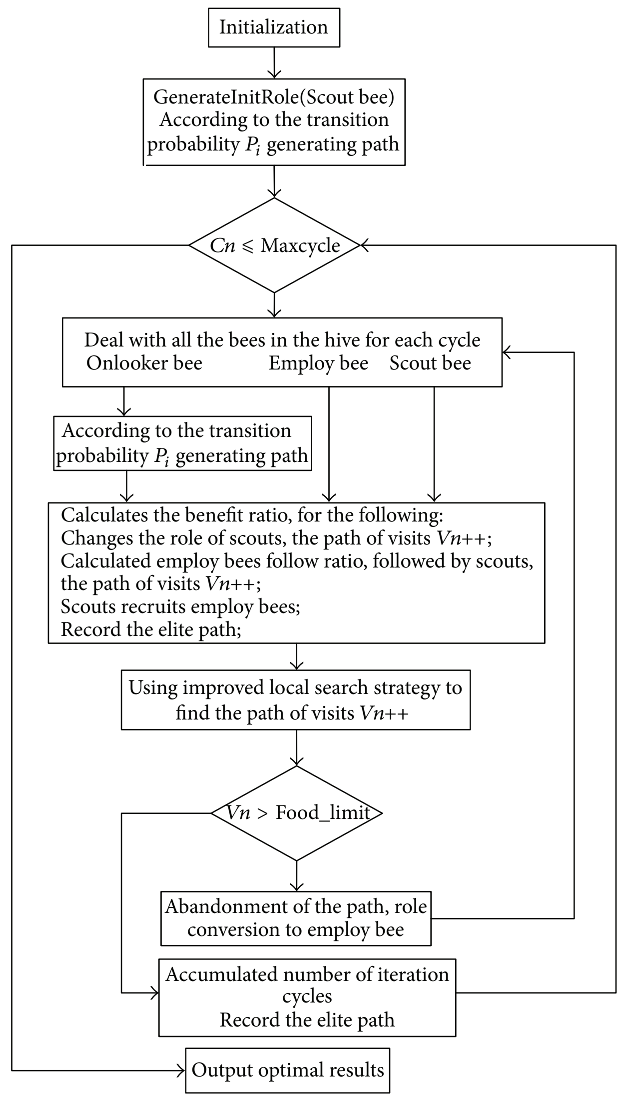


Figure 2: Data collection of mobile Sink based on ABC algorithm flowchart.

5. Performance Analysis

5.1. Simulation Environment. We used the MATLAB simulator to conduct performance analysis of the proposed method. In our simulation scenarios, 200 sensor nodes and a mobile Sink were deployed uniformly initially at random in a 500 × 500 m^2 square area; other parameter settings are listed in Table 1 [23]. The ABC algorithm parameters included population quantity of 50, limit value of 200, and iterations of 60. Sensor nodes generated 10 bytes of data every 1 min and sent it to the cluster head node for storage. The maximum time delay permitted by the network was 20 min, a round of data collection was completed by the mobile Sink also every 20 min, and the mobile Sink collected about 1.5 K bits of data from each cluster head node. When mobile Sink moved at a constant speed of V_{Sink}, the data-range of the total mobile Sink path length was 1000 m–7000 m.

For the purposes of this study, we built the energy consumption model and radio model of transmitting a k-bit packet transceiver according to the working energy model of the sensor node, energy model, and MWSN communication radio model shown in Figure 3.

Table 1: Simulation environment parameters.

Parameter	Value
Network size	500 × 500 m^2
Node number	200
Radius	80 m
V_{Sink}	5 m/s
Initial energy	0.5 J
E_{elec}	50 nJ/bit
E_{fs}	10 pJ/bit/m^2
E_{mp}	0.0013 pJ/bit/m^4
Data size	4000 bits

In Figure 3, E_{elec} represents the wireless communication transmitting circuit and the receiving circuit, each of which transmit/receive 1 bit of data packets to consume energy; E_{amp} represents an enlarged section of transmitting circuit packet

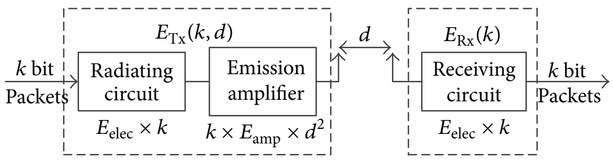


Figure 3: Energy model and MWSN communication radio model.

units required per bit of energy consumed. The WSN energy consumption model combines two models of free space and multipath attenuation, and the energy consumption of a node as it sends data is calculated via (13) [23]. According to the distance between the sending node and the receiving node, different energy consumption models can be used to measure the energy required for the sending node to transmit data, where the source node sends l bytes of data to another node from d. See the following:

$$E_{\mathrm{Tx}}(l, d) = \begin{cases} l \times E_{\mathrm{elec}} + l \times \varepsilon_{fs} d^2, & d < d_0 \\ l \times E_{\mathrm{elec}} + l \times \varepsilon_{\mathrm{amp}} d^4, & d \geq d_0, \end{cases} \tag{13}$$

where l is the length of the data in bits and d is the data transmission distance in meters. $E_{\mathrm{Tx}}(l)$ is the power consumption of the data sent by the sending circuit length of l, $E_{\mathrm{Tx}}(l, d)$ is the length of l data sent to the distance of d as energy is consumed, and the model gives a threshold value of d_0. After the node receives the message, the energy consumption is as follows:

$$E_{\mathrm{Rx}}(l) = l \times E_{\mathrm{elec}}. \tag{14}$$

The energy consumption of cluster head node during data fusion is

$$E_{Ax} = l \times E_{DA}\left(1 + \frac{N}{k} - 1\right) = l \times E_{DA} \times \frac{N}{k}. \tag{15}$$

The threshold d_0 is determined by the following formula:

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{\mathrm{amp}}}}, \tag{16}$$

where E_{elec} is connected to the channel encoding, modulation, filtering, spread spectrum signals, and other factors and $\varepsilon_{fs} d^2$ and $\varepsilon_{\mathrm{amp}} d^4$ depend on the specific bit error rate conditions.

We also performed simulation experiments to determine the performance related to average energy consumption, network lifetime, network latency, network connectivity, network load balance, and network reliability. A schematic diagram of the MWSN clustering process is shown in Figure 4.

From here on, "random walk" refers to the random walk algorithm, "ACO" to the traditional ant colony algorithm, and "ABC" to our proposed algorithm as they apply to the mobile Sink.

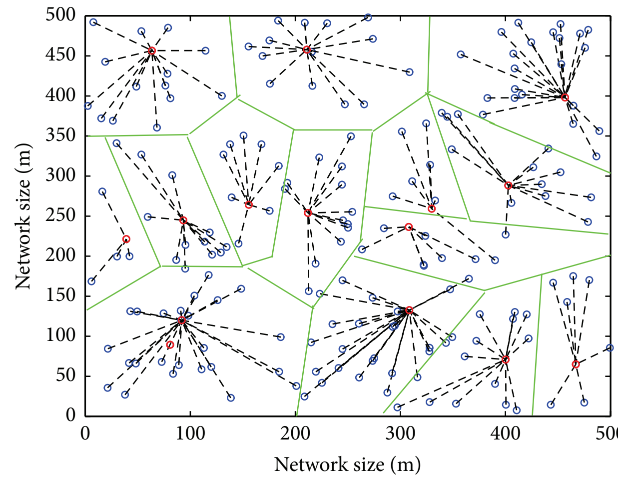


Figure 4: MWSN clustering.

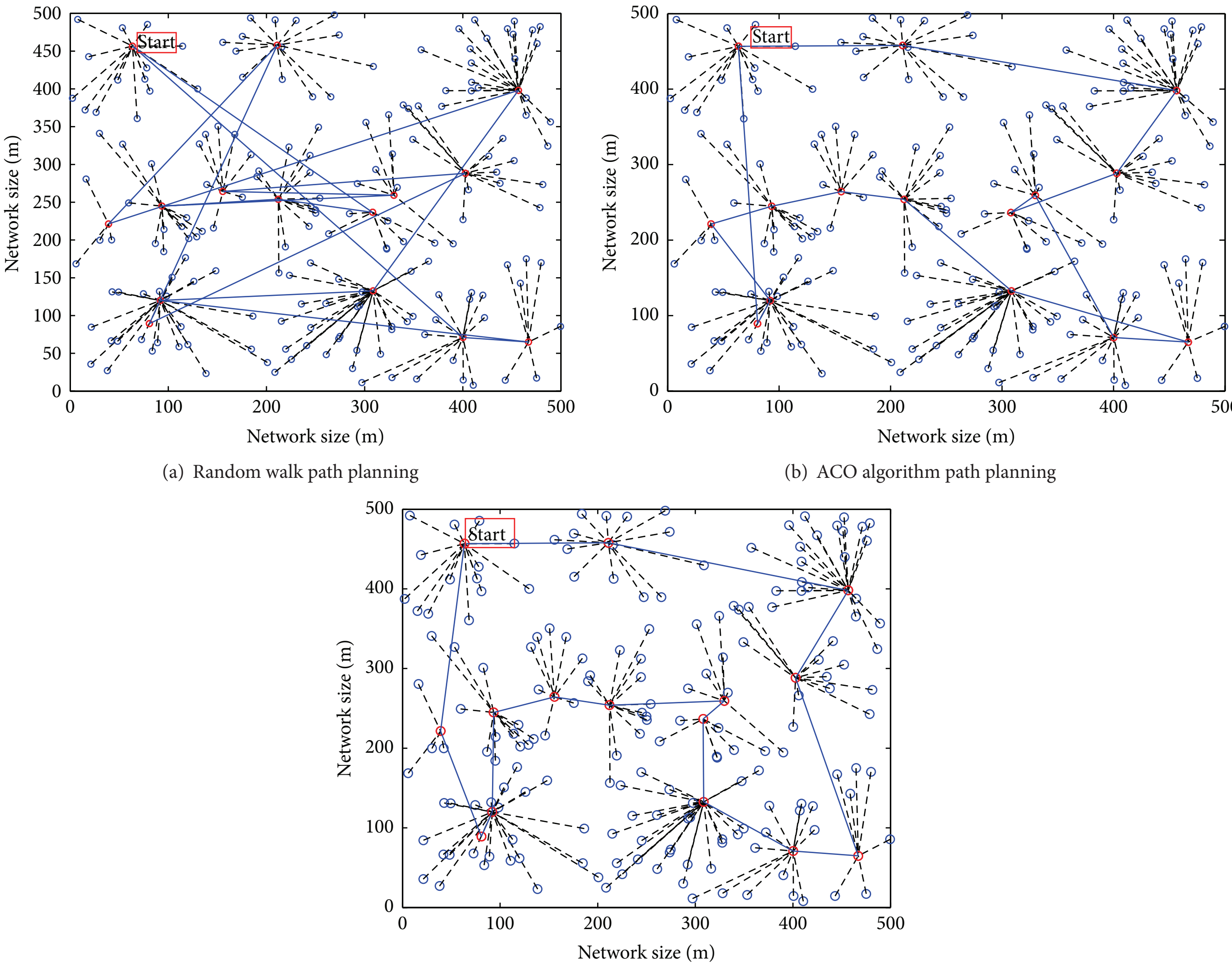
5.2. Performance Analysis

5.2.1. Mobile Path Planning. Figure 5 shows a comparison among the data collection mobile path algorithms in the simulated MWSN. The total path length across which the mobile Sink conducted data collection of all the nodes in the monitoring area according to the three algorithms is shown in Figure 6.

As shown in Figures 5(a), 5(b), and 5(c), the random walk algorithm results in a highly disordered data collection path; the ACO algorithm showed slightly better results, where the ergodic path of the mobile Sink was relatively short. The ACO path did not identify the optimal routes across all cluster head nodes, however, while the ABC algorithm consistently identified the shortest path of movement for all nodes in the simulated network. As shown in Figure 6, the moving path of the random walk was sporadic and unpredictable and path lengths fluctuated considerably, with an average around 4000 m. The ACO algorithm found an optimal path around 40 iterations with average length of about 2400 m. The ABC algorithm found an optimal path at only 34 iterations and at average length of only 1800 m.

5.2.2. Energy Consumption. Energy consumption is an important indicator of network performance. The total energy consumption of the three network algorithms is shown in Figure 7(a). As the number of simulation iterations increased, network energy consumption gradually increased for all three though random walk showed the largest increase in energy consumption, followed by the ACO algorithm and finally the proposed algorithm, which saved 18.2% energy compared to random walk and 4.5% energy compared to ACO.

We next simulated the same scenarios but iteratively increased the number of nodes (100, 200, 300, . . . , 1000 sensor nodes) in a 500 m × 500 m field, as shown in Figure 7(b). As the number of nodes increased, the energy consumption of all three algorithms gradually increased, but again, random



(a) Random walk path planning

(b) ACO algorithm path planning

(c) ABC algorithm path planning

Figure 5: Mobile Sink path planning.

walk consumed the most energy; and again, the ABC algorithm consumed the least energy (and at a relatively stable level), while the ACO algorithm performed second best. In effect, the energy consumption of the ACO algorithm was reduced considerably after the modifications we made to create the ABC algorithm.

5.2.3. Network Load Balancing. Load balancing is an important indicator of network lifetime, as a balanced load is essential to extending the life cycle of the entire WSN. The load balancing factor (LBF) provides a convenient and effective assessment for network performance analysis. L_{LBF} is defined as the reciprocal variance of sensing nodes (including cluster head nodes) of members within the network, where the greater the L_{LBF} is, the better the network load is balanced. See the following [24]:

$$L_{\mathrm{LBF}} = \frac{n_c}{\sum_{i=1}^{n_c} \left(x_i - u\right)^2}, \tag{17}$$

where n_c is number of WSN sensor nodes, x_i is the number of sensor nodes of the ith cluster head member, and u is the average number of nodes in all cluster head nodes. A comparison between the load balancing properties of the three algorithms is shown in Figure 8.

As shown in Figure 8, the load balance of the random walk mobile Sink path planning method grew poorer and less stable as the number of simulation iterations increased. The ACO algorithm consumed energy more uniformly and maintained better network load balance, but the ABC algorithm was most balanced; further, the load balance actually grew increasingly better as the number of iterations increased.

5.2.4. Number of Cluster Heads. Too few cluster heads in a network create cluster coverage areas that are too large, requiring excessive energy to transmit data between member nodes and cluster heads over the greater distance. Conversely, too many cluster heads also lead to excess energy consumption because cluster heads inherently consume much more

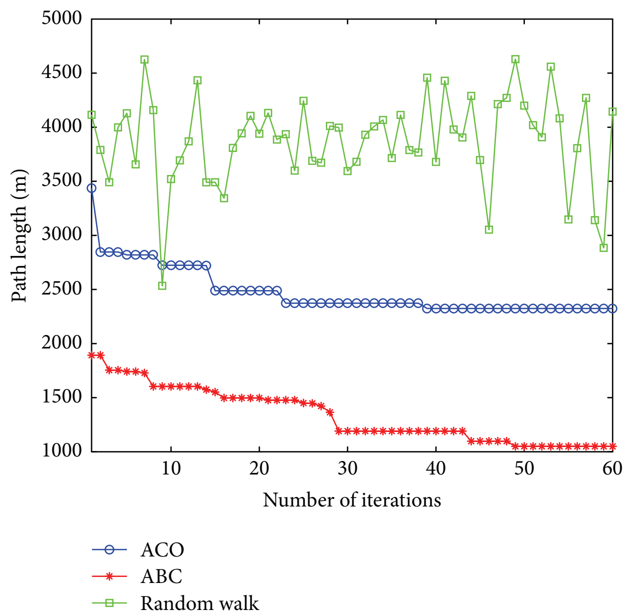


Figure 6: Total length of mobile path.

energy than member nodes. The appropriate number of cluster heads must be chosen to ensure minimum energy consumption throughout the entire network. A comparison of the number of cluster heads resulting from the three algorithms is shown in Figure 9, where the proposed algorithm selected more reasonable numbers of cluster heads than random walk or ACO and thus led to a network that consumed a more reasonable amount of energy.

5.2.5. Network Latency. We used the transmission delay (i.e., latency) of successfully received data packet to measure the real-time performance of various protocols. Data transmission time at the source node was recorded as T_s, the reception time at the Sink node was recorded as T_r, and average transmission delay was calculated as follows:

$$T_{\text{trans}} = \frac{1}{N_r}\sum_{i=1}^{N_r}\left(T_{ri} - T_{si}\right), \tag{18}$$

where N_r is the total number of successfully received packets. The network latency of the three algorithms is shown in Figure 10(a); as expected, random walk showed the largest delay (nearly 2 s) initially which then gradually decreased. The latency of ACO and ABC algorithms was initially relatively large, around 0.8 s, mainly because swarm intelligence algorithms are random during the first iterations while searching the optimal path. After subsequent learning and optimization, the final delay of ACO was about 0.2 s, while that of ABC algorithm was about 0.1 s.

We next simulated the same scenarios but increased the number of nodes $(100, 200, 300, \ldots, 1000$ sensor nodes) in a $500\,\text{m} \times 500\,\text{m}$ field, as shown in Figure 10(b). As the number of nodes increased, the network latency of the three algorithms again gradually increased, but again random walk resulted in the largest network latency and ABC the smallest and most stable.

5.2.6. Network Connectivity. The continuous motion discretization method is generally used to calculate the rate of network connectivity in a mobile network. According to this method, network topology does not change within a relatively short time period. In the network at a given moment, the node traversal method also can be used to calculate network connectivity; first an initial node is selected and then directly connected nodes, binary-hop connected nodes, and triple-hop connected nodes are searched from it sequentially until the node number connected to the initial nodes does not further increase. See the following:

$$N_{\text{con}} = \frac{N_l}{n}, \tag{19}$$

where N_l is the number of neighboring nodes in the communication range and n is the number of nodes in the network. A comparison of network connectivity results among the three methods is shown in Figure 11.

As shown in Figure 11, as simulation iterations increased, the network connectivity rate of random walk was low and volatile, ranging between 0.2 and 0.75, while that of ACO was higher and more stable, ranging between 0.5 and 0.75; that of ABC was highest and most stable overall, but with some sizable fluctuations at certain points, ranging between 0.45 and 0.8. On the whole, the network connectivity of the artificial bee colony algorithm was best.

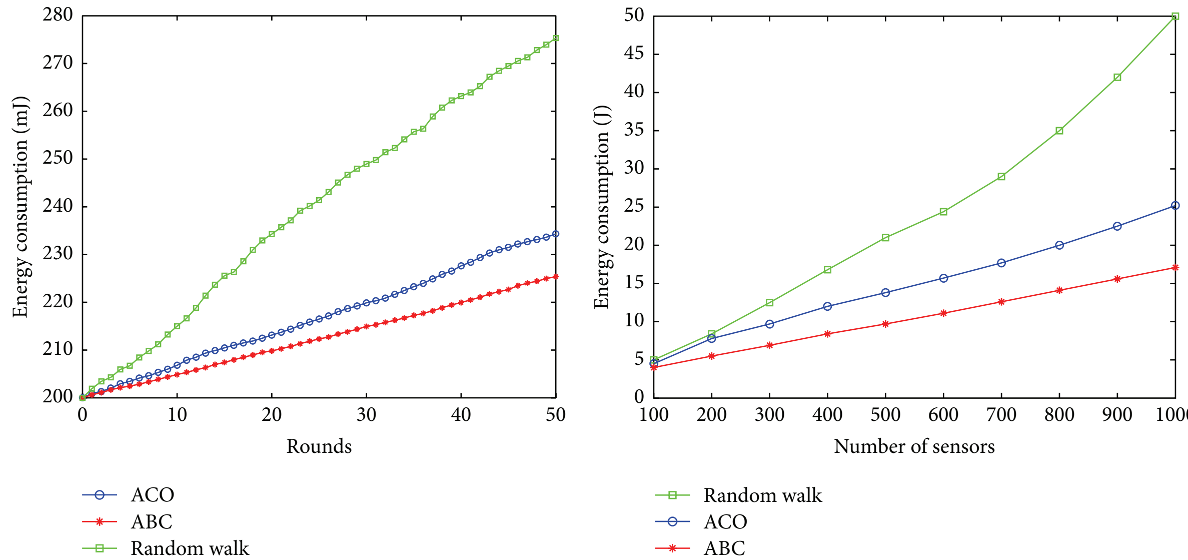
5.2.7. Network Integrated Reliability. The integrated network reliability of R_{net} is comprised of network node connectivity reliability I_1, network connectivity rate I_2, and network capacity I_3 and is expressed as follows:

$$R_{\text{net}} = 0.1667 I_1 + 0.5 I_2 + 0.3333 I_3. \tag{20}$$

Network node connectivity reliability I_1 refers to the interconnected reliability of end-to-end nodes, and the reliability matrix is calculated in line with the distance between nodes. According to the reliability matrix and the random edge reliability matrix sample and after Monte Carlo Analysis, we determined average node connectivity reliability after 50 simulation iterations. Network capacity I_3 is the network's probability of survival, which is usually obtained by dividing the surviving nodes by the number of all network nodes. A comparison of the network reliability of the three algorithms is shown in Figure 12.

As shown in Figure 12, as simulation iterations increased, the integrated network reliability of random walk gradually decreased and was highly volatile (0.65 on average). That of ACO was relatively stable, ranging from 0.72 to 0.88 with an average of 0.78, while that of ABC was highly favorable, ranging between 0.7 and 0.9 at an average of 0.83. Clearly (and at this point, as expected), the ABC algorithm was the most reliable of the three.

In short, the simulation results altogether showed that the proposed algorithm has the highest collection efficiency, lowest energy consumption, minimum latency, and most reliability of the three algorithms tested.



(a) Increasing number of iterations

(b) Increasing number of nodes

Figure 7: Changes in energy consumption.

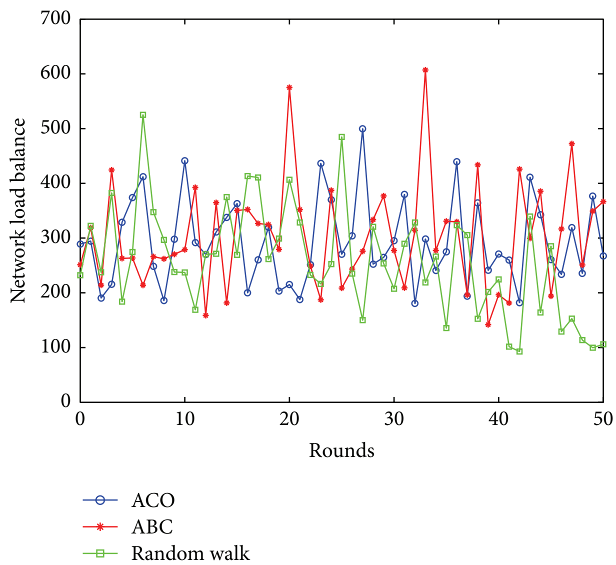


Figure 8: Network load balancing.

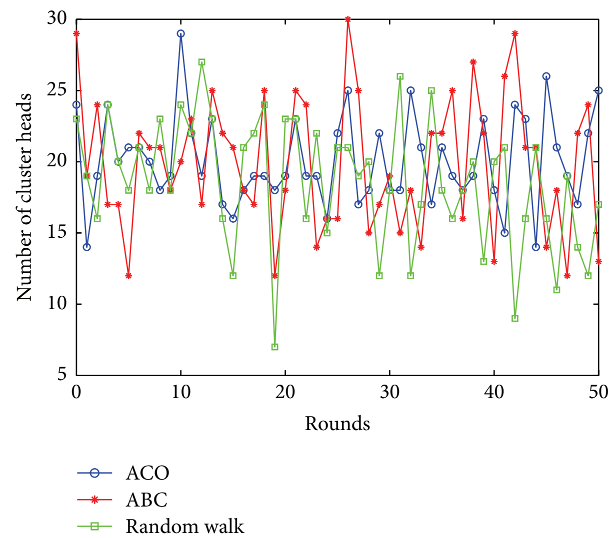
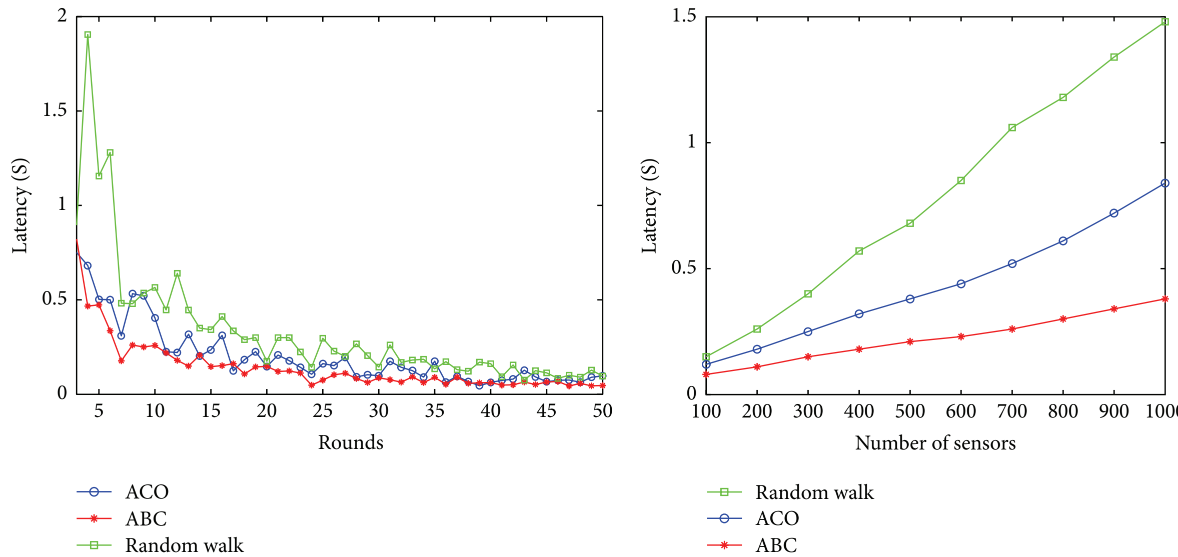


Figure 9: Number of cluster heads.

6. Conclusions and Future Research Directions

In this study, we explored the use of mobile Sinks to collect data to solve the energy consumption bottleneck problem inherent to static networks by analyzing the relationship between mobile Sink data collection and energy consumption. By accounting for the selection of the cluster head node, the route from nodes to cluster heads, and shortest route of the mobile Sink, we built a heuristic artificial bee colony algorithm that can be applied to maximize data collection and minimize total energy consumption while optimizing network reliability. Simulation results show that, compared to similar existing algorithms, the proposed algorithm improves WSN throughput, collects data more efficiently, and saves energy.

In the future, we plan to extend this research from various aspects. First, we intend to introduce a data fusion mechanism into the sensor node and to combine it with the mobile Sink data collection algorithm in order to even further improve network performance and reliability while decreasing data collection latency. In addition, because the method proposed here only takes the mobility of a single Sink node into account, in the future we plan to apply it to networks with multiple mobile Sinks. Though multiple Sinks increase the maintenance cost of network routing, they also can further



(a) Increasing number of iterations

(b) Increasing number of nodes

Figure 10: Network latency.

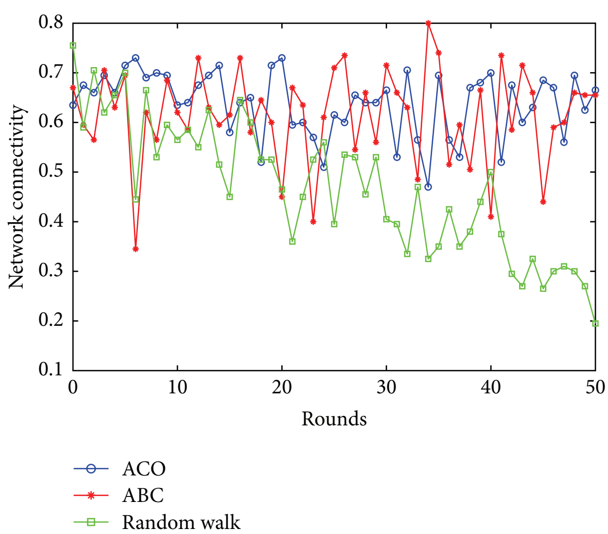


Figure 11: Network connectivity.

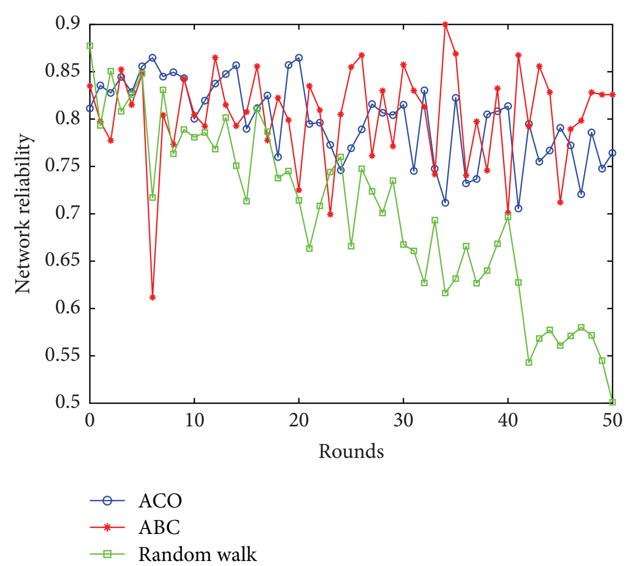


Figure 12: Network reliability.

improve energy utility, fill the energy hole, increase network communication capacity, and avoid extra communication expense, thus prolonging network lifetime, which essentially reflects the future of data collection in MWSN.

Competing Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgments

The authors would like to thank the anonymous reviewers for helpful comments which helped them improve the technical quality of the paper. This study was supported by International S&T Cooperation Program of China (2015DFA10490), the Natural Science Foundation of China (61571113 and 61240032), and the Specialized Research Fund for the Doctoral Program of Higher Education (no. 20130092110060).

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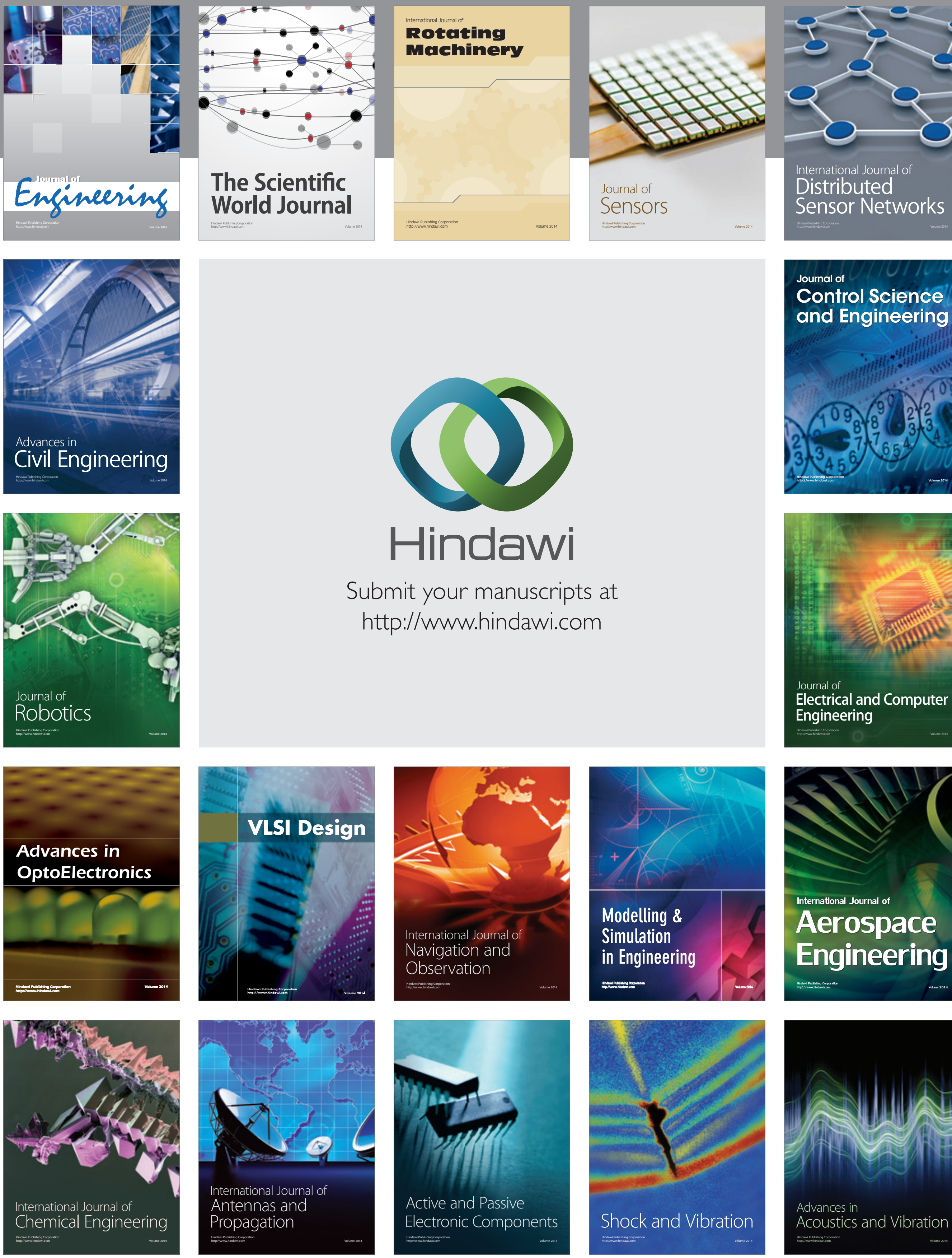
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