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An enhanced ACO-based mobile sink path determination for data gathering in wireless sensor networks

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Abstract
By facilitating the data delivery in wireless sensor networks, the movement of mobile sink can enhance the network connectivity and sensory coverage. However, the optimal path determination of mobile sink is a NP-hard optimization problem. By jointly considering the cluster-based routing and sink mobility, this paper proposes an enhanced ACO-based movement scheduling of mobile sink for data gathering in wireless sensor networks. To meet the delay requirements and balance the energy consumption of the sensor nodes, the optimal cluster heads selection is introduced. Then, an enhanced ACO-based movement scheduling algorithm is proposed to obtain the shortest path of mobile sink by traversing the network. The simulation results show that our proposed method can offer a promising performance in terms of reducing data delivery latency and extending the lifetime of the network.

Keywords: Wireless sensor networks, Data gathering, Mobile sink, Ant colony optimization

1 Introduction

With the development of wireless communication and embedded computing technology, wireless sensor networks (WSNs) have attracted extensive attention due to their practicality in monitoring, communicating, and reporting [1]. WSNs are usually composed of sensor nodes, which are provided with sensing and data processing units and capable of short-range wireless communication. Ceaselessly, WSNs show broad application prospects in the fields of national defense and military, national security, intelligent transportation, environmental monitoring, anti-terrorism and disaster resistance, etc. By integrating the functions of data collection, processing and transmission, WSNs expand people's ability to obtain information prominently. However, the sensor nodes are equipped with built-in batteries, and the energy is very limited due to their small size [2]. To minimize the energy expense caused by long-distance transmission, the data collected by the sensor node need to be forwarded to the base station through multi-hop. Since the sensor nodes around the base station must bear more communication load, their energy will be exhausted in advance. This phenomenon leads to "hot spot" problems and energy holes. Thus, the data collected by the nodes cannot be forwarded to the base station, and the network will work abnormally in severe cases [3]. The above problems have become the bottleneck restricting the application of wireless sensor networks.

Although some studies employ data aggregation with multi-hop manner or non-uniform deployment of sensors to reduce the energy consumption as much as possible, the "hot spot" problem still exists. To overcome above problem and improve the lifetime of WSNs, various schemes with mobile sink gathering data via random or controlled movement are introduced to save the overall network energy [4]. Within the communication range, the sensor nodes can deliver their monitoring data to the mobile sink when it halts at the sojourn positions nearby via single-hop or multi-hop manner. Hence, the mobile sink can traverse all nodes in its vicinity, and the overall energy consumption can be reduced by optimizing the data gathering path. However, it should be noted that the longer path of the mobile sink will lead to higher delay of data delivery due to the requirement of large number of rendezvous points' visit. In particular, data gathering with multi-hop transmission will further aggravate the time delay in contrast with the intermediate data aggregation by single-hop manner. In addition, the limitation of sink movement velocity usually leads to adverse impact on data collection efficiency. Most of the applications have strict requirements for data delay [5]. It is necessary to ensure the delay and minimize the energy consumption of network and guarantee that the entire network performance will be seriously affected.

This paper aims to extend the network lifetime by employing the clustering mechanism and optimizing the travel path of the mobile sink. An enhanced ant colony optimization (ACO) algorithm is introduced to determine the length of the mobile sink's trajectory over the selected RPs. The noteworthy contributions of the proposed research work are as follows:

1. To evaluate the delay in data gathering, the optimal path determination of mobile sink is formulated.
2. To meet the delay requirements and balance the energy consumption of the sensor nodes, the optimal cluster heads selection is introduced.
3. By jointly considering the cluster-based routing and sink mobility, an enhanced ACO-based movement scheduling algorithm is proposed to obtain the shortest path of mobile sink by traversing the network.

The paper is organized as follows: several previous related works are surveyed in Sect. 2. In Sect. 3, the system model used in this work and assumptions are discussed. Section 4 describes the proposed method. Simulation results and comparison to other works are given in Sect. 5, and Sect. 6 provides some concluding remarks.

2 Related work

To alleviate the problems of hot-spot and energy holes, researchers introduce mobile data gathering scheme to collect sensed data from sensors within the range of short transmission. The scheduling of mobile sinks can show many advantages in terms of the balanced energy consumption among different sensor nodes and the improvement of network lifetime. Also, it can facilitate the sensor's data restore and forwarding with sparse node distribution.

For wireless sensor networks with dense nodes, Sharifkhani et al. [6] proposed a transmission scheduling algorithm to solve the problem of system energy consumption optimization, which can achieve the tradeoff between the probability of successful packet arrival at the mobile sink and the energy consumption. In order to balance energy consumption and data collection delay, Li et al. [7] proposed a multi-hop routing mobile data collection algorithm based on transmission distance constraint. Aiming at minimizing the path length of mobile sink, Tashtarian et al. [8] established a mixed integer linear programming model and designed data reporting time for transmitting the buffered data. Tseng et al. [9] employed mobile mule to realize the overall optimization of cache management from the system level, and proposes a distributed storage management strategy for sensor nodes in different groups. To minimize the data gathering tour length, Chanak et al. [10] proposed a quad tree-based data gathering scheme to link all separated sub-networks in monitoring system. Thomson et al. [11] designed a mobility aware duty cycling algorithm to obtain dynamic communication threshold, which can reduce conflicts between channels among the sensor nodes and the mobile sink.

Since the mobile sink's movement for traversing the rendezvous points (RPs) leads to high delay in data delivery, it will restrict the application with high real-time requirements. Some rendezvous-based approaches have been investigated, and the concept of controlled mobility of sensory data gathering has been conceived. From the perspective of energy saving, Naween et al. [12] utilized mobile data collectors within a predefined time interval to maximize the network lifetime. To alleviate the problems of energy saving and data collection delay, Sharma et al. [13] designed a rendezvous-based routing protocol to balance node's energy consumption and minimize data delivery latency. Karakaya et al. [14] designed a scheduling algorithm to make the mobile sink run at a constant speed along the fixed track and collect data from the encountered sensor nodes, in which the stationary node can predict the arrival time of the mobile sink and efficiently switch between wake-up and sleep states to save energy consumption. Senturk et al. [15] proposed a mobile data collector assignment and scheduling strategy to reduce the waiting delay of visiting RPs and ensure that the sensor node buffer in each partition will not overflow.

The data gathering scheme based on mobile sink effectively reduces the energy consumption of static nodes and makes the energy consumption of sensor nodes more balanced in the whole network [16]. Selecting RPs from within a network is a multinomial optimization problem. In addition, the mobility of sink will also cause plenty of time delay in data collection [17]. Most of the existing RPS construction algorithms only consider the length or energy consumption of the mobile sink's path planning and do not consider the delay of data collection and data traffic [18].

3 System model

3.1 Network model

Assuming that N sensor nodes are randomly deployed in $M \times M$ rectangular monitoring area, clustering technology is employed to generate clusters with equal communication

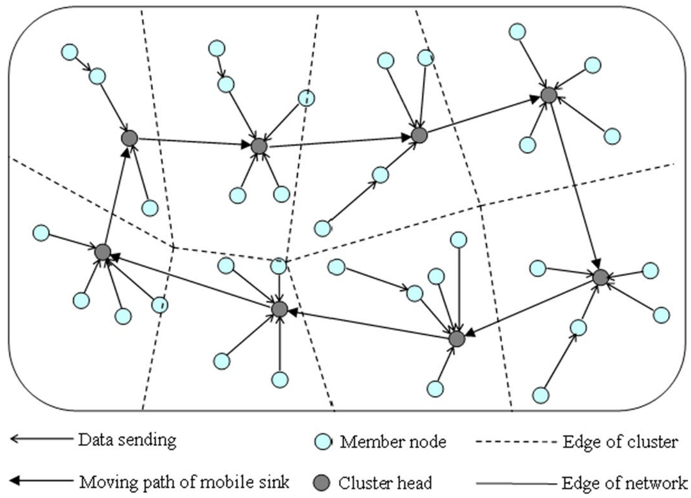

Fig. 1 Network model

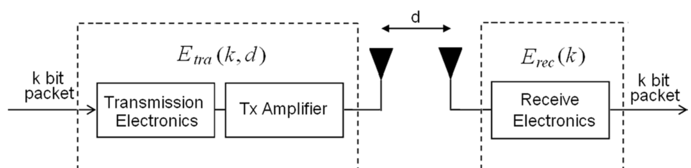

Fig. 2 Energy consumption model

radius, and the number of clusters is n. The network model is shown in Fig. 1. To facilitate the analysis, the assumptions of the network model are summarized as follows:

1. All sensor nodes have unique identification and will not move after deployment.
2. All sensor nodes are isomorphic, equipped with same battery level during initialization.
3. Mobile sink only makes uniform linear motion between the RPs, and the time of data fusion is ignored.
4. All nodes will be classified into cluster head nodes and member nodes. Among them, the cluster head node will be responsible for collecting and caching the data from the member nodes.
5. To reduce the energy consumption caused by long-distance transmission, the sensor nodes can transmit data to cluster head nodes through multi-hop mode.

3.2 Energy consumption model

The simplified first-order radio model [19] is considered to analyze the energy consumption of the sensor nodes in the network scenario, which is shown in Fig. 2. If the transmission distance is less than or equal to the threshold distance d_0, the free space model is applied. Otherwise, the multipath fading is used in the transmitter amplifier. The energy consumed for transmitting k-bits packet over a distance d can be expressed by

$$E_{\mathrm{tra}}(k,d) = \begin{cases} kE_{\mathrm{elec}} + k\varepsilon_{\mathrm{fs}}d^2, & \text{if } d \le d_0 \\ kE_{\mathrm{elec}} + k\varepsilon_{\mathrm{amp}}d^4, & \text{otherwise} \end{cases} \tag{1}$$

where E_{elec} represents the energy consumption of electronic circuitry in the wireless communication module. Besides, $\varepsilon_{\mathrm{fs}}$ and $\varepsilon_{\mathrm{amp}}$ represent the compulsory amplifier energy consumption for free space and multipath fading channels, respectively.

The energy consumed by receiving k-bits packets is given by

$$E_{\mathrm{rec}}(k) = kE_{\mathrm{elec}} \tag{2}$$

Suppose Q_t^i and Q_r^i indicate the amount of data received and sent by the sensor node s_i, respectively, the total energy consumption in each round can be calculated as follows:

$$E_{\mathrm{total}} = \sum_{i=1}^{N} (E_{\mathrm{tra}}Q_t^i + E_{\mathrm{rec}}Q_r^i) \tag{3}$$

Assuming that the amount of data generated by each node per round is q, for the sensor node s_i the relationship between the amount of data received Q_r^i and the amount of data sent Q_t^i can be described by: $Q_t^i = Q_r^i + q$. Let H_i represent the number of hops from the member node to its corresponding cluster head, then the amount of data sent can be expressed by:

$$\sum_{i=1}^{N} Q_r^i = \sum_{i=1}^{N} H_i q \tag{4}$$

Furthermore, the energy consumption of all nodes in each round can be expressed as:

$$\begin{aligned} E_{\mathrm{total}} &= \sum_{i=1}^{N} (E_{\mathrm{tra}}Q_t^i + E_{\mathrm{rec}}Q_r^i) = \sum_{i=1}^{N} [E_{\mathrm{tra}}(Q_r^i + q) + E_{\mathrm{rec}}Q_r^i] \\ &= q\left[NE_{\mathrm{tra}} + (E_{\mathrm{tra}} + E_{\mathrm{rec}})\sum_{i=1}^{N} H_i\right] \end{aligned} \tag{5}$$

It can be seen that the minimization of energy consumption of the whole network is equivalent to the minimization of the sum of hops of all nodes. On the one hand, the number of hops from each member node to its cluster head is related to the network topology and the position of the cluster head. On the other hand, the mobile sinks need to move along the trajectory and collect data from cluster heads as the RPs. Therefore, the selection of data collection points and the path planning of mobile sink need to be optimized to reduce the overall network energy consumption and meet the needs of data transmission delay.

3.3 Delay analysis

During the phase of the data gathering, the mobile sink will move along the trajectory and perform the data collection from all cluster heads. The cluster heads traversed by the mobile sink in turn can be represented by a sequence $\{c_1, c_2, \ldots, c_k\}$, and the delay in data gathering can be expressed as

$$T_D = \sum_{i=1}^{k} \left(T_{c_{i-1},c_i} + \tilde{T}_{c_i} \right) \tag{6}$$

where T_{c_{i-1},c_i} represents the time interval within the mobile sink is moving between two adjacent cluster heads and T_{c_{i-1},c_i} represents the dwelling time of the mobile at the cluster head c_i.

For the delay threshold D_c in practical application, the constraint should be satisfied by

$$T_D \leq D_c \tag{7}$$

4 Our proposed methods

4.1 Cluster head selection

Assuming that the velocity of the mobile sink is V_{m}, the maximum length of mobile sink's trajectory under the delay constraint D_c is $L = V_{\mathrm{m}} D_c$. In this case, the more RPs visited by the mobile sink node, the smaller the routing cost from the member nodes to the cluster heads. Therefore, as many cluster head nodes as possible can reduce the energy consumption caused by multi-hop transmission. The selection of cluster heads should take into account of both of energy consumption of their members in the process of data relay and the energy dissipation impacting the operation lifetime of networks. The optimization objective of the data gathering strategy is to obtain the optimal RPs and a data collection path for a mobile sink, which should achieve energy-efficiency and lifetime enhancement in varying environmental conditions. To avoid the occurrence of node's energy exhaust, the sensor nodes with more residual energy will have the higher chance of becoming cluster heads. In addition, some candidate nodes to be selected as final cluster heads or not will have little impact on the overall energy consumption of each round. To improve energy efficiency, those sensor nodes can be excluded. At the beginning of the next round, the selected cluster heads will notify the neighboring nodes with the communication radius to join the cluster and the clusters will be constructed and the respective routing for data delivery will be done. Then, the mobile sink implements the traversal process of the RPs and fulfills the data gathering. Considering the impact of the selection of the cluster heads on the traversal path planning and the number of hops from member nodes, the election weight of the cluster head to be selected can be defined as follows:

$$\rho(i) = (1 - w) \left| \frac{\min\left\{\sum_{j\in U-i} H_j - \min\left\{\sum_{j\in U} H_j\right.\right.}{\mathrm{TSP}(U) - \mathrm{TSP}(U - i)} \right| + w \frac{E_{\mathrm{res}}(i)}{\sum_{j\in U} E_{\mathrm{res}}(j)} \tag{8}$$

where U denotes the set of candidate cluster heads, $\mathrm{TSP}(U)$ is the shortest trajectory length by traversing the cluster head node set to be selected, and $\min\left\{\sum_{j\in U-i} H_j\right\}$ represents the total number of hops from member nodes to cluster heads after removing the sensor node from U. Besides, $E_{\mathrm{res}}(i)$ is the residual energy of sensor node s_i and w is the weight of residual energy for cluster head's selection.

After the cluster heads are selected, the neighboring nodes need to be notified to form a cluster. The specific steps are as follows: each cluster head uses the discontinuous

Carrier Sense Multiple Access (CSMA) protocol to broadcast an adv message, which contains the node ID and message type. Each member node determines which cluster it belongs to by selecting the cluster head. The selection of cluster head is determined by the communication cost, which is determined by the strength of the broadcast signal received by the node from each cluster head. Generally speaking, the closer the distance, the lower the communication cost. In addition, it is assumed that the channel is symmetric. If a member node receives the strongest broadcast message signal from a cluster head, the communication cost between the cluster head and the member node will be minimal. This can make the cluster head closer to the member nodes, unless there are obstacles blocking it. When the signal strength is equal, the member nodes can randomly decide which cluster to choose. After each member node decides its ownership, it must notify the selected cluster head that it is willing to become a member of the cluster. Each member node sends a join req to the cluster head using a discontinuous protocol. The message field contains the node ID and cluster head ID. After receiving the request information from each member node, the cluster head establishes a TDMA schedule for the member node and sends the scheduling information to the member nodes in the cluster. This not only reduces the conflict between data messages, but also enables the wireless communication modules of cluster member nodes to remain closed outside their respective transmission stages. After all nodes in the cluster receive the TDMA schedule, the cluster forms and begins to enter the stable state phase.

4.2 Mobile path planning

After the cluster heads are determined, the problem of the mobile sink's trajectory for data gathering can be regarded as a traveling salesman problem (TSP) [20, 21]. In large-scale networks, the problem space will grow exponentially and it is impossible to find an accurate solution in polynomial time. Heuristic algorithm can be used to solve such problem. The ACO algorithm proposed by Marco Dorigo is simulated by the foraging behavior of ants [22–24]. In the process of foraging, ants will leave pheromones. Each ant will obtain the pheromones left by other ants for searching along the path. According to the left pheromones, ants will find the shortest foraging path. ACO has many advantages such as strong robustness, high precision and parallelism, and easy to implement [25, 26].

In this paper, the probability of the ant to select the next location can be determined by

$$P_{ij}^{k}(t) = \begin{cases} \frac{[\tau_{ij}(t)]^{\alpha}\cdot[\eta_{ij}(t)]^{\beta}}{\sum_{u\in N_{Ki}}[\tau_{iu}(t)]^{\alpha}\cdot[\eta_{iu}(t)]^{\beta}}, & k \in \text{allowed} \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

where $P_{ij}^{k}(t)$ is the probability of ant k from the i-th cluster head to the j-th cluster head at time t. $\tau_{ij}(t)$ represents the amount of information on the path from the path (i,j). allowed indicates the position that the k-th ant is allowed to access in the next step, i.e., the cluster head node sequence that the mobile sink has not traversed.

The cluster head caches the data from it member nodes transfer to the mobile sink directly when the mobile sink is dwelling at the resident point within the communication range [27, 28]. Since the amount of data of member nodes is related to the number of hops to the corresponding cluster head, the data gathering of large-scale clusters should be traversed by mobile sink, which can be helpful to reduce the average delay of the network. Therefore, the heuristic function should be examined in aspects of both of the distance from the adjacent cluster head and the amount of data of member nodes of the large-scale cluster. It is necessary to give priority to gather the sensory data of large-scale clusters. Therefore, the heuristic function will be defined as:

$$\eta_{ij}(t) = \sum_{l \in \text{cluster}_j} H_l / d\left(c_i, c_j\right) \tag{10}$$

where $d\left(c_i, c_j\right)$ is the distance from the i-th cluster head to the j-th cluster head, and $\sum_{l \in \text{cluster}_j} H_l$ represents the sum of hops of all member nodes of the j-th cluster.

The adjustment method of information volume adopts the following rules:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij} + \rho\Delta\tau_{ij}(t) \tag{11}$$

where ρ is the information volatilization coefficient and $\Delta\tau_{ij}(t)$ is the pheromone increment on the path (i,j).

After the ants completing a foraging, the pheromone update rules of each path can be calculated as

$$\Delta\tau_{ij}^{k}(t) = \begin{cases} \frac{\mu}{L_k}, & \text{if ant } k \text{ traverse } \left(i,j\right) \text{ in current cycle} \\ 0, & \text{otherwise} \end{cases} \tag{12}$$

where μ indicates the pheromone strength and L_k is the total length of the path taken by the k-th ant.

5 Experimental results and analysis

In this section, MatLab is used to build a simulation platform to analyze the performance of the proposed algorithms in the mobile sink environment. The sensor nodes are randomly deployed at a 400 m × 400 m rectangular monitoring area, and each sensor node carries out continuous data monitoring at the speed of 20bit/s during the operation cycle. Besides, the delay requirement is set to 10 min. The parameters used in enhanced ACO algorithm are shown in Table 1, and other parameters are listed in Table 2, respectively. All results in the simulation test are obtained according to the mean values of 20 random tests. To verify the performance of the algorithm, our proposed method is compared with the classical methods Optimizing LEACH, VGEE [22] and EDC [23] in terms of network delay and average energy consumption.

We performed various simulations runs on all methods with the same network coverage strategy, and the lifetime of each round is defined as the duration when the

Table 1 Parameters in enhanced ACO algorithm

Parameters	Value
α	2
β	3
ρ	0.45
μ	0.8

Table 2 Simulation parameters

Parameters	Value
Number of sensors	Range from 50 to 400
Channel model	Wireless channel
MAC protocol	802.11ad
Speed of the mobile sink	5 m/s
Initial energy of all sensor nodes	5 J
E_{elec}	50 nJ/bit
ε_{fs}	0.0013 pJ/bit/m^4
ε_{amp}	10 pJ/bit/m^2
w	0.5

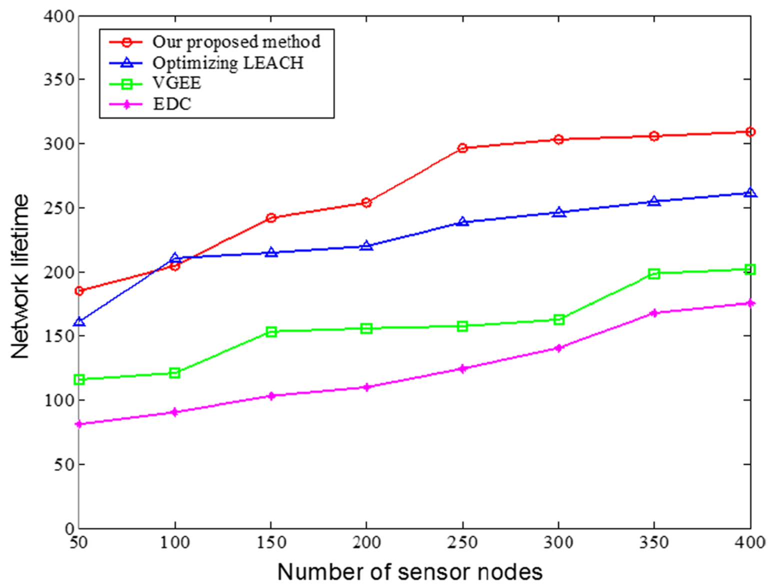

Fig. 3 Comparison of network lifetime

WSN network gradually reduces until it cannot effectively cover the area. Figure 3 shows the comparison of the lifetime of the WSN network under different number of sensor nodes. With the increase in the number of nodes, the lifetime shows an upward trend. With the increase in WSN network nodes, even if a few sensor nodes cannot work in normal state due to energy depletion, the entire network can also maintain the operation. The simulation result shows that the life time of WSN network corresponding to VGEE and EDC method is shorter. The reason is that the mobile sink in VGEE dwelled more time and results in more events. In EDC, the numbers of hops will be increased significantly as the number of nodes increased, which will cause the nodes near the mobile sink to consume more energy and result in premature death. The lifetime of the proposed method is slightly lower than that of Optimizing LEACH algorithm when the number of sensor nodes is lower than 100. But with the increase in the network scale, our algorithm is gradually prominent and has the longest network life time. It is due to the fact that the moving trajectory adjustment strategy of our proposed method performs more efficiently, which can make the energy consumption of all nodes more balanced.

In Fig. 4, we compare the node's load variance with different sensor nodes. The load balancing is also an important factor to reflect the effect of the movement of mobile sink and the overhead of sensors around the RPs. The effective data gathering scheme should be able to balance the energy consumption of sensor nodes by reasonable trajectory adjustment and prolong the network lifetime. Hence, the network communication will not be affected due to the early depletion of some node energy. From the results, it can be observed that the node load variance in our proposed method remains in a relatively stable variation range. With the increase in network scale, it has more obvious advantages than other algorithms. When the nodes in the network are densely distributed, the load variance of sensor nodes in VGEE and EDC increases significantly. Especially in EDC, the routing paths are updated in time and it causes the sensor nodes with more overhead. In our proposed method and Optimizing LEACH, the mobile sink can adjust the size of its moving trajectory and avoid the premature energy depletion of some nodes. Therefore, the node's load variance is relatively stable, and the node's overhead in the network can keep a balanced state in a long time. The experimental results also show that the load variance of our proposed method decreases slightly with the increase in nodes, so as to ensure the balanced energy consumption and improve the lifetime of the whole network.

Figure 5 shows the performance comparison of data delivery latency. More sensor nodes mean that more data from source nodes should be uploaded to the mobile sink, and the data gathering have to operate through a long time due to the multi-hop transmission. The latency in data delivery will be increased, while the mobile sink halts the RPs and collects data from the sensors in vicinity. In Fig. 5, it can be noticed that our proposed method and Optimizing LEACH had better performance than

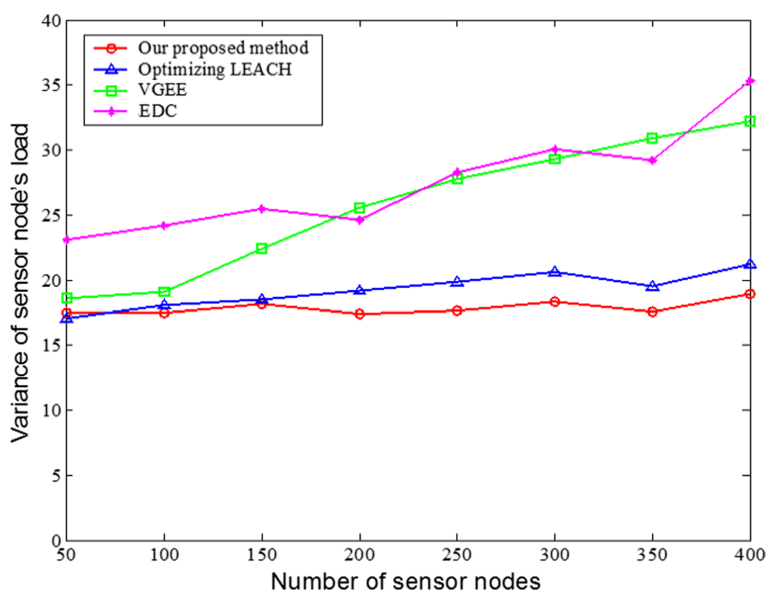

Fig. 4 Comparison of node's load variance

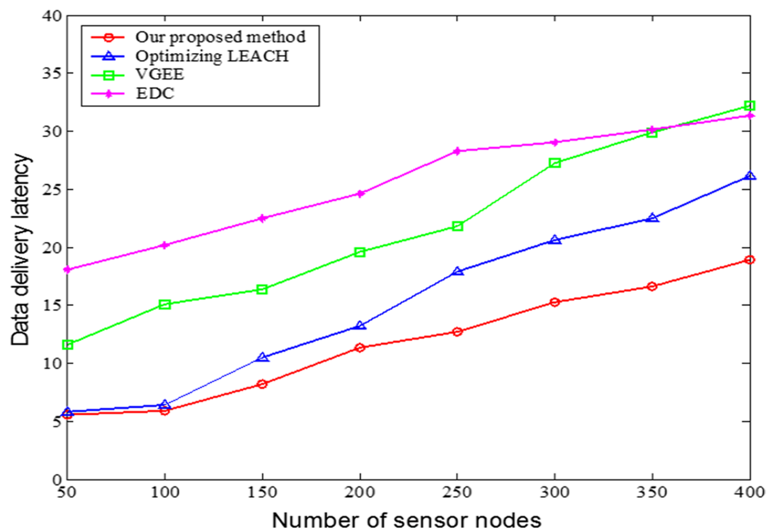

Fig. 5 Comparison of data delivery latency

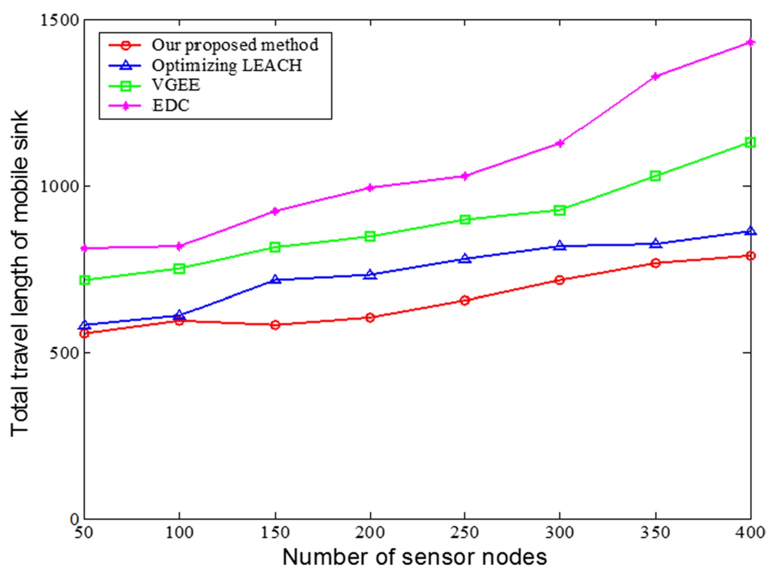

Fig. 6 Comparison of total length of mobile sink's trajectory

VGEE and EDC. As the number of sensor nodes increases, the RPs traverse strategy in our proposed method can obtain an optimal routing path to the mobile sink. Therefore, our proposed method can make mobile sinks spend less time in moving and obtain the lowest data delivery latency.

Figure 6 shows comparison of total length of mobile sink's trajectory under the constraints of which the path length does not exceed the given delay limit. From the experimental results, it can be seen that the mobile path of sink nodes increases with the increase in sensor nodes. In VGEE, the nodes close to the mobile sink will be selected as the root nodes to dynamically construct the number of routes. When the number of sensor nodes is small, the mobile sink shows better data gathering efficiency. However, the total path length of mobile sink increases sharply with the increase in the number of sensor nodes. Also, we can observe that our proposed algorithm is always less than that of other algorithms. This is because the path selection strategy of our proposed method considers the hops for data delivery and sensor node's load comprehensively, and improves the data gathering efficiency of mobile sink by optimizing the traversal sequence of cluster heads. It also shows that our proposed method has good scalability.

6 Conclusion

In this paper, an enhanced ACO-based movement scheduling of mobile sink for data gathering in wireless sensor networks is proposed. To meet the delay requirements and balance the energy consumption of the sensor nodes, the optimal cluster heads selection is introduced. Then, an enhanced ACO-based movement scheduling algorithm is proposed to obtain the shortest path of mobile sink by traversing the network. The simulation results show that our proposed method can offer a promising performance in terms of reducing data delivery latency, and extending the lifetime of the network. In the future work, we will investigate the data gathering under the condition of multiple mobile sinks and the cooperative communication between them.

Abbreviations

WSNs	Wireless sensor networks
ACO	Ant colony optimization
RP	Rendezvous point
TSP	Traveling salesman problem
TSP	Traveling salesman problem
LEACH	Low energy adaptive clustering hierarchy

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Author contributions
ZW proposes the theoretical analysis and carries out experiments. GW conceived of the study and participated in its design and coordination and helped to draft the manuscript. Both authors read and approved the final manuscript.

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Declaration

Competing interests
The authors declare that they have no competing interests.

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