Computer Networks 160 (2019) 33–40

Contents lists available at ScienceDirect

Computer Networks

journal homepage: www.elsevier.com/locate/comnet

Enhanced clustering and ACO-based multiple mobile sinks for efficiency improvement of wireless sensor networks

Muralitharan Krishnan[a], Sangwoon Yun[b], Yoon Mo Jung[c,*]

[a] AORC, Sungkyunkwan University, Suwon 16419, South Korea
[b] Department of Mathematics Education, Sungkyunkwan University, Seoul 03063, South Korea
[c] Department of Mathematics, Sungkyunkwan University, Suwon 16419, South Korea

ARTICLE INFO

Article history:
Received 8 January 2019
Revised 10 May 2019
Accepted 21 May 2019
Available online 24 May 2019

Keywords:
Wireless sensor networks
Clustering
Network lifetime
Routing
Multiple mobile sinks
Optimization techniques

ABSTRACT

The use of enhanced clustering techniques and multiple mobile sinks can improve the data-collection efficiency and reduce the energy consumption of wireless sensor networks. Most of the existing approaches use static sinks and multihop routing, which can cause data loss and the early death of sensor nodes, leading to energy-hole problems and inefficient data collection. Nowadays, sensors produce time-sensitive data, and hence, lossy data-collection approaches must be avoided. In order to overcome the aforementioned issues and improve the network lifetime, we propose an enhanced clustering methodology with multiple mobile sinks for efficient data collection. The performance of the proposed method is tested and compared with that of the existing algorithms LEACH, GA, and PSO. The simulation results show that the proposed approach improves the network lifetime significantly and reduces data loss.

1. Introduction

Sensors are small electronic devices used to monitor or measure changes in real-time environments [1]. They are usually inexpensive and low-power-consuming devices, which are capable of processing and transferring data to a base station. After successful deployment, the sensor nodes form a network, by self-organization, which is called the wireless sensor network (WSN). The primary work of a sensor node is to log the analog information of environmental changes and convert it into digital information with the help of analog-to-digital converters. In addition to logging information, the sensor nodes also act as repeaters to forward the data from other sensor nodes to the base station through single or multihop communication. Generally, the nodes are operated with limited battery resources, and the process of recharging or replacing the battery after deployment is tedious. Thus, the limited lifetime of battery is one of the fundamental issues in WSNs [2–4]. Sensor technology has various applications, which include industries, automated homes, military applications, modern health care, environmental monitoring, and security, to name a few [5–9].

In WSNs, information from the sensor nodes is usually transferred to the sink through multihop communication, in order to reduce the energy consumption of the nodes. Though such a data-forwarding approach improves the overall lifetime of the network, it also causes energy-hole problems and the premature death of sensor nodes [10,11]. In particular, with this approach, the sensor nodes close to the sink forward not only their own data to the sink but also the data from their neighboring nodes. Hence, the nodes near the sink will lose their energy sooner and die. This makes forwarding the data of other nodes to the base station highly challenging, and leads to network-partition problems, degradation of the quality of service, and decreases the network lifetime [12]. In order to minimize the aforementioned issues, a number of techniques such as clustering and routing have been proposed in the literature; a few of them are discussed below.

Clustering is one of the most important approaches to improve the network lifetime in WSNs. Clustering is the process of partitioning the entire region into a number of subregions, called clusters [13–16]. Each cluster has a bunch of sensors, called cluster members, and one among them acts as a cluster head. Cluster members are responsible for sensing the environment and the cluster head collects the data from the cluster members. The advantages of clustering are as follows. (i) Data fusion: The amount of data to be transmitted to the base station can be reduced by fusing data together; consequently, the energy consumption during transmission is reduced. (ii) Energy balance: During network operation, periodically changing the cluster head prevents the premature death of sensors and minimizes data loss [6,17].

* Corresponding author.
E-mail address: yoonmojung@skku.edu (Y.M. Jung).

https://doi.org/10.1016/j.comnet.2019.05.019
1389-1286/

Recently, mobile sinks (MSs) were introduced to reduce the number of hops traveled by a data packet in a network. Instead of nodes forwarding data to a static sink in a multihop fashion, MSs travel to all cluster heads to collect data directly in a single hop and supply all the data to the base station when they reach the base station. Existing literature show that MSs improve the network lifetime and performance of WSNs significantly [18–21]. In general, MSs are moving objects that are capable of collecting data, and are equipped with powerful transceivers and unlimited battery power. They are robots or unmanned aerial vehicles, which can travel all over the field to collect the data of interest generated by the sensors in their trajectories. A mobile sink starts the data-collection process by touring each cluster head periodically. The traversing route for an MS is supplied by the base station. As this approach collects data packets directly from the cluster heads without using any data-forwarding mechanism, it avoids data collisions and improves the lifetime of the sensor network [22].

However, a proper path should be provided for each MS to collect the data from the cluster heads with acceptable energy consumption. Simulating the biological behavior of insects has been found to be useful for finding an optimal path [23,24]. The ant colony optimization (ACO) algorithm is inspired by the natural behavior of ants, and is classified as an artificial-intelligence technique [25,26]. ACO finds a solution based on the food-searching behavior of ants using a special chemical called pheromone. In the early stages of search, ants move randomly in search of food, and along the way, they deposit a certain amount of pheromone. After the discovery phase, a set of paths are available with different pheromone intensities. The rest of the ants choose the path with the highest pheromone intensity to reach the food, depositing pheromones along the way. Finally, the path with the highest pheromone intensity is considered as the best path.

Deployment, clustering, and routing in WSNs require the consideration of additional constraints such as storage capacity, data collection, efficient usage of battery power, and communication [27–31]. In this paper, an energy-efficient ACO-based routing algorithm with multiple MSs is proposed for WSNs. First, the low-energy adaptive clustering hierarchy (LEACH) algorithm is used to cluster the network into several subregions. Then, a routing algorithm finds an optimal path for each MS to visit all cluster heads and return to the starting point. In the case of multiple MSs, the cluster heads are divided into a finite number of disjoint subsets and each subset is assigned to one MS. Every MS starts its travel from its initial position, traverses all the cluster heads in the assigned subset, and ends the tour at the same initial position.

The main objective of this work is to improve the network lifetime while ensuring that all data are collected efficiently. In this work, we consider that all the MSs begin and end their travel at the same location. The main contributions of this work are summarized below:

- A modified-LEACH algorithm is proposed to cluster the sensor nodes.
- Multiple MSs are introduced for efficient data collection, and the proposed algorithm substantially increases the network lifetime.
- The ACO technique is employed with multiple MSs to reduce data loss and enhance the network lifetime of WSNs.
- Simulation results are compared with those of existing techniques (LEACH, GA, and PSO) for several scenarios to affirm the effectiveness of the proposed approach.

The remainder of this paper is organized as follows: Section 2 explains the system model with preliminaries, definitions, energy model, and network model. Section 3 explains the proposed algorithm with clustering, route formation, ACO, and route optimization. Section 4 highlights the obtained simulation results for various scenarios, and Section 5 concludes the paper.

2. System model

2.1. Definitions and preliminaries

- S: Set of sensor nodes deployed in a region, $S = \{s_1, s_2, s_3, \ldots, s_n\}$.
- P: Set of cluster heads, $P = \{CH_1, CH_2, CH_3, \ldots, CH_p\},\ p \le n$.
- ϵ_{fs}: Energy consumption in the free-space model.
- ϵ_{mp}: Energy consumption in the multipath model.
- E_{lx}: Energy required for the radio unit.
- E_{tx}, E_{rx}: Energy required for transmission and reception.
- x: Number of bits transferred or received per second.
- d: Data transfer distance over a wireless medium
- $dis(CH, MS)$: Distance between the cluster head CH and mobile sink MS.
- $E_r(i)$: Residual energy of the sensor node s_i.
- E_i: Initial energy of the sensor node s_i.
- E_t: Total energy of the network.
- T_h: Threshold energy for a sensor to be selected as a cluster head.
- p: Number of cluster heads.
- q: Number of mobile sinks.
- Lnd: Last node that dies.
- p_i: ith subset of P.
- l_i: Number of CH in p_i.
- V: Set of vertices.
- A: Set of arcs.
- p_{il_i}: Number of cluster head assigned to the mobile sink MS_i.
- $R_{i,k}$: kth route of the mobile sink MS_i.
- $rD(R_{i,k})$: Total distance traveled by MS_i.
- r_D: Route distance of the mobile sink MS.

2.2. Energy model

The basic radio model was used as an energy model for sending and receiving the data [32]. The energy consumption can be categorized as (i) the energy consumption of the transmitter for operating the radio unit and (ii) the energy consumption of the power amplifier. The energy consumption for sending (transmission radio unit) x bits of data over a distance d can be calculated as

$$E_{tx}(x, d) = \begin{cases} E_{lx} \cdot x + \epsilon_{fs} \cdot x \cdot d^2, & \text{for } d \le d_0, \\ E_{lx} \cdot x + \epsilon_{mp} \cdot x \cdot d^4, & \text{for } d > d_0, \end{cases} \quad (1)$$

where E_{lx} is the energy required to transmit data over the wireless medium and ϵ_{fs} and ϵ_{mp} represent the energy consumptions in the free-space model and multi-path model, respectively. To receive x bits of data, the energy required by the receiver is given by:

$$E_{rx}(n) = E_{lx} \cdot x. \quad (2)$$

2.3. Network model

Sensor nodes are randomly deployed in a region, and they have the following features: (a) They are static and not mobile. (b) Initially, all nodes have equal amounts of energy and their batteries are neither replaceable nor rechargeable during operation. (c) Every sensor has sensing, processing, and communication capabilities. In order to reduce the energy consumption of a node, the network is clustered with the help of an enhanced LEACH algorithm. Then, MSs are introduced in the network to collect data from the cluster heads and deliver them to the data-collection unit. Single or multiple MSs perform the data-collection activity and they have unlimited energy. The locations of the cluster heads are available at

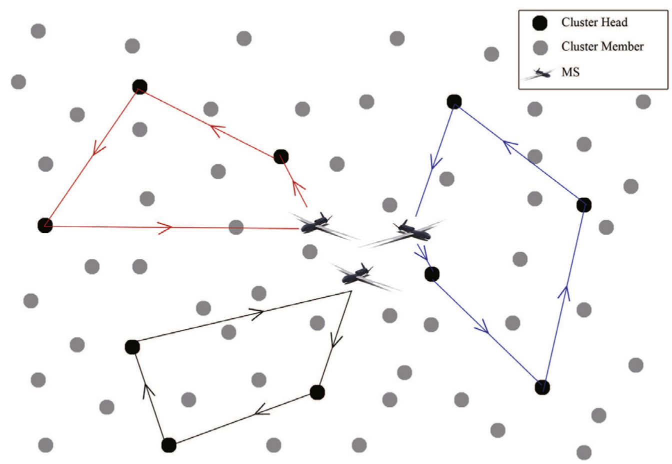

Fig. 1. Network model for multiple mobile sinks.

the base station, and the base station is responsible for providing the route information to the MSs. Usually, the MSs are controlled by the base station. Fig. 1 shows the network model for multiple mobile sinks. In Fig. 1, the gray dots represent sensor nodes, the black dots represent cluster heads, the flight symbols denote MSs, and solid lines represent the trajectory of the MSs.

We consider a WSN with multiple MSs; its description is given below: The given undirected graph $G = (V, A)$ consists of a set of vertices V and a set of edges A. In the undirected graph G, every edge in A is assumed to have a positive cost, which is the distance between the vertices incident at each edge. If q denotes the total number of MSs, each MS travels a subset of cluster heads (CHs) to collect data. For that purpose, let $\{P_i\}_{i=1}^{q}$ be a partition of the entire set of CHs where P_i has l_i CHs, such as $P_i = \{p_{i1}, \cdots, p_{il_i}\}$. Our aim is to minimize the sum of the distances over which the MSs travel to all the vertices of the assigned subset P_i of V exactly once to collect data from CHs.

3. Proposed algorithm

3.1. Clustering

The LEACH algorithm is modified and implemented in the proposed clustering approach. Sensors are deployed in the given region to be monitored and are partitioned into a number of clusters through the following steps. The total residual energy of the network E_t is calculated as

$$E_t = \sum_{i=1}^{n} E_r(i), \tag{3}$$

where $E_r(i)$ denotes the residual energy of the node i. Then, to find a threshold value, the average residual energy of the sensors is calculated by

$$T_h = \begin{cases} \frac{p_{ch}}{1 - p_{ch}(r_{no} \mod 1/p_{ch})} \cdot \frac{E_t}{E_i} & \text{if } h \in H, \\ 0 & \text{otherwise}, \end{cases} \tag{4}$$

where p_{ch} is the required percentage of cluster heads, H is the set of nodes that are not selected as a cluster head in the most recent $1/p_{ch}$ rounds, E_i denotes the total initial energy of all the nodes in H, and r_{no} is the present round number.

In each round, all the sensors generate a random value between 0 and 1. The generated value of each sensor is compared with the predefined threshold T_h. If the obtained value of a sensor s_i is less than T_h, s_i will be selected as a cluster head. In contrast, when two or more sensors generate the same random value, the sensor node with the highest residual energy is selected as the cluster head for that particular cluster.

Once cluster heads are selected, they send a broadcast message to all other sensor nodes. Based on the signal strength or communication range of the sensors, the rest of the sensor nodes join a cluster head. Finally, the cluster heads send a time-division multiple access (TDMA) broadcast message to their members, with scheduling information for data transmission and reception to avoid data collisions in the network.

3.2. Route formation

Nowadays, multiple mobile sinks (MMS) solutions are receiving wide attention from researchers of WSN, owing to their potential to help achieve effective network lifetime and efficient data collection. We consider an MMS network with p cluster heads and q MSs in a WSN environment. Each MS is assigned to a subset of cluster heads having a single starting point. At each round, all cluster heads should be visited at least once by one of the MSs and each MS should visit at least one cluster head. One of the main objectives of the proposed approach is to reduce the travel distance of the MSs without any data loss.

Data collection using MS is similar to the traveling salesman problem (TSP). It is an NP-hard problem and near-optimal solutions can be reached by applying a heuristic algorithm. The proposed routing approach involves the following steps: (i) Assigning each disjoint subset of cluster heads to each MS. (ii) Finding the order of visit (path) for each MS. For achieving efficient energy utilization and for obtaining an optimal route for each MS, an average number of cluster heads is assigned to each MS, which is obtained as follows:

$$N_{CH}(MS) = n(CH)/n(MS) \tag{5}$$

where $N_{CH}(MS)$ denotes the average number of cluster heads assigned to an MS, $n(CH)$ represents the number of cluster heads, and $n(MS)$ represents the number of MSs.

For each MS, the MS members (cluster heads) are assigned based on a distance matrix, whose entries consist of the distances between the cluster heads and MSs in the network. The distance matrix is presented as

$$dis(MS, CH) = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1p} \\ d_{21} & d_{22} & \cdots & d_{2p} \\ \cdots & \cdots & \cdots & \cdots \\ d_{q1} & d_{q2} & \cdots & d_{qp} \end{bmatrix} \tag{6}$$

where the row index represents the MS number and the column index represents the cluster head number. The assignment of cluster heads to each MS is determined by the minimum value in the corresponding column of the distance matrix. A more detailed explanation is given below.

The members of the ith MS MS_i can be represented as a subset of P, i.e.,

$$P_i \subset P \tag{7}$$

where i is the index of the MS and $i = 1, 2, 3, \cdots, q$. Based on the conditions given below, a subset of cluster heads (P_i) is formed and assigned to MS_i. The distances between the cluster heads and MSs $dis(MS_i, CH_j)$ in the network are compared. CH_j is assigned to the subset of MS_i, if $dis(MS_i, CH_j)$ value is minimal in $i = 1, 2, 3, \cdots, q$. For example, if the distance between MS_3 and CH_1 is less than that of the other mobile sinks, CH_1 will be assigned to MS_3. Similarly, all the cluster heads are assigned to their corresponding MSs. If a cluster head has the minimal distance with multiple mobile sinks, then the cluster head is randomly assigned to any one of those mobile sinks.

$$\min_{i=1,\cdots,q} dis(MS_i, CH_1), \cdots, \min_{i=1,\cdots,q} dis(MS_i, CH_p) \tag{8}$$

By using (8), a finite number of disjoint subsets of cluster heads CH_j are formed for all the MSs MS_i. As described in Section 2.3, P is partitioned into a number of disjoint subsets P_i, $i = 1, \cdots, q$, where $P_i = \{p_{i1}, \cdots, p_{il_i}\}$.

The kth route of the i-th MS MS_i is represented as

$$R_{i,k} = \{\text{Pos}_{init}(MS_i), \text{Pos}(P_i), \text{Pos}_{init}(MS_i)\} \tag{9}$$

where $\text{Pos}_{init}(MS_i)$ denotes the initial position of MS_i and $\text{Pos}(P_i)$ represents the cluster head positions in P_i.

To find the total route distance rD traveled by MS_i, we compute the following:

$$rD(R_{i,k}) = dis(MS_i, p_{i1}) + \sum_{j=1}^{l_i-1} dis(p_{ij}, p_{i,j+1}) + dis(p_{il_i}, MS_i) \tag{10}$$

Here, $dis(\cdot, \cdot)$ denotes the distance between CHs or between a CH and an MS. The MS MS_i starts from the initial position, visits all CHs in P_i in the increasing order of indices, and finally returns to the initial position.

The best ordering of p_{ij} in P_i is the one with the least tour length $rD(R_{i,k})$. Thus, to decide the ordering of p_{ij} in P_i for each k, we have the following optimization problem:

$$\min_{R_{i,k}} rD(R_{i,k}) \tag{11}$$

It is TSP, which is NP-hard. To bypass this difficulty, we adapt ACO, which is given in Section 3.3. Algorithm 1 explains the multiple mobile sinks route formation and Fig. 2 illustrates the overall flow of the proposed algorithm.

Algorithm 1 MMS Route Formation.

Input: MS and CH coordinates
Output: Routing path for multiple MSs

% Calculate avg. no. of CHs assigned to MS:
$N_{CH}(MS) = n(CH)/n(MS)$
Construct the distance matrix $disMat(\cdot,\cdot)$ for MSs and CHs using (11).
% Assign CH to the closest MS:
loop $j := 1$ to q
    $I = \text{argmin} disMat(:, j)$
end loop
if $|I| == 1$ **then**
    Assign CH_j to MS_I
else
    Assign CH_j to MS_i, $i \in I$ randomly.
end if
Call ACO for routing
Perform data collection
Repeat process until Lnd

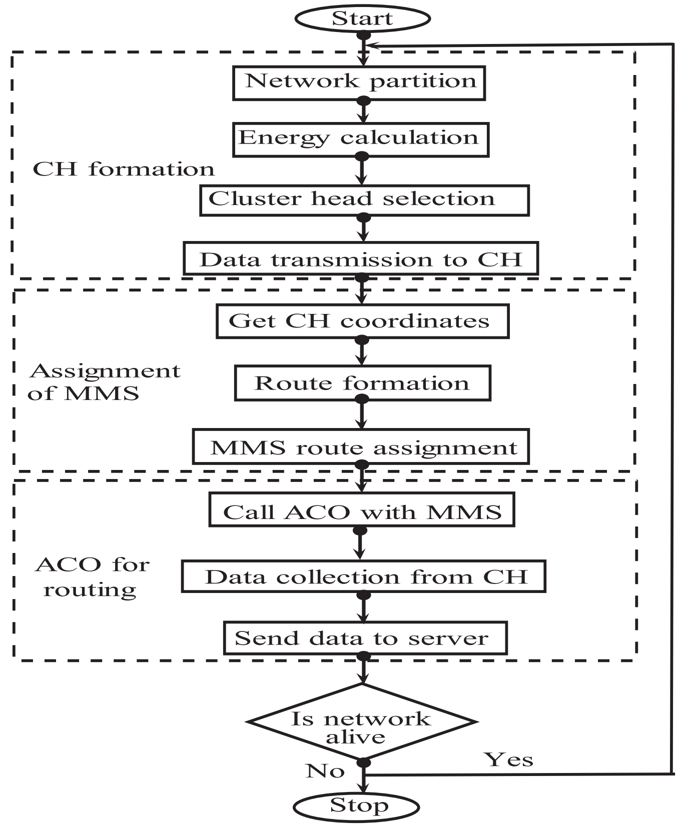

Fig. 2. Work flow.

3.3. Ant Colony Optimization (ACO)

ACO is a metaheuristic algorithm, which is used in many domains to solve optimization problems. One such problem is finding the shortest path between two points. In general, ACO consists of a group of ants, called the ant system. They work in a group to perform a complex task in an optimal manner to find food for their survival (solution). It is well known that the metaheuristic approach is robust and adaptable for managing a broad range of combinatorial optimization problems. According to the survey [33–35], ACO can produce better results than other algorithms. Thus, we apply an ACO algorithm to find an optimal path from the set of available cluster heads with efficient routing and effective data collection.

In ACO-based algorithms, artificial ants are designed to mimic real ant behaviors, to find an optimal path. After the initial deployment, each ant travels from one cluster head to another and deposits its pheromone. Solution paths are constructed based on their travel and the pheromones are stored and updated. After successful completion of their travel, the solutions are evaluated. The best solution is the one that has the most pheromone. Other ants may follow and deposit pheromones on the same path during their visit to construct solutions. Based on the amount of pheromone, the path for the next iteration or visit is chosen.

The concept of MS was introduced to avoid the hot-spot problem and data loss and to increase the lifetime of WSNs. MS can dynamically adapt the best routing path with the help of the ACO algorithm and can traverse and acquire data from all the cluster heads. Initially, the base station collects the positions of the cluster heads and decides a route for MSs using ACO. The first MS travels a set of cluster heads, and the second MS travels another set of unvisited cluster heads. In a similar manner, all the cluster heads are visited by a group of MSs. The number of MSs is varied from 1 to q, to evaluate the performance of the MS approach.

The routing process turns extremely complex when more than one MS is deployed. The increased complexity is due to the need to find the appropriate MS for a cluster head and to solve the ordinary shortest path algorithm repeatedly for all MSs. The main objective of MMS is to minimize the total routing distance, which can increase the network lifetime. The ACO algorithm computes and assigns a unique route list to each MS. The MS starts traveling from the nearest cluster head in the list and it visits all the cluster heads in the list. The cluster heads visited are recorded in the route list until all the cluster heads are visited by one of MSs. In this manner, an effective solution is constructed. In the algorithm, we use k number of ants; therefore, k solutions can be constructed.

3.4. Route optimization

For ACO-based route optimization, each ant selects the next cluster head independently. The following probabilistic formula is applied for the probability $Pr(t)_{ij}^k$ of the kth ant moving from the cluster head i to the cluster head j:

$$Pr(t)_{ij}^k = \begin{cases} \dfrac{[\tau_{ij}(t)]^\alpha \cdot [\eta_{ij}]^\beta}{\sum\limits_{l\in \text{allowed}_k} [\tau_{il}(t)]^\alpha \cdot [\eta_{il}]^\beta}, & \text{if } j \in \text{allowed}_k \\ 0, & \text{otherwise,} \end{cases} \tag{12}$$

where $\tau_{ij}(t)$ is the pheromone information on the path from the ith cluster head to the jth cluster head, which can be expressed by the intensity of the pheromone between the ith cluster head and the jth cluster head. $\eta_{ij}(t)$ is obtained from $1/d_{ij}$, where d_{ij} is the distance from the cluster head i to the cluster head j. allowed$_k$ denotes the cluster heads that are not visited by ant k. α and β are constant parameters, whose values are used to adjust the influence of pheromones. These parameters also assist the ants in their decision making.

In order to achieve better results, the pheromone trail values of the ants are updated in each iteration. It helps showcase the ants performance and evaluate the quality of the solution. The update process is considered as a key factor of the self-learning mechanism of ACO and helps ensure improvement of the subsequent solutions. The trail updating mechanism includes local and global updates. The local update is done with the following equation:

$$\tau_{ij}(t+1) = (1-\rho)\cdot\tau_{ij}(t) + \Delta\tau_{ij}, \tag{13}$$

where ρ denotes the pheromone evaporation rate, which controls the speed of evaporation, t denotes the iteration counter, $\rho \in [0, 1]$ is the parameter that regulates the reduction of τ_{ij}, and $\Delta\tau_{ij}$ is the pheromone value in the current iteration, which is deposited on all the edges. $\Delta\tau_{ij}$ can be expressed as follows:

$$\Delta\tau_{ij} = \sum_{k=1}^{M} \Delta\tau_{ij}^k. \tag{14}$$

The amount of pheromone left by each ant k leaving the ith cluster head and arriving at the jth cluster head is computed by

$$\Delta\tau_{ij}^k = \frac{Q}{L_{ij}}, \tag{15}$$

where Q is a constant and L_{ij} is the distance the ant k travels from the cluster head CH_i to the cluster head CH_j.

This update mechanism encourages it to find a shorter path routing and increases the probability of achieving an optimal route. This process is repeated until the predetermined number of iterations is reached or an appropriate solution is found. The final solution can be considered as an optimal solution for an MS to travel.

4. Results

The proposed approach is designed to increase the network lifetime through efficient routing and data collection using MMS. There are a number of definitions available for the network lifetime in the WSN literature [36]. As we implement MSs in this work, we define the network lifetime as the time at which the last node dies in the network. To prove the efficiency of the proposed approach, the following scenarios are considered: Scenario (1) demonstrates the conventional clustering with the proposed routing algorithm for data collection. Scenario (2) demonstrates the proposed enhanced clustering with the ACO-based routing approach for data collection. In addition, we also analyze the packet loss ratio and performance of the approaches, by varying the number of MSs. We also compare the network lifetime measured at the first node death, last node death, and the number of nodes alive in each round. Furthermore, the proposed approach is compared with the existing methods such as LEACH, genetic algorithm (GA), and particle-swarm optimization (PSO). Simulations are carried out using Matlab 2017Ra with different network sizes (100–500 nodes) and the simulation details are given in Table 1.

Table 1
Simulation details.

Parameters	Value
Network area	200. 200 m^2
Number of sensors	100–500
Type of sensors	Static
Sensor energy	0.5 J
Number of rounds	2000–5000
Clustering method	Dynamic
Cluster head probability	0.05
Data collection	MMS
Number of MS	1–3
E_{Tx}	4.602 μJ/bit
E_{Rx}	2.34 μJ/bit
E_{fs}	$1.0e^{11}$
E_{mp}	$1.3e^{15}$

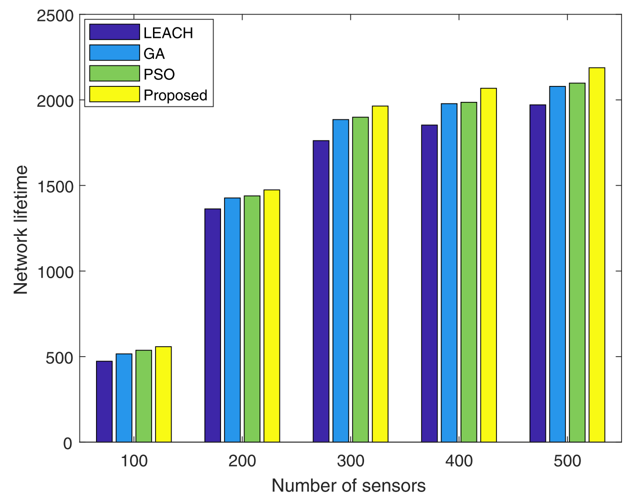

Fig. 3. First node dead.

4.1. Scenario 1

The network lifetime comparisons measured at the first and last node deaths are shown in Figs. 3 and 4, respectively. With the implementation of MS in the proposed approach, the data-forwarding mechanism can be avoided for data collection, and hence, the energy consumption for data forwarding can be neglected. It helps the proposed approach achieve the best network lifetime, as is clearly observable from these figures; the proposed method achieves longer network lifetime than the existing methods.

Fig. 6 shows the average energy consumption of nodes until the first node dies. It can be observed that the energy consumption of the proposed method is less than that of the existing methods.

4.2. Scenario 2

The network lifetime comparisons measured at the first and last node deaths are shown in Figs. 7 and 8, respectively. The similar

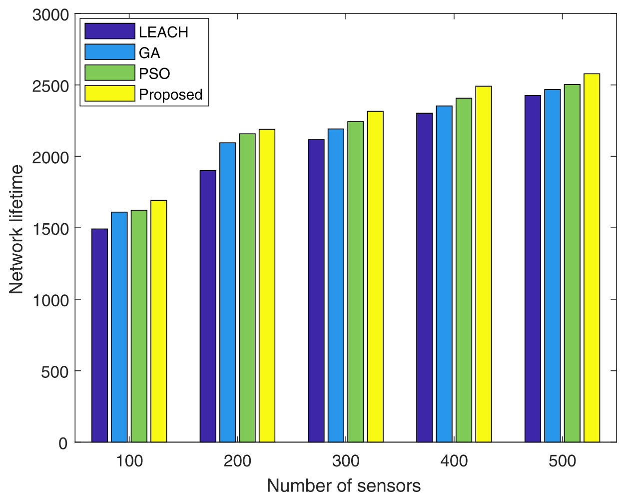

Fig. 4. Last node dead.

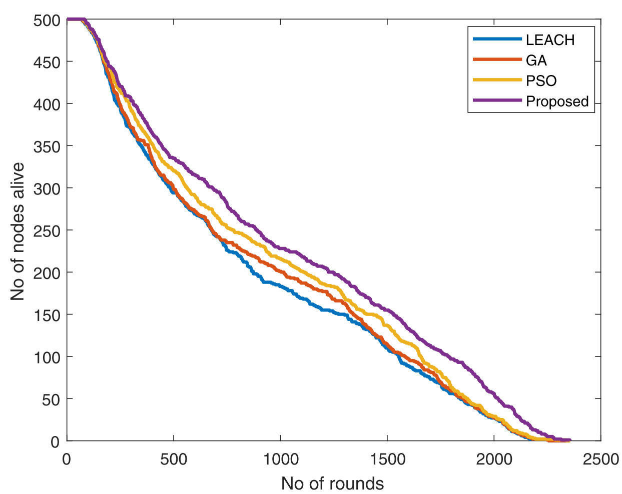

Fig. 5. Number of nodes alive.

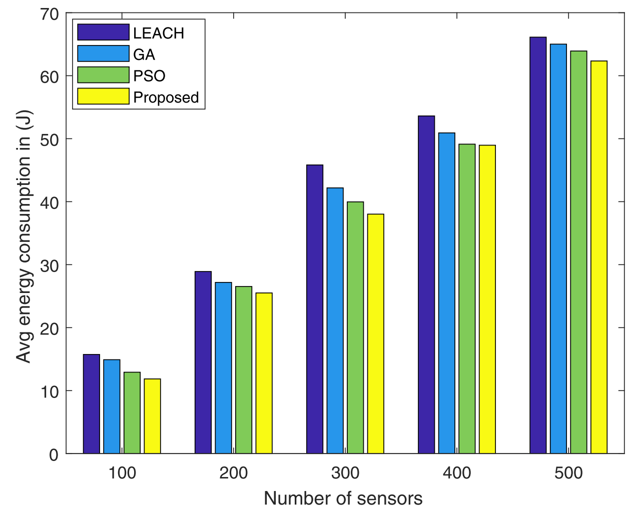

Fig. 6. Average energy consumption till first node dead.

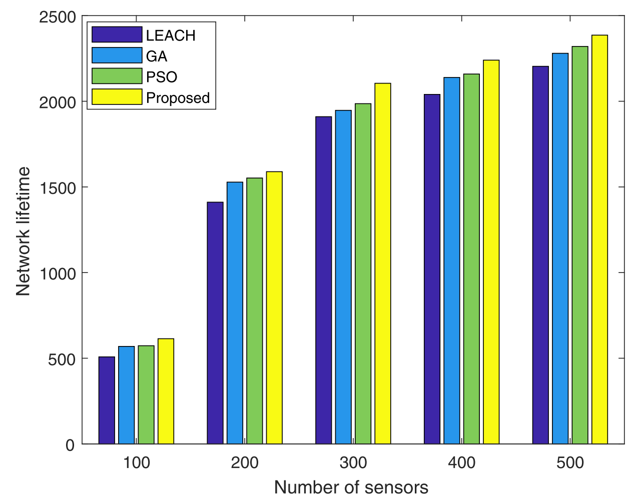

Fig. 7. First node dead.

results are observed as scenario 1 but with slightly extended network lifetime. Figs. 5 and 10 show comparisons of the number of nodes remaining alive along with the number of rounds. As the number of rounds increases, the number of alive nodes decreases gradually. We can notice from these figures that the proposed method maintains a larger number of alive nodes in each round, compared to the existing methods. From Fig. 5, it can be clearly noticed that the number of dead nodes increases along with the number of rounds. In Fig. 5, the sensor nodes drain their energy between 300 and 2100 iteration rounds. Similarly, in Fig. 10, the nodes start draining their energy completely between 400 and 2700 iteration rounds. The proposed method maintains a more balanced curve in both scenarios. Therefore, the energy consumption of the proposed approach is more balanced than that of the existing methods. It also achieves a longer network lifetime and avoids the energy-hole problem.

From Fig. 9, it is clearly observable that the energy consumption of the proposed method is minimal, compared to that of existing methods. Moreover, the energy consumption is marginally reduced when compared to that of the conventional routing method. This can be clearly seen in Fig. 9 because of the implementation of MSs.

Table 2
Average packet loss in %.

No. of Sen.	LEACH	GA	PSO	Prop.
100	0.0307	0.0297	0.0291	0.0290
200	0.0312	0.0310	0.0294	0.0295
300	0.0318	0.0306	0.0308	0.0302
400	0.0319	0.0310	0.0313	0.0310
500	0.0325	0.0317	0.0316	0.0315

4.3. Packet loss ratio

The average packet loss ratios for several network sizes are shown in Table 2. Table 2 also proves that the packet loss ratio of the proposed approach is minimal, compared to that of the existing approaches. The general data-forwarding mechanism is replaced by MS i.e., multihop data routing is avoided. Moreover, in this experiment, we have implemented MMS to perform efficient data collection.

Table 3 illustrates the average packet loss ratio for different numbers of MMS. We also observe that, with a larger number of MSs, the packet loss ratio is less. For example, in Table 3, when the number of MSs is 1, the packet loss ratio of the proposed approach is 0.0285 and when the number of MSs is increased to 3, the packet loss ratio decreases to 0.0073. Therefore, it is clear that

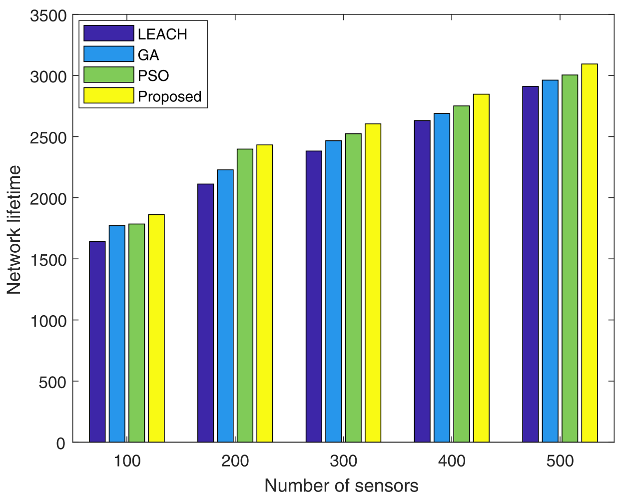

Fig. 8. Last node dead.

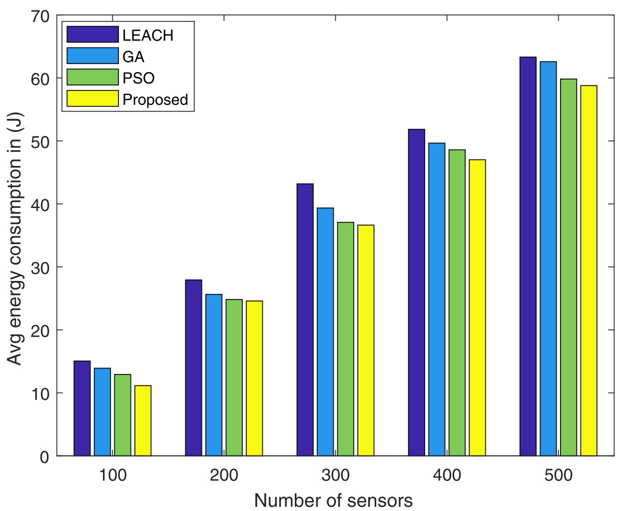

Fig. 9. Average energy consumption till first node dead.

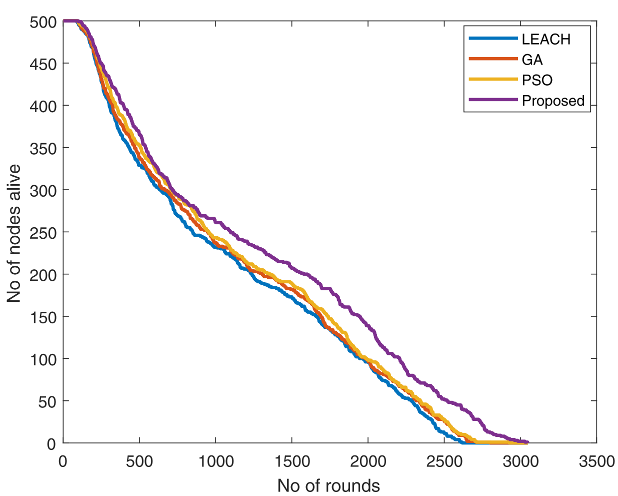

Fig. 10. Number of nodes alive.

Table 3
Average packet loss in %.

No. of MS	LEACH	GA	PSO	Prop.
1	0.0289	0.0288	0.0286	0.0285
2	0.0205	0.0199	0.0197	0.0193
3	0.0083	0.0081	0.0078	0.0073

Table 4
Comparison table.

No. of CH	Alg.	M = 1	M = 2	M = 3
10	LEACH	695.3201	696.7107	712.5994
	GA	640.1803	645.7826	652.6086
	PSO	567.2219	565.7812	598.1218
	Prop.	540.4212	540.4212	544.1588
20	LEACH	976.1456	970.8788	970.8788
	GA	924.1587	924.1587	912.4044
	PSO	892.3862	891.2813	891.1049
	Prop.	840.2244	846.1592	853.8613
30	LEACH	1133.7891	1137.1888	1119.8383
	GA	1070.1621	1088.4103	1096.5366
	PSO	1010.3861	1013.9038	1017.4618
	Prop.	0988.7075	0996.1931	0997.9895

the data-collection efficiency of the proposed method is greater than that of the existing approaches, and that it improves with increase in the number of MSs.

4.4. Performance of MSs

From Table 4, we can conclude that our proposed method and the employment of ACO algorithm for routing can solve the MMS problem. The proposed approach produces a high-quality solution. The comparison of numerical simulations are shown in Table 4, for various sizes of cluster heads and MSs. The result of ACO-based routing is superior to that of the existing algorithms and closer to an optimal solution.

Based on the experimental results, we can prove the superior performance of the proposed method. The network lifetimes measured by the first node death and the last node death, the number of alive nodes, and the average energy consumption of the proposed method outperform those of LEACH, GA, and PSO.

5. Conclusion

We proposed a novel MMS approach to improve the data-collection efficiency and network lifetime of WSNs. A modified LEACH-based clustering technique was implemented to group the sensor nodes and to elect cluster heads. In this case, MS worked similar to a robot and collected data from the cluster heads of the network. With the ACO-based MS approach, routing became more suitable and adaptable to dynamic changes in the WSN topology. MMS shortened the time taken to gather the data from all clusters, increased the network lifetime, and helped avoid data losses. The simulation results confirmed that the proposed routing scheme greatly reduced the total traveling distance when compared to the existing algorithms. Furthermore, it could prolong the network lifetime significantly, compared to the existing schemes using only a static sink. In the future, MS can be implemented with other bio-inspired algorithms to find the effectiveness of the algorithms and the mobility of the sensor nodes will be considered.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was supported by the National Research Foundation of Korea NRF-2016R1A5A1008055. The corresponding author was supported by NRF-2016R1D1A1B03931337. The second author was supported by NRF-2016R1D1A 1B03934371.

References

[1] J. Roselin, P. Latha, S. Benitta, Maximizing the wireless sensor networks lifetime through energy efficient connected coverage, Ad Hoc Networks 62 (2017) 1–10.
[2] G. Anastasi, M. Conti, M.D. Francesco, A. Passarella, Energy conservation in wireless sensor networks: a survey, Ad Hoc Networks 7 (3) (2009) 537–568.
[3] T. Rault, A. Bouabdallah, Y. Challal, Energy efficiency in wireless sensor networks: a top-down survey, Comput. Networks 67 (2014) 104–122.
[4] M. Krishnan, V. Rajagopal, S. Rathinasamy, Performance evaluation of sensor deployment using optimization techniques and scheduling approach for k-coverage in wsns, Wireless Networks 24 (3) (2018) 683–693.
[5] M. Dong, X. Liu, Z. Qian, A. Liu, T. Wang, Qoe-ensured price competition model for emerging mobile networks, IEEE Wireless Commun. 22 (4) (2015) 50–57.
[6] P. Chatterjee, S.C. Ghosh, N. Das, Load balanced coverage with graded node deployment in wireless sensor networks, IEEE Trans. Multi-Scale Comput. Syst. 3 (2) (2017) 100–112.
[7] O. Cayirpunar, E. Kadioglu-Urtis, B. Tavli, Optimal base station mobility patterns for wireless sensor network lifetime maximization, IEEE Sens. J. 15 (11) (2015) 6592–6603.
[8] E. Fadel, V. Gungor, L. Nassef, N. Akkari, M.A. Malik, S. Almasri, I.F. Akyildiz, A survey on wireless sensor networks for smart grid, Comput. Commun. 71 (2015) 22–33.
[9] C.T. Kone, A. Hafid, M. Boushaba, Performance management of ieee 802.15.4 wireless sensor network for precision agriculture, IEEE Sens. J. 15 (10) (2015) 5734–5747.
[10] M.K. Watfa, H. Al-Hassanieh, S. Salmen, A novel solution to the energy hole problem in sensor networks, J. Netw. Comput. Appl. 36 (2) (2013) 949–958.
[11] J. Yan, M. Zhou, Z. Ding, Recent advances in energy-efficient routing protocols for wireless sensor networks: a review, IEEE Access 4 (2016) 5673–5686.
[12] Zaheeruddin, D. Lobiyal, S. Prasad, Ant based pareto optimal solution for qos aware energy efficient multicast in wireless networks, Appl. Soft Comput. 55 (2017) 72–81.
[13] S.K. Gupta, P.K. Jana, Energy efficient clustering and routing algorithms for wireless sensor networks: Ga based approach, Wireless Pers. Commun. 83 (3) (2015) 2403–2423.
[14] P. Kuila, P.K. Jana, Energy efficient clustering and routing algorithms for wireless sensor networks: particle swarm optimization approach, Eng. Appl. Artif.Intell. 33 (2014) 127–140.
[15] P.C.S. Rao, P.K. Jana, H. Banka, A particle swarm optimization based energy efficient cluster head selection algorithm for wireless sensor networks, Wireless Networks 23 (7) (2017) 2005–2020.
[16] C. Li, J. Bai, J. Gu, X. Yan, Y. Luo, Clustering routing based on mixed integer programming for heterogeneous wireless sensor networks, Ad Hoc Networks 72 (2018) 81–90.
[17] E.A. Khalil, B.A. Attea, Energy-aware evolutionary routing protocol for dynamic clustering of wireless sensor networks, Swarm Evolut. Comput. 1 (4) (2011) 195–203.
[18] A. Kaswan, V. Singh, P.K. Jana, A multi-objective and pso based energy efficient path design for mobile sink in wireless sensor networks, Pervasive Mob. Comput. 46 (2018) 122–136.
[19] A. Mehrabi, K. Kim, Maximizing data collection throughput on a path in energy harvesting sensor networks using a mobile sink, IEEE Trans. Mob. Comput. 15 (3) (2016) 690–704.
[20] J. Wang, Y. Cao, B. Li, H. jin Kim, S. Lee, Particle swarm optimization based clustering algorithm with mobile sink for wsns, Future Gen. Comput. Syst. 76 (2017) 452–457.
[21] M. Khalily-Dermany, M. Nadjafi-Arani, Itinerary planning for mobile sinks in network-coding-based wireless sensor networks, Comput. Commun. 111 (2017) 1–13.
[22] S. Yang, U. Adeel, Y. Tahir, J.A. McCann, Practical opportunistic data collection in wireless sensor networks with mobile sinks, IEEE Trans. Mobile Comput. 16 (5) (2017) 1420–1433.
[23] T. Wang, G. Zhang, X. Yang, A. Vajdi, Genetic algorithm for energy-efficient clustering and routing in wireless sensor networks, J. Syst. Software 146 (2018) 196–214.
[24] G.P. Gupta, S. Jha, Integrated clustering and routing protocol for wireless sensor networks using cuckoo and harmony search based metaheuristic techniques, Eng. Appl. Artif.Intell. 68 (2018) 101–109.
[25] A. Mohajerani, D. Gharavian, An ant colony optimization based routing algorithm for extending network lifetime in wireless sensor networks, Wirel. Netw. 22 (8) (2016) 2637–2647.
[26] A.H. Fareen Farzana, S. Neduncheliyan, Ant-based routing and qos-effective data collection for mobile wireless sensor network, Wireless Networks 23 (6) (2017) 1697–1707.
[27] S. Mini, S.K. Udgata, S.L. Sabat, Sensor deployment and scheduling for target coverage problem in wireless sensor networks, IEEE Sensors J. 14 (3) (2014) 636–644.
[28] Y. Yun, Y. Xia, Maximizing the lifetime of wireless sensor networks with mobile sink in delay-tolerant applications, IEEE Trans. Mobile Comput. 9 (9) (2010) 1308–1318.
[29] H.U. Yildiz, K. Bicakci, B. Tavli, H. Gultekin, D. Incebacak, Maximizing wireless sensor network lifetime by communication/computation energy optimization of non-repudiation security service: node level versus network level strategies, Ad Hoc Networks 37 (2016) 301–323.
[30] T. Bhatia, S. Kansal, S. Goel, A. Verma, A genetic algorithm based distance-aware routing protocol for wireless sensor networks, Comput. Electr. Eng. 56 (2016) 441–455.
[31] W.-H. Liao, Y. Kao, R.-T. Wu, Ant colony optimization based sensor deployment protocol for wireless sensor networks, Expert Syst. Appl. 38 (6) (2011) 6599–6605.
[32] W.B. Heinzelman, A.P. Chandrakasan, H. Balakrishnan, An application-specific protocol architecture for wireless microsensor networks, IEEE Trans. Wireless Commun. 1 (4) (2002) 660–670.
[33] A.M. Adrian, A. Utamima, K.-J. Wang, A comparative study of ga, pso and aco for solving construction site layout optimization, KSCE J. Civil Eng. 19 (3) (2015) 520–527.
[34] M. Li, Efficiency improvement of ant colony optimization in solving the moderate ltsp, J. Syst. Eng. Electron. 26 (6) (2015) 1300–1308.
[35] B. Hu, R. Chen, D. Zhang, G. Jiang, C. Pang, Ant colony optimization vs genetic algorithm to calculate gene order of gene expression level of alzheimer's disease, in: 2012 IEEE International Conference on Granular Computing, 2012, pp. 169–172.
[36] I. Dietrich, F. Dressler, On the lifetime of wireless sensor networks, ACM Trans. Sen. Netw. 5 (1) (2009) 5:1–5:39.

Krishnan Muralitharan received the B.Sc. degree in Electronics and M.C.A. degree in Computer Science from Bharathiar University, Coimbatore, Tamilnadu, India, in 2001 and 2004, respectively. He received the Ph.D in Computer Applications from Anna University, Tamilnadu, India, in 2016. Currently, he is working as a Post-doctoral Researcher in AORC, Sungkyunkwan University, Suwon, South Korea. His current research interests includes smart grid networks, wireless sensor networks and optimization techniques.

Sangwoon Yun received the B.S. and M.S. degrees in mathematics from the Yonsei University, Seoul, Korea, in 1995 and 1999, respectively and Ph.D. degree in mathematics from the University of Washington, Seattle, in 2007. He is currently an Associate Professor of Mathematics Education at Sungkyunkwan University, Seoul. His research interests include optimization, image processing, data analysis, and scientific computing.

Yoon Mo Jung received the B.S. and M.S. degrees in mathematics from the Yonsei University, Seoul, Korea, in 1998 and 2000, respectively and Ph.D. degree in mathematics from the University of Minnesota, Minneapolis, in 2007. He is currently an Assistant Professor of mathematics at the Sungkyunkwan University, Suwon. His research interests include image processing, data analysis, inverse problems, and scientific computing.