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Optimal Coverage Multi-Path Scheduling Scheme with Multiple Mobile Sinks for WSNs

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Abstract: Wireless Sensor Networks (WSNs) are usually formed with many tiny sensors which are randomly deployed within sensing field for target monitoring. These sensors can transmit their monitored data to the sink in a multi-hop communication manner. However, the 'hot spots' problem will be caused since nodes near sink will consume more energy during forwarding. Recently, mobile sink based technology provides an alternative solution for the long-distance communication and sensor nodes only need to use single hop communication to the mobile sink during data transmission. Even though it is difficult to consider many network metrics such as sensor position, residual energy and coverage rate etc., it is still very important to schedule a reasonable moving trajectory for the mobile sink. In this paper, a novel trajectory scheduling method based on coverage rate for multiple mobile sinks (TSCR-M) is presented especially for large-scale WSNs. An improved particle swarm optimization (PSO) combined with mutation operator is introduced to search the parking positions with optimal coverage rate. Then the genetic algorithm (GA) is adopted to schedule the moving trajectory for multiple mobile sinks. Extensive simulations are performed to validate the performance of our proposed method.

Keywords: WSNs, mobile sink, trajectory scheduling, network performance.

1 Introduction

Sink mobility as a significant optimization method has been widely used in different types of routing protocols for wireless sensor networks (WSNs) [Wang, Wu, Tseng et al. (2012); Gao, Wang, Wu et al. (2019); Wang, Cao, Li et al. (2019); Srilakshmi and Sangaiah (2019)]. By adopting mobile sink, following advantages can be obtained. Firstly, sink mobility helps alleviate the limited energy problem of sensors [Ren, Zhang, Zhang et al. (2015); Wang, Gao, Liu et al. (2019)]. It reduces the average transmission distance

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between sensors and the sink by access to the areas with dense sensors. Secondly, the energy distribution of the network will be more even because with the sink moving, sensors take turns to be the traffic hubs for data forwarding and the 'hot spots' problem is greatly alleviated [Wang, Gao, Liu et al. (2019); Pan, Lee, Sghaier et al. (2019); Gao, Wang, Wu et al. (2019)]. Thirdly, the network connectivity can be improved because the mobile sink can move to the isolated areas and the sparse networks can be connected [Wang, Gao, Yin et al. (2018); Song, Liu, Shao et al. (2019); Wang, Gao, Liu et al. (2019); Nguyen, Pan and Dao (2019)].

In spite of the above advantages the mobile sink brings, some challenges are also troubling the researchers. One of the significant problems for the mobile sink technology is the moving trajectory scheduling [Wang, Gao, Liu et al. (2019); Pan, Kong, Sung et al. (2018); Liu and Zhao (2019); Wang, Gao, Wang et al. (2019)]. Due to the huge amounts of sensors, it's impossible for the mobile sink to traverse the sensors one by one. Therefore, the moving trajectory of the mobile sink should be elaborately designed to enhance the efficiency of data gathering. The data gathering schemas for WSNs can be classified into three types, clustering-based schema, data mule-based schema and rendezvous-based schema [Rhim, Tamine, Abassi et al. (2018); Wang, Zhang, Li et al. (2014); Meng, Pan, Tseng et al. (2019); Wu, Chen, Wang et al. (2019); Wang, Gu, Liu et al. (2019); Pan, Kong, Sung et al. (2018); Yu, Choi, Lee et al. (2018)]. In clustering-based schema, the data collector is usually a fixed sink and all sensors transmit the data to the sink using multi-hops communication. Mule-based schema usually adopts a mobile sink to gather information. The mobile sink moves along a predefined or casual path for data gathering and when the mobile sink enters the transmission range of the nearby sensors, the data transmission begins. In rendezvous-based schema, a set of parking positions are firstly selected and the mobile sink only stops at park positions for data gathering.

In this paper, a single-hop based trajectory scheduling method called TSCR-M using heuristic algorithms is presented. In TSCR-M, all sensors are preferable to adopt single-hop communication within their transmission range to upload their monitored data to the mobile sink. We firstly utilize an improved particle swarm optimization algorithm to search the park positions for the mobile sink and those park positions cover as much sensors as possible. Meanwhile, the overlapped coverage rate is minimized. Then the genetic algorithm is introduced to schedule optimal loops for mobile sinks. Mobile sinks travel along the loops and only stops at the park positions for data gathering. Quantities of simulations prove the efficiency of our presented method in aspects of energy consumption, network lifetime and the efficiency of data gathering.

The rest sections of this paper are organized as follows: A brief summary of some parallel work is given in Section 2. Section 3 illustrates the system model which contains the network and energy model. In Section 4, we specifically introduce the presented TSCR-M algorithm. In Section 5, numerous simulations are conducted and the results are analyzed. Finally, we conclude the whole paper in Section 6.

2 Related work

In Lu et al. [Lu, Sun and Pan (2018)], authors design an optimal trajectory for the mobile sink using an improved artificial bee colony algorithm. In this work, authors consider the total energy consumption problem as the minimization of the total hop counts between the sensors with the rendezvous. Then the rendezvous points for the mobile sink are elaborately chosen in advance to improve the efficiency of data gathering using the artificial bee colony algorithm. Finally, authors enhance the performance of the artificial bee colony algorithm by introducing the cumulative factor and Cauchy mutation operator.

In Sun et al. [Sun, Zhao, Feng et al. (2019)], authors present a path scheduling algorithm for multi-sink nodes using an improved particle swarm optimization. The sensing field is divided by regular hexagons and in each hexagon, mobile sink can park at the center point or the centroid point of sensors. Then the moving path of different sinks and park positions are scheduled using a hybrid positive and negative particle swarm optimization algorithm.

In Soni et al. [Soni and Mallick (2018)], authors present a novel method based on regular hexagons for sensors deployment. It divides the sensor field into regular hexagons. In each regular hexagon, there is only one active sensor as well as the others keep sleeping to preserve energy. The side length of the regular hexagon is elaborately designed so that sensors in any two adjacent hexagons can communicate with each other.

In Ma et al. [Ma, Yang and Zhao (2013)], authors present a tour scheduling method based on spanning tree for mobile sinks. The polling points are firstly chosen for the mobile sinks to stop for data collecting. The algorithm adopts two strategy to choose the polling points. Mobile sinks can choose the sensors or explore other locations of the sensing field as the polling points. Average cost of the polling points is calculated to evaluate their quality. Then the spanning tree is decomposed into several subtrees for each sink.

In Kuila et al. [Kuila and Jana (2014)], authors utilize particle swarm optimization (PSO) to plan the moving path for the mobile collector. Common sensors and gateways are contained in the network. The main contribution of this paper is to establish a novel mapping between sensors and the virtual particles.

In Wang et al. [Wang and Chen (2018)], authors present a reliable and efficient data gathering algorithm called EARTH considering the changed sensing rate of sensors and limited memory space. In EARTH, the minimal spanning tree of sensors is firstly constructed by Dijkstra algorithm. Afterwards, candidate rendezvous points are selected according to the ancestor-descendant relationship between sensors and accumulative number of packets. Then the final rendezvous points are selected according to hop counts and distance. Additionally, authors also present an enhance version of EARTH by introducing the strategies of rendezvous points replacement and consolidation.

3 System model

3.1 Network model

We consider the network is a large-scale sensing field and a set of sensors denoted by $\{s_1, s_2 \dots \dots s_n\}$ are randomly deployed by vehicles. Following assumptions are made to conveniently conduct the simulations.

(1). Sensors are equipped with global positioning systems (GPS) and they can exchange the information with neighbors [Park, Salim, Jo et al. (2019)].

(2). Sensors are initialized with the same energy and they cannot be charged.

(3). Mobile sinks can freely travel the sensing field and they are not energy limited.

(4). The acceleration time of the mobile sink is ignored and it only stops at park position for data gathering.

3.2 Energy model

The energy model we used is the same as LEACH [Heinzelman, Chandrakasan and Balakrishnan (2000)]. Suppose that a sensor s_i sends a k-bit data to the target node s_2 and their Euclidean distance is represented as $\hat{L}(s_i, s_j)$. The total energy used during the data transmission can be calculated using Eq. (1).

$$E_{Tx}(s_i, s_j, k) = \begin{cases} (E_{elec} + \varepsilon_{fs} \cdot \hat{L}(s_i, s_j)^2) \cdot k & if\ \hat{L}(s_i, s_j) \leq d_0 \\ (E_{elec} + \varepsilon_{mp} \cdot \hat{L}(s_i, s_j)^4) \cdot k & if\ \hat{L}(s_i, s_j) > d_0 \end{cases} \tag{1}$$

where E_{elec} is the Radio Frequency (RF) energy consumption coefficient. ε_{fs} and ε_{mp} denote the amplification factor for free-space model and multi-path fading model respectively. d_0 denotes a threshold value to switch the different models and it can be calculated by Eq. (2).

$$d_o = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \tag{2}$$

The energy consumption used for receiving k-bit data is only corresponded to the amount of received data and it can be calculated by Eq. (3).

$$E_{Rx} = E_{elec} \cdot k \tag{3}$$

4 Our proposed TSCR-M algorithm

4.1 Coverage problem transformation

Traditional multi-hops transmission is widely applied in WSNs especially those large-scale networks. As the energy model describes, when the transmission distance exceeds a threshold value, the energy consumption used for transmission will rapidly increase. Multi-hop transmission saves energy by using the relay nodes to decrease the transmission distance between two sensors with large distance. However, much energy is dissipated during the data forwarding. Nowadays, advanced sink mobility technology and Multi-User Multiple-Input Multiple-Output (MU-MIMO) technology provides an alternative solution for the long-distance communication [Miao, Sun, Wang et al. (2016)]. Sensors only needs to use single hop transmission to upload the data to the mobile sink when it approaches.

In mobile sink-based networks, the moving trajectory is significant to the performance of the network such as network latency and energy consumption. The moving trajectory can also be decomposed into many park positions and the mobile sink only stops at the park position for data gathering. We expect sensors in the network to communicate with the mobile sink within one hop and that represents the park position will cover as much sensors as possible within one hop. Therefore, we firstly transfer the problem of moving trajectory into the coverage problem. An illustration of coverage problem is shown as Fig. 1.

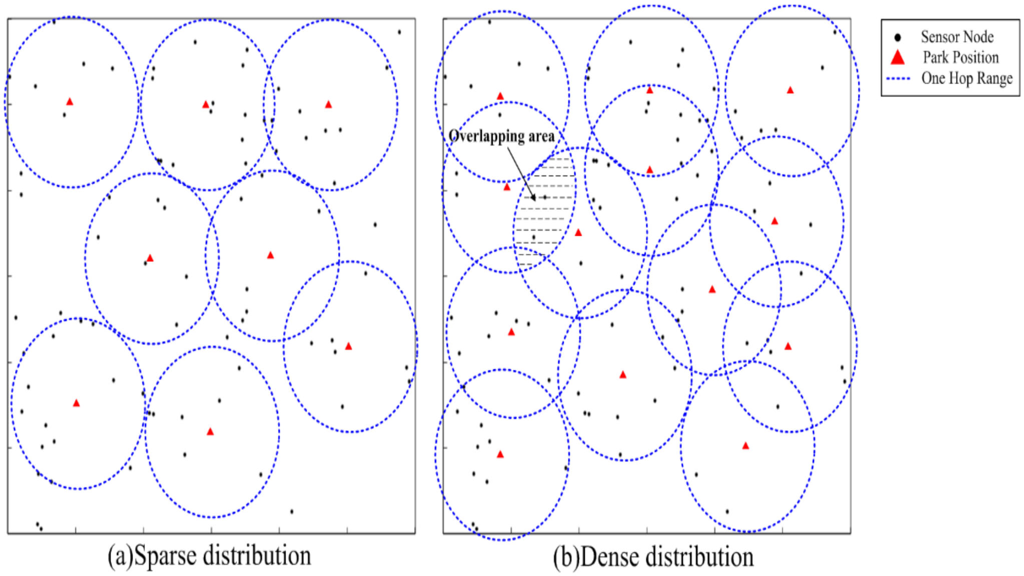

Figure 1: Different strategies for coverage problem

As we can see from Fig. 1, there are two strategies to set the park positions in the network, sparse distribution and dense distribution. In sparse distribution, park positions are more evenly distributed in the whole network and the number of park position is less than that in dense distribution. The target of sparse distribution is to adopt as few park positions as possible to cover as much sensors as possible. Therefore, the outlier may be ignored and they still use multiple hop communication to transmit data to the closest park position. In dense distribution, almost every sensor is considered by the park position. Each sensor is covered by at least one park position and many sensors are covered by more than one park positions. Although the dense distribution increases the coverage rate, its disadvantages are also obvious. Sensors in these overlapped areas are unnecessary to be repeatedly visited and those redundant park positions increased the itinerary of the mobile sink. We consider the advantages of both strategies and introduce an improved particle swarm optimization (PSO) to determine the best locations of these park positions.

4.2 Park positions selection using PSO

Particle swarm optimization (PSO) is a meta-heuristic optimization algorithm and it is inspired by the bird foraging. The individual adjusts its solution by learning from the companions and the workflow of the traditional PSO is shown as Fig. 2. Traditional PSO suffers from the local optimal solution and slow convergence. Therefore, we adjust the control factors and introduce the mutation operator to improve the performance of PSO.

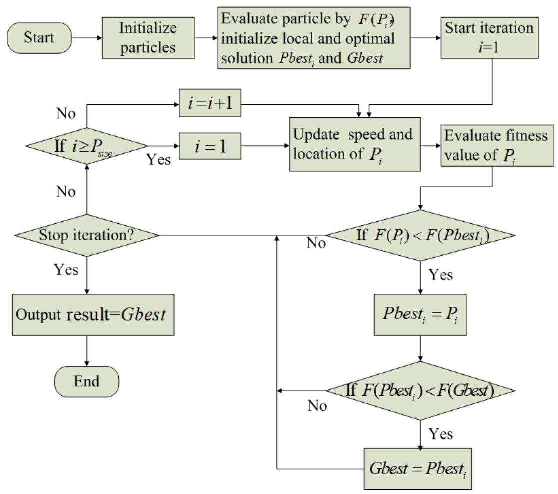

Figure 2: The workflow of the traditional PSO

We firstly definite the fitness function of PSO. Less park positions are expected to cover more sensors. Therefore, the park positions should be evenly distributed in the network and the overlapped areas should be decreased. The fitness function is defined as Eq. (4).

$$F(P) = \frac{r_{overlap\_cover}}{r_{cover}} \tag{4}$$

where $r_{overlap\_cover}$ represents the percentage of the covered sensors which are within one hop transmission of more than one park positions. r_{cover} represents the percentage of covered sensors which are within one hop transmission of at least one park position. Less fitness value means the park positions cover more sensors and there are fewer overlapped areas in the network. The target of PSO is to minimize the fitness function. Then we will have a specific illustration of the improved PSO.

We use a particle to denote a whole solution for all the park positions and all the particles can be denoted as a matrix P.

$$P = \begin{bmatrix} p^1 \\ p^2 \\ p^2 \\ \vdots \\ p^n \end{bmatrix} = \begin{bmatrix} x_{pp_1}^1, y_{pp_1}^1, x_{pp_2}^1, y_{pp_2}^1 \cdots\cdots x_{pp_m}^1, y_{pp_m}^1 \\ x_{pp_1}^2, y_{pp_1}^2, x_{pp_2}^2, y_{pp_2}^2 \cdots\cdots x_{pp_m}^2, y_{pp_m}^2 \\ x_{pp_1}^3, y_{pp_1}^3, x_{pp_2}^3, y_{pp_2}^3 \cdots\cdots x_{pp_m}^3, y_{pp_m}^3 \\ \vdots \\ x_{pp_1}^n, y_{pp_1}^n, x_{pp_2}^n, y_{pp_2}^n \cdots\cdots x_{pp_n}^n, y_{pp_n}^n \end{bmatrix} \tag{5}$$

where $(x_{pp_j}^i, y_{pp_j}^i)$ denotes the j-th park position (pp) in the i-th solution. Then the velocity of each dimension V is randomly initialized and it is limited to the interval of -50 and 50. The local optimal solution P_{ibest} records the optimal solution for the i-th particle. The global optimal solution G_{best} records the optimal solution for all the particles. The initial values of P_{ibest} and G_{best} are set as infinity. Following steps are contained during the iteration.

Step 1: The fitness value of each particle is calculated according to the fitness function.

Step 2: Each particle compares its current fitness value with P_{ibest}. If the current fitness value is less than P_{ibest}, update P_{ibest} with the current fitness value. Then select the minimal fitness value of the current particles and compare it with G_{best}. If the minimal fitness value is less than G_{best}, update G_{best} with the minimal fitness value.

Step 3: Next, the velocity of each particles will be updated by Eq. (6).

$$V_{t+1} = \eta V_t + \alpha \cdot rand() \cdot (P_{ibest} - P_t) + \beta \cdot rand() \cdot (G_{best} - P_t) \quad (6)$$

where η represents the inertia coefficient and α, β denotes the learning factor of local and global information respectively. The $rand()$ function generates a random number between 0 and 1. The updated V will be check to see whether it exceeds the limit. Additionally, η is a self-adaptable parameter and it changes with the number of iterations for better searching strategy. The update of η can use the following formula.

$$\eta = \eta_{max} - (\eta_{max} - \eta_{min}) \cdot \frac{Iter}{Iter_{max\_PSO}} \quad (7)$$

where η_{max} denotes the maximal value of η and η_{min} denotes the minimal value of η. $Iter$ denotes the current number of iterations and $Iter_{max}$ denotes the maximal number of iterations. Then the locations of the particles can be updated by the velocity.

$$P_{t+1} = P_t + V_{t+1} \quad (8)$$

Similarly, the updated P will also be checked to see whether it oversteps the boundary.

Step 4: Finally, we introduce the mutation operator to avoid obtaining the local optimal solution. Each dimension of the particles has a probability to vary and the variable dimension will be randomly assigned a value within the boundary.

Repeat the above steps until the algorithm achieves its maximal number of iterations. After numerous iterations, the park position of the mobile sinks is shown as Fig. 3.

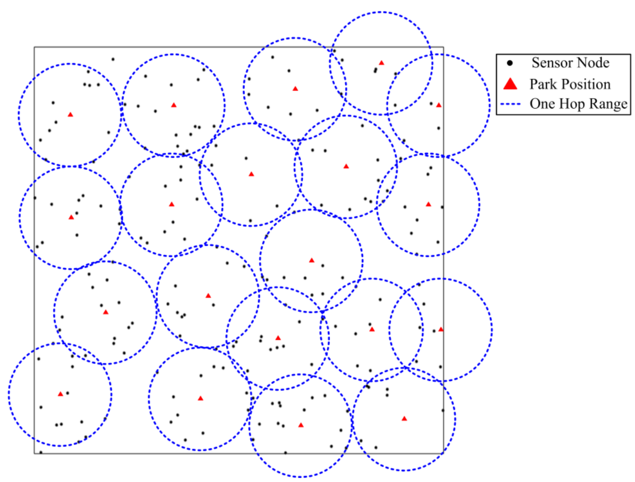

Figure 3: Park position selection using PSO

4.2 Multi-path scheduling using GN

As we consider the network model is a large-scale sensing field, one mobile sink needs to traverse all the park positions and that results in severe network latency. Therefore, we introduce multiple mobile sinks for data gathering. Mobile sinks are deployed at different regions of the sensing field and multi-path needs to be planned using genetic algorithm (GA). GA simulates the process of biological evolution and it performs a multi-directional search by maintaining a group of potential solutions supporting the formation and exchange of information in these directions. The workflow of GA is shown as Fig. 4.

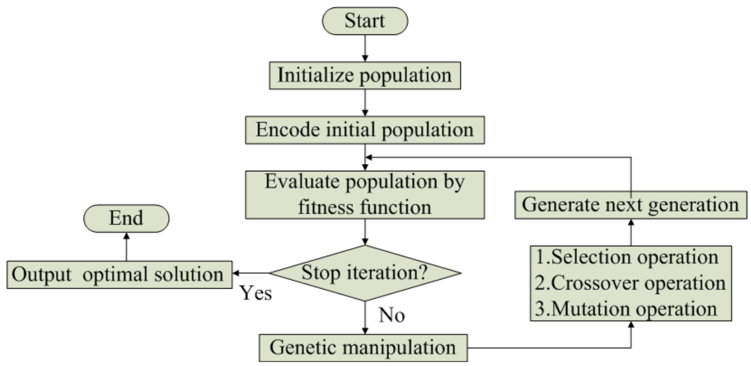

Figure 4: The workflow of GA

Similarly, we firstly define the fitness value of GA. The target of GA is to find multiple moving paths for the mobile sinks and each path needs to be as short as possible. The longest path scheduled for one of the mobile sinks means the maximal delay of the network. Therefore, we defined the fitness function as the longest path of the mobile sinks and it can be represented by Eq. (9).

$$F(P) = max\ (L) \tag{9}$$

where L records the path length of different mobile sinks.

The sequence of the park positions which represents the traversal order of different mobile sinks is randomly initialized and then we encode the sequence as a population. The population contains two parts, traversal sequences and break points. For example, when the traversal sequence is $S = (6,2,3,5,9,4,1,7,8)$ and the break point is $B = (2,5)$, that means the travelling paths of three mobile sinks are $(6,2,3)$, $(5,9,4)$ and $(1,7,8)$ respectively. Multiple populations are generated to search for the best solution of the moving paths. Following steps are sequentially executed before achieving the maximal number of iterations.

Step 1: The fitness values of the populations are calculated to evaluate the quality of each population and then the optimal population is recorded.

Step 2: Determine if the algorithm reaches the number of its iterations. If the algorithm reaches the number of maximal iterations, it will output the optimal population and end iteration. Otherwise, the mutation operation will be conducted.

Step 3: Then we group all the populations. In each group, we select the optimal population to conduct the mutation operation. The mutation operation mainly contains the following forms.

(1). Randomly flip the fragments in the sequence of the optimal population.

(2). Randomly swap the different nodes in the sequence of the optimal population.

(3). Randomly translate a fragment in the sequence of the optimal population.

(4). Randomly modify the break points of the optimal population.

(5). Randomly flip the fragments in the sequence and modify the break points of the optimal population.

(6). Randomly swap the different nodes in the sequence and modify the break points of the optimal population.

(7). Randomly translate a fragment in the sequence and modify the break points of the optimal population.

(8). Preserve the original optimal population.

Step 4: Finally, the next generation of populations are generated using the above rules.

Then the above steps are repeatedly executed until the algorithm reaches its maximal number of iterations. Finally, the scheduled multi-path for mobile sinks is shown as Fig. 5. In Fig. 5, we adopt three mobile sinks for data gathering. The number of mobile sinks can be adjusted according to the requirement.

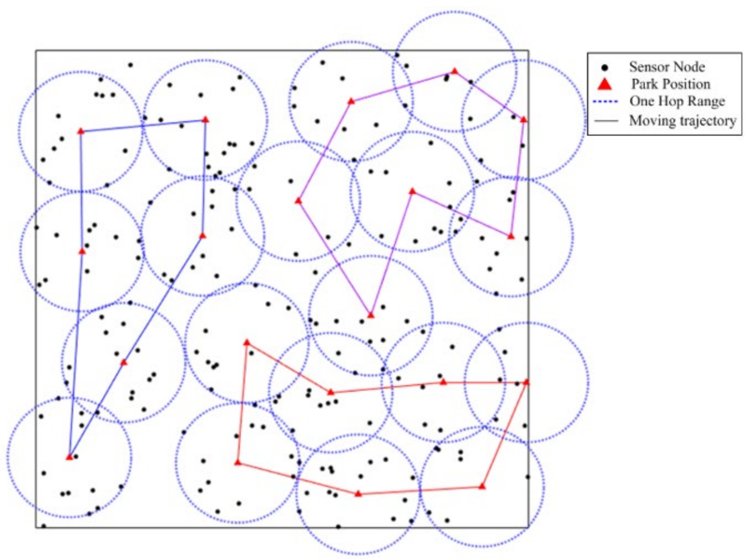

Figure 5: Multi-path scheduling using GA

5 Performance evaluation

In order to have a systematic evaluation of our presented TSCR-M, we compare it with some parallel works such as LEACH [Heinzelman, Chandrakasan and Balakrishnan (2000)], SHDGP [Ma, Yang and Zhao (2013)], HPNPSO [Sun, Zhao, Feng et al. (2019)] and MWR [Miao, Sun, Wang et al. (2016)] in aspects of energy consumption, network lifetime and network delay. The time interval of the network is round and each sensor should transmit a data package to the mobile sink in a round. Simulations are conducted in a virtual environment using MTLAB R2016A.

5.1 Network parameters

Some parameters in PSO and GA have a significant influence on the performance of the network. Therefore, we conduct numerous simulations to achieve the optimal parameters. The relevant parameters of PSO and GA are listed in Tab. 1.

Table 1: Parameters of PSO and GA

Parameter name	Description	Value
n	The number of particles	100
m	The number of park positions	20
η	Inertia coefficient	0.5
η_{max}	Maximal value for inertia coefficient	0.5
η_{min}	Minimal value for inertia coefficient	0.1
α	Learning factor of local information	0.4
β	Learning factor of global information	0.6
$Iter_{\max\_PSO}$	Maximal number of iterations of PSO	500
s	The size of populations	128
T_{min}	The minimal traversing number	5
$Iter_{\max\_GA}$	Maximal number of iterations of GA	500

The network parameters are also listed in Tab. 2.

Table 2: Parameters of the network

Parameter name	Description	Value
S	Side length of the sensing field	[500,1000,1500,2000] m
N	The number of sensors	[100,200,300,400]
MS	The number of mobile sinks	[1,2,3,4]
E_{elec}	RF energy consumption coefficient	50nJ/bit
E_{fs}	Amplification factor for free-space model	10 pJ/bit/m^2
E_{mp}	Amplification factor for multi-path model	0.0013 pJ/bit/m^4
Tr	Transmission range of sensors	87.7 m
E_0	The initial energy of sensors	0.1 J
V_m	The moving speed of the mobile sink	5 m/s
T_m	Data gathering time in park positions	10 s

5.2 Comparison of energy consumption

We firstly compare the energy consumption between different algorithms in a 1000×1000 sensing field. As we have previously assumed, the mobile sink only stops at park positions for data gathering. More mobile sinks can only reduce the average traveling length and have no influence to the energy consumption. 200 sensors are randomly deployed and only one mobile sink is introduced when calculate the energy consumption. The average values of multiple simulations are recorded and the simulation result is shown as Fig. 6. In Fig. 6, we can clearly see that the performance of LEACH and HPNPSO is obviously worse than our presented algorithm. SHDGP performances better than our presented TSCR-M only before 570 rounds. Both SHDGP and TSCR-M are single-hop-based routing schema, so, they consume less energy.

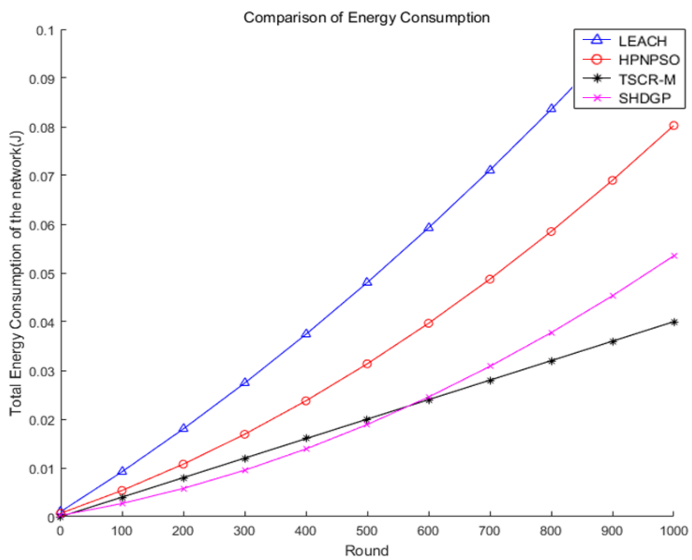

Figure 6: Comparison of energy consumption between different algorithms

5.3 Comparison of network lifetime

Then we compare the network lifetime of different algorithms. We still adopt one mobile sink in our proposed algorithm and the sensing field is set as 1000×1000 m. 200 sensors are randomly deployed and different algorithms adopt the same network model. Simulation result is shown as Fig. 7. From Fig. 7, we can obviously see that sensors begin to die at 600, 680, 800 rounds in LEACH, SHDGP and HPNPSO respectively. However, in TSCR-M, there are dead sensors in about 900 rounds.

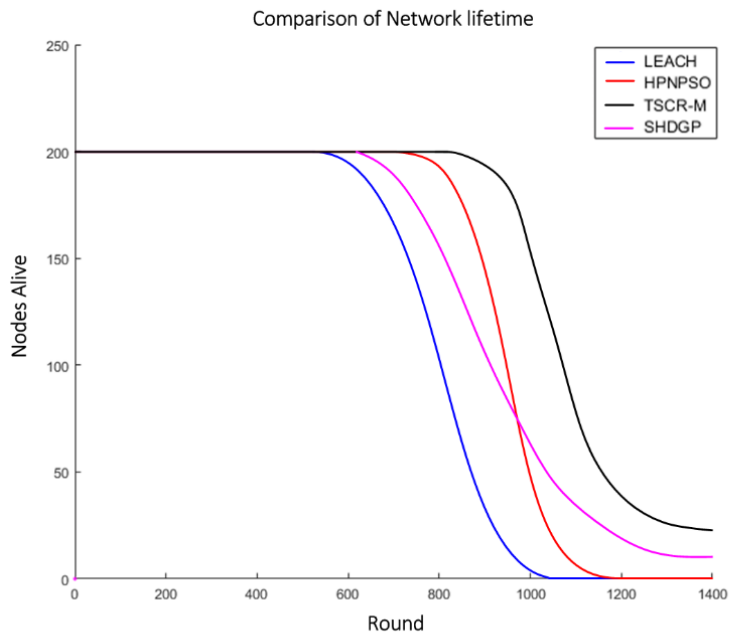

Figure 7: Comparison of network lifetime between different algorithms

5.4 Comparison of network delay

Network delay is an important characteristic for some delay-sensitive applications. Therefore, the routing schema should reduce the network delay while extending the network lifetime. In this paper, we define the network delay as the time when the mobile sink gathers all the data packages from sensors in a round. This means that in multi-sink schema, the most travelling time the mobile sink used is as the network delay. The travelling time of the mobile sink can be calculated using Eq. (10).

$$T = \frac{L_m}{V_m} + T_m \cdot N_m \tag{10}$$

where L_m denotes the travelling length of the mobile sink and N_m denotes the number of park positions the mobile sink visits. We compare the network delay of different algorithms in different network parameters and the simulation result is shown as Fig. 8. In Fig. 8, TSCR-3M denotes three mobile sinks are adopted in our proposed algorithm. When there is only one mobile sink in the network, our presented algorithm performances better than other algorithms. Introducing more mobile sinks can decrease the travelling time, however, with the number of mobile sinks increasing, the trend of performance improvement is gradually decreasing. Therefore, we suggest that two mobile sinks in TSCR-M will be a good choice.

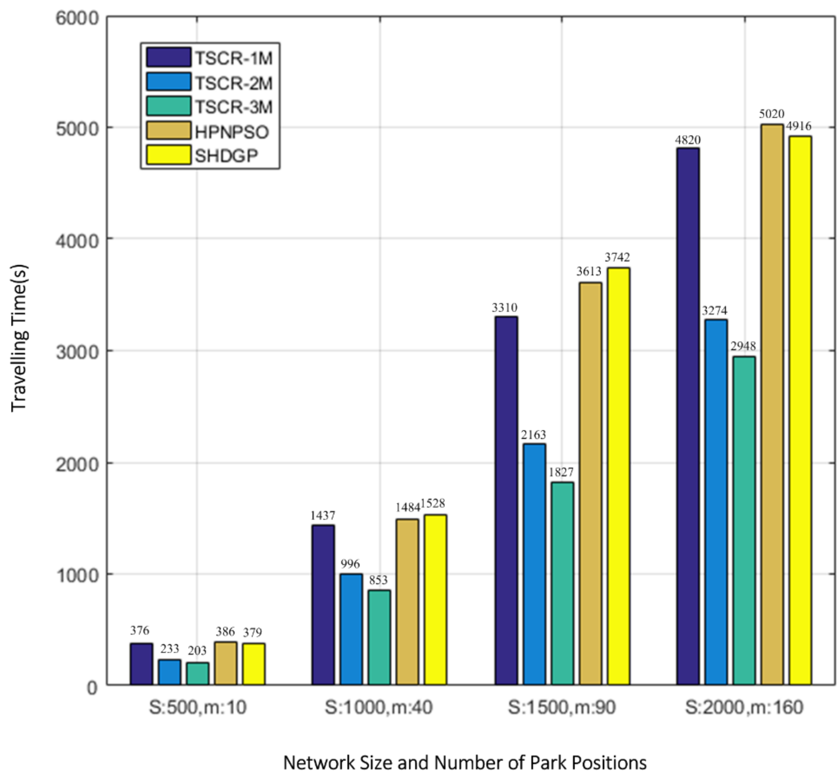

Figure 8: Comparison of network delay between different algorithms

5.5 Discussion of coverage and overlapped coverage rate

Finally, we explore the suitable number of park positions in different scale of networks. The number of park positions can be firstly calculated by Eq. (11).

$$m = \left\lfloor \frac{S^2}{\pi d_0^2} \right\rfloor \tag{11}$$

Then we change the number of park positions and observe the changes of coverage rate and overlapped coverage rate. We also change the number of sensors and the simulation result is shown as Fig. 9. Fig. 9 illustrates that too few park positions will greatly decrease the coverage rate and too many park positions will greatly increase the overlapped coverage rate. A suitable number of park positions will balance the coverage rate and overlapped coverage rate. Additionally, we can also find that in dense network, more park positions are needed to achieve the high coverage rate and low overlapped coverage rate.

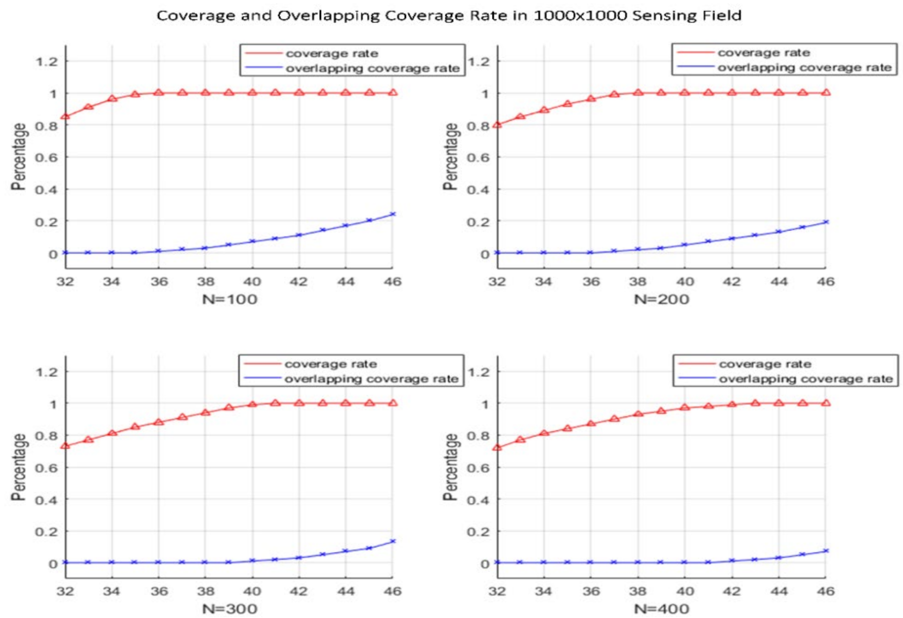

Figure 9: Coverage and overlapped coverage rate

6 Conclusion

In this paper, we have presented TSCR-M which is a single-hop based routing algorithm supported for multiple mobile sinks in WSNs. There are mainly two parts in TSCR-M, park positions selection and multi-path scheduling for mobile sinks. Park positions are first selected using an improved PSO algorithm considering the coverage and overlapped coverage rate of sensors. Then GA is introduced to schedule the efficient moving path for multiple mobile sinks. The reduced energy and enhanced network lifetime compared to some parallel works substantiate the efficiency of our proposed algorithm.

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Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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