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Energy-Aware Data Gathering Mechanism for Mobile Sink in Wireless Sensor Networks Using Particle Swarm Optimization

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ABSTRACT In order to mitigate the hot spot problem and prolong the network lifetime, data gathering with mobile sink is an effective measure to enhance the system performance. However, the movement strategy of sink node can be regarded as traveling salesman problem, which can hardly obtain the solution with polynomial running time. To address above problem, an energy-aware data gathering mechanism for mobile sink in wireless sensor networks using particle swarm optimization is introduced. Firstly, the mathematical model is established according to the total energy consumption and delay constraints for mobile sink's data collection. Then, the optimal rendezvous points are selected to aggregate data originated from the source nodes through multi-hop relay, and the aggregation tree will be constructed for data transmission. The spanning tree is encoded into particles, and the random method is designed to generate the data collection spanning tree with constrain of tree height limit. Furthermore, a particle swarm optimization strategy with adaptive elite mutation is designed to improve the population diversity and avoid falling into the local optimal solution prematurely. Experimental results show that the proposed method can meet the delay requirements and reduce the total energy consumption of the network.

INDEX TERMS Wireless sensor networks, data gathering, particle swarm optimization, energy efficiency.

I. INTRODUCTION

Wireless sensor networks (WSNs) are composed of plenty of sensor nodes, which have limited processing power and wireless communication capability. The sensor nodes monitor the surrounding environment, and then transmit the data to sink through single-hop or multi-hop mode. Due to high energy consumption for long-distance wireless communication, those tiny and resource limited sensor nodes usually communicate with each other with multi-hop manner. However, the nodes closer to the sink consume more energy than other nodes because they undertake more forwarding tasks. Energy consumption imbalance often leads to energy holes, network segmentation and other problems [1]. In addition, some applications with strict real-time requirements need the sensor nodes to transmit the collected data to the sink in a short time. Therefore, the lifetime and transmission delay will be regarded as important evaluation indicators for data gathering in WSNs [2], [3].

During the phase of multi hop routing, the sensor nodes close to the sink should relay the packets of other nodes and its battery power will be depleted earlier. As the situation worsened, the entire WSNs will be disconnected and result in the loss of network coverage and connectivity. Therefore, the strategy of mobile sink is proposed to address above problem [4]. The mobile sink or a mobile agent can act as a data collector, move around the monitoring region and go through the rendezvous points for data gathering. This strategy can greatly shorten the communication path from node to sink and make the load more balanced among the sensor nodes [5]. Also, it should be noted that the selection of optimal rendezvous points for the mobile sink is a NP-hard problem [6]. The complexity of sink mobile strategy mainly comes from the following two factors: one is that sink has unlimited possibilities to select the rendezvous points. The other is that it needs to select a reasonable location from the feasible resolutions to achieve the optimal data

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gathering performance. The conventional solutions focus on maintaining the energy consumption balance as much as possible and reducing the delay of network communication owing to the mobile sink's movement [7]. The strategy adopted by most methods is to reconstruct the whole network into several routing trees or clusters, and the mobile sink node polls all relay node to obtain the data of the whole network [8], [9].

In this paper, we propose an energy-aware data gathering mechanism for mobile sink in wireless sensor networks using particle swarm optimization, which we name it EDGMS for short. Firstly, the mathematical model is established according to the total network energy consumption and delay constraints in mobile sink data collection. Then, the optimal rendezvous points to be visited by a mobile sink will be selected and the aggregation tree will be constructed for data transmission. The spanning tree is encoded into particles, and the random method is designed to generate the data collection spanning tree with constrain of tree height limit. Furthermore, a particle swarm optimization strategy with adaptive elite mutation is designed to improve the population diversity and avoid falling into the local optimal solution prematurely. The extensive simulation results show that EDGMS can reduces the transmission delay, balance energy consumption, and prolongs network lifetime.

II. RELATED WORK

In recent years, there have been plenty of WSNs applications with mobile devices to improve the efficiency of data gathering [6], [10], [11]. Also, the mobility features brings new research challenges, such as the movement patterns, the update of the device's location, ensure of the network coverage. The above factors will affect the performance of the network significantly. Some of the previous works have considered that the centralized method can be applied by mobile sinks through the selection of the traversal path.

Guo *et al.* [12] partitioned the network into several disks, searched for the rendezvous points of a sink node in each disk, and solved the shortest path traversing all rendezvous points by using quantum genetic algorithm. According to the geographical location of nodes, Kumar *et al.* [13] proposed a clustering algorithm, and used the classic traveling salesman algorithm to find the shortest path through all cluster centers. By dividing the monitoring area into several grids, Wang *et al.* [14] established the objective function with limited data transmission delay by one-hop data gathering from sensor nodes to mobile sink. Genetic algorithm was applied to solve the problem, and the optimal mobile path of sink nodes was obtained. According to the number of hops to the nearest rendezvous point and the number of sub nodes, Salarian *et al.* [15] proposed a weighted rendezvous planning algorithm to assign the weights of all sensor nodes. Several nodes with larger weight are selected as RP points, and the shortest path of sink node traversing all RP points is calculated based on traveling salesman theory. By analyzing the forwarding hops and estimating the transmission time, Boler and Yenduri *et al.* [16] designed a simplistic hop resilient multi-sink routing protocol to generate the routing table by forwarding hops and estimating transmission time to improve energy utilization. Wang *et al.* [17] partitioned the whole network into several sub-domains with virtual grids, and presented an intelligent data gathering scheme with data fusion based on a neural network to improve network performance. Those methods assume that sink node can collect and analyze the information of all sensor nodes, and the time complexity increases rapidly with the increase of the number of sensor nodes. Therefore, they are more suitable for the network with sparse density and fewer hops for node's data transmission.

To further increase the flexibility of the system and meet the delay limitation, the rendezvous-based data collection approaches have been emerged. The rendezvous points is defined as exact locations or data buffer node, which will be visited by mobile sink and conduct direct delivery of monitoring data. Without any extra route packet and location information, Huang *et al.* [18] presented an adaptive beacon interval strategy to ensure high-reliability for data gathering. To achieve low-complexity and reduced control overheads, Liu *et al.* [19] designed the proactive data reporting protocols for mobile sink-based data collection. The main advantages of the protocols include sufficient flexibility in the movement of mobile sinks and no requirements of GPS devices or predefined landmarks. Yang *et al.* [20] introduced a detour-aware mobile sink tracking method to allocate specific nodes as region agents, which can increase the packet delivery ratio and decreased energy consumption. To shorten total length of routing paths and reduce routing energy consumption, Zhu *et al.* [21] proposed a Greedy Scanning Data Collection Strategy, which can effectively overcome the shortcomings of determined trajectory or random walk in traditional methods. By setting the threshold value of energy exhausting nodes, Wang *et al.* [22] presented an enhanced power efficient gathering in sensor information systems algorithm to resolve the hot spot problem.

Some techniques focus on the ultimate objective of improvement of the network lifetime and maintaining of the system stability. Basagni *et al.* [35] presented a linear optimization model of sink node's movement based on the grid distribution of the sensor nodes, defined the coefficient of variation according to the residual energy and variance of nodes and used a heuristic method to find a near-optimal tour. Wang *et al.* [23] proposed an energy-aware sink relocation algorithm for wireless sensor networks, which defines the maximum capacity path for data gathering. By adaptively adjusting the communication radius and selecting data relay according to the residual energy level of nodes, the algorithm can achieve the balance of energy consumption under the condition of mobile sink's data gathering. Wang *et al.* [24] proposed an improved ant colony optimization-based approach with mobile sink, which employs the cluster heads to perform data collection and directly deliver to mobile sink through short-range communications. To maximize the lifetime of large-scale wireless sensor networks, Lee *et al.* [25]

introduced a linear programming mode to resolve the optimal sojourning pattern of mobile sink, and proposed a simple practical heuristic algorithm to find an optimal mobility trajectory for data gathering. By taking into account of the initial position, data collection route and residence time of mobile sink, Kaswan *et al.* [26] established a mixed integer linear programming model and proposed a greedy maximum residual energy algorithm. The sensor nodes with more residual energy have priority to be selected as relay nodes for data forwarding, and mobile sink makes path planning to traverse those nodes to complete the data collection of the whole network.

Note that when there are enough sensor nodes, the time complexity of choosing the optimal traversal path will be exponential. That is ultimately a NP-hard problem. Therefore, for large-scale WSNs, conventional optimization methods may require high computing time and huge space. Multi objective particle swarm optimization (PSO) is a promising and reasonable method to solve above problem. In addition, PSO has the following advantages: 1) using real numbers to encode the solution; 2) few design parameters; 3) easy to implement.

III. SYSTEM MODEL

A. NETWORK MODEL

It is assumed that all sensor nodes are randomly deployed in a rectangle area with the size of $M \times M$, and most of the sensor nodes will utilize the multi hop mode to communicate with mobile sink. By constructing the virtual tree structure, the nodes close to the mobile sink's trajectory will be selected as access node. The other nodes away from the mobile sink act as member nodes will choose a certain overlay node as their destinations. The data gathering occurs when the mobile sink moves along a fixed path periodically with constant speed and exchange with the overlay nodes. Some assumptions are made regarding the deployment of sensor nodes in the following:

(1) All the chosen nodes are considered as static after deployment, and they can communicate with other nodes through single-hop or multi-hop within the communication radius.

(2) The location of the mobile sink can be sent to the sensor nodes within a partition rather than all around the network. In addition, the mobile sink has enough computing capacity, energy and storage capacity.

(3) Each member node can only select one relay node, and the sensor node can obtain its own location information.

B. PROBLEM DESCRIPTION

During the process of actual data gathering, the nodes close to the mobile sink's trajectory will be chosen as access node, which is responsible for the data aggregation from all nodes in a local dissemination tree. Hence, the power consumption is independent of the transmission distance between adjacent nodes. Accordingly, the following energy model can be adopted to estimate the energy consumption:

$$E = \varepsilon_r \Psi_r^i + \varepsilon_t \Psi_t^i, \tag{1}$$

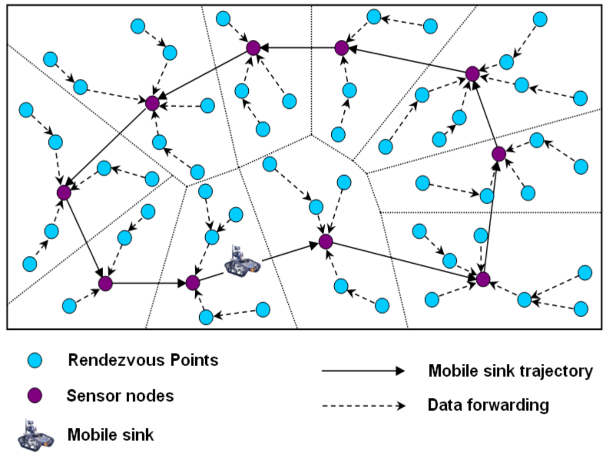

FIGURE 1. Data collection process based on mobile sink.

where ε_t and ε_r denote the transmission and reception power of each member node for data upload and reception, respectively. Besides, Ψ_r^i and Ψ_t^i denote the receiving bits and transmitting bits for node i.

All nodes are assumed to have the same total amount of data collected per traversal round of the mobile sink. Then, the relationship between the amount of data received and the amount of data sent by any node i can be written as: $\Psi_t^i = \Psi_r^i + q$, and q denotes the total amount of data generated by each node per round.

Considering that all member nodes forward data to their destinations along the local dissemination trees, then the relationship between the total amount of data received by all nodes and the sum of hops can be written as:

$$\sum_{i=1}^{n} \Psi_r^i = \sum_{i=1}^{n} H_i^* q, \tag{2}$$

where H_i denotes the hops from member node i to its destination access node. If node i itself is a access node, then $H_i = 0$.

Therefore, the total energy consumption per traversal round of the mobile sink can be expressed as the sum of the hops as follows:

$$\begin{aligned} E_{total} &= \sum_{i=1}^{n} (\varepsilon_r \Psi_r^i + \varepsilon_t \Psi_t^i) = \sum_{i=1}^{n} [\varepsilon_t (\Psi_r^i + q) + \varepsilon_r \Psi_r^i] \\ &= q[n\varepsilon_t + \sum_{i=1}^{n} (\varepsilon_t + \varepsilon_r) H_i] \end{aligned} \tag{3}$$

Next, the time delay in the process of data collection should be considered, which is related to the path length from the access node to the rendezvous points. Suppose L_k denote the path length from k-th rendezvous point to the mobile sink, and it is a random variable and obeys the Poisson distribution. The sum of all sub nodes to the rendezvous points $Len = \sum_{i=1}^{n} L_i$, and the total path length obeys the normal distribution approximately. The probability relationship between the total path length and the sample expectation can be expressed as a function:

$$\phi(\gamma) = \lim_{n\to\infty} \Pr\left\{ \frac{1}{\sigma\sqrt{n}} \left(\sum_{i=1}^{n} L_i - n\mu \right) \le \gamma \right\}, \quad (4)$$

where μ and σ represent the expectation and standard deviation of the total path length, respectively

Let Len_{opt} denote the optimal total path length. According to the central limit theorem, the probability that the total path length is greater than the optimal total path length can be calculated as follows:

$$\begin{aligned} &\Pr\left\{Len > Len_{opt}\right\} \\ &= 1 - \Pr\left\{Len \le Len_{opt}\right\} \\ &= 1 - \Pr\left\{ \frac{Len - n\mu}{\sigma\sqrt{n}} \le \frac{Len_{opt} - n\mu}{\sigma\sqrt{n}} \right\} \\ &= 1 - \phi\left(\frac{Len_{opt} - n\mu}{\sigma\sqrt{n}} \right). \end{aligned} \quad (5)$$

When the probability $\Pr\left\{Len > Len_{opt}\right\}$ is low, the probability to obtain lower value of Len_{opt} is large. Otherwise, it indicates that the probability of the path length approaching the optimal solution is very high. Obviously, when $\Pr\left\{Len > Len_{opt}\right\}$ is maximum, the total path length $Len = 0$, i. e., all nodes in the network will become relay nodes.

To enhance the scalability of the protocol and balance the delay and energy consumption, $\frac{Len_{opt}-n\mu}{\sigma\sqrt{n}} = 0$ and the probability of getting the maximum value of total path length will be greater than 0.5.

In order to meet the delay requirements and minimize the overall energy consumption of the network, it is necessary to optimize the sink trajectory in wireless sensor networks [23]. With the constraint of the delay limitation, the optimal sink path is solved to reduce the overall energy consumption of the whole network. Suppose that in a certain traversal round, and the moving speed of mobile sink is v_{sink}, and the delay constraint is d_0. Thus, the upper limit of the sink's moving distance can be expressed as $L_m = v_{sink} d_0$. Therefore, the mathematical description of the optimization problem can be given by:

$$\begin{aligned} &\min\{E_{total}\}, \\ &s.t.\ \frac{1}{n}\sum_{i=1}^{n} L_i \le \mu, \quad TSP(v_{sink}) \le L_m,\ H_i \le H_{\max}. \end{aligned} \quad (6)$$

IV. OPTIMIZATION ALGORITHM

Particle swarm optimization is a random search algorithm based on swarm intelligence, which was proposed by Kennedy and Eberhart in 1995 [31]. The main idea is derived from the simulation of foraging behavior of birds and fish. The individuals in the population are regarded as particles without mass and volume in the search space, and each particle represents a candidate solution with two attributes, i.e., velocity and position [32]. In addition, the speed updating of the particles consists of cognitive learning, social learning and inertia movement.

During the problem solving, the flight trajectory of particles is affected not only by their current extreme value *pbest* and global extreme value *gbest*, but also by their own shift inertia value w [33]. In order to enhance the diversity of the population and eliminate the influence of the unreasonable shift inertia value, a particle swarm optimization strategy with adaptive elite mutation is designed to improve the population diversity and avoid falling into the local optimal solution prematurely.

A. PARTICLE SWARM INITIALIZATION

It is assumed that m denotes the particle population size, $t_{\max}$ is the maximum number of iterations, t is the number of iterations. Each particle corresponds to a path planning scheme, which includes the rendezvous points set and traversal path T_p. A sequence $P = \{P_1, P_2, \cdots, P_m\}$ with the length m is used to represent a spanning tree, and P_i is the parent node of the i_th node. For node i, it is necessary to find a path with constrain of the limited hop number to corresponding rendezvous point. Thus, the specific steps are as follows:

Step 1: Initializing a matrix X of size $n \times n$, and $x_{ij} = 0$. The minimum number of hops from each node to the rendezvous point in the topology graph is calculated. The nodes are arranged in descending order according to the hop number, and the sequence is written as Ω. If the maximum hop number is greater than the tree height constraint $H_{\max}$, it can be deduced that there is no spanning tree satisfying the tree height limit in above topology graph, and the execution will end.

Step 2: For the j-th node in the sequence Ω, we need to determine whether it has a parent node. If no parent node exists, the height H_j will be initialized as 1 and $x_{ij} = 1$. Subsequently, initializing the empty parent set S_{parent} and saving all relay nodes in the path from the i-th node to the rendezvous point. Then, the node i can be added to the sequence P.

Step 3: If node i is a rendezvous point or has a parent node, go to Step 5.

Step 4: If the neighboring node j of node i satisfies the following conditions, i.e., the node j is not in sequence P, The hop number of node j is less than or equal to $H_{\max} - 1$, and $x_{ij} = 0$, the node j can be added to the parent set S_{parent}.

Step 5: Enter the process to judge whether the parent_ set is empty not. If the set S_{parent} is not null, choose a node k randomly from S_{parent}, set the parent node of node i and the value of H_i plus one.

Step 6: If $\frac{1}{n}\sum_{k=1}^{n} L_k \le \mu$ and $TSP(v_{sink}) \le L_m$, push the node k into the sequence Ω and go to step 3;

Step 7: For all nodes, the optimal path to rendezvous points has been obtained and the algorithm will be terminated.

B. PARTICLE MUTATION

In this paper, each particle should be randomly selected and its parent node will be changed dynamically to realize particle mutation. Besides, the spanning tree after mutation should meet the tree height limit. Let T be a spanning tree of graph $G = (V, E)$, and its corresponding coding sequence is $Q = \{Q_1, Q_2, \cdots, Q_N\}$, decode p to get the corresponding spanning tree T. the specific steps of mutation of spanning tree are as follows

Step 1: Select a node randomly and remove its connection with the parent node. Then the original spanning tree T will be evolved to two trees, one of trees T_r takes the node i as the root node, and corresponding rendezvous points act as the root of other tree T_c continuously.

Step 2: If the height H_i of T_r is lower than $H_{\max}$, traverse the tree T_c. If node j is the neighbor node of node i and $H_j + 1 \le H_{\max}$, node j can be added to the sequence P. After traversing, the node from parent_set will be selected randomly as the parent node of node i.

The information of particle i is represented by d-dimensional vector D, and the particle position is $x_i(t) = (x_{i,1}, x_{i,2}, \cdots, x_{i,D})$. In addition, the velocity of particle i is $v_i(t) = (v_{i,1}, v_{i,2}, \cdots, v_{i,D})$, and the velocity of the next iteration can be calculated as follows:

$$v_{i,j}(t+1) = wv_{i,j}(t) + c_1 rnd_1(pbest_{i,j} - x_{i,j}(t)) + c_2 rand_2(gbest_j - x_{i,j}(t)) \tag{7}$$

where w is the inertia weight. c_1 and c_2 are cognitive learning factor and social learning factor, respectively. $rand_1$ and $rand_2$ are two random numbers with uniform distribution on the interval [0,1]. Besides, $pbest$ represents the value of best personal experience, and $gbest$ represents the global best solutions.

Then, the position of the particle i in the next iteration can be expressed as:

$$x_{i,j}(t+1) = x_{i,j}(t) + v_{i,j}(t+1) \tag{8}$$

To fully obtain the environmental information and maintain the diversity of the population in the evolution process, we use the reverse learning strategy to define generalized opposition-based learning action. Then, two individuals in the population will be randomly selected, and the inertia weight can be modified by using the difference between individuals as:

$$w = \delta \left(x_{u,j}(t) - x_{v,j}(t)\right) \tag{9}$$

where δ is the differential coefficient, which is used to control the population search range. u and v are two random integers, and $u, v \in [1, N]$.

In addition, in order to further reduce the possibility of particles falling into local optimum, the adaptive elite mutation strategy is introduced to help the particles jump out of the local optimum [34], [35]. $gbest$ will be regarded as the population elite particle, and the value of $gbest$ is adaptively mutated in the process of population evolution of each generation. If the fitness value of the mutated new individual $gbest^*$ is better than that of the original $gbest$, the original value of $gbest$ should be replaced and participate in next round of evolution. The new global optimal individual will attract other particles in the subsequent evolution process, so as to help particles jump out of the local optimal position

$$gbest^* = gbest + \Gamma\left(\Lambda(i)\right) \tag{10}$$

$$\Lambda(i) = \exp\left(-\frac{\theta t}{t_{\max}}\right)\left(1 - \frac{1}{r_{\max}} * \left|gbest(i) - \frac{1}{N}\sum_{j=1}^{N} pbest[j][i]\right|\right) \tag{11}$$

where $\Gamma(\cdot)$ is the perturbation function, and can be defined as $\Gamma(x) = \frac{1}{\pi}\arctan(x)$. The variable $\Lambda(i)$ is used to adaptively control the mutation size. Besides, θ is an undetermined constant, $r_{\max}$ indicates the largest distance in each dimension, and $pbest[j][i]$ indicates the position of the particle j in the i-th dimension.

Next, the mutation operation is analyzed theoretically as follows. In the initial stage of population iteration, the performance of particles may be not ideal, and the mutation value will be large, which can cause enough disturbance to the population and expand the solution space [36], [37]. However, with the deepening of iteration, the mutation value will gradually decrease, so as to ensure the smooth convergence of the problem to the optimal value. Additionally, adaptive mutation will obtain larger mutation value when the population extremum tends to be consistent, which enhances the search ability of the algorithm. Conversely, when the population search is sufficient, the variation value reduction can avoid the turbulence of the optimal value, and thus accelerating the convergence speed of the algorithm.

According to the above analysis, the value of $gbest$ can achieve a large amount of variation through the disturbance function at the initial stage of the algorithm. Thus, it will cause enough turbulence to the search space, and enhance the global search ability of the algorithm. With the proceeding of the iterations, the mutation rate gradually decreases, thus effectively avoiding the oscillation of the optimal solution and accelerating the convergence rate of the population [38], [39].

V. PERFORMANCE EVALUATION

We evaluated the performance of the proposed mechanism via simulations using MATLAB, and compare with several mobile sink based data gathering schemes. The sensor nodes are randomly deployed in a field with dimensions $400m \times 400m$, and the initial energy of sensor node is set to $2J$. Besides, we assume that there is no energy constraint with mobile sink. The values of the experimental parameters are shown in Table 1.

Firstly, the performance of the proposed algorithm is evaluated in terms of computation time and iteration times, and the results are shown in Figure 2 and 3. It can be seen from the experiment that with the increase of the number of sensor nodes, the maximum, average and minimum computation time of the algorithm show an overall increasing trend. Moreover, we also can observe that the computation time and the iteration times will increase linearly with the number of sensor nodes. It shows that our proposed algorithm has good scalability.

TABLE 1. The experimental parameters.

Parameters	Value
Target area	400m’400m
Number of sensor nodes	100~800
Initial energy	2J
Transmission range	40m
The transmission power	100nJ
The reception power	20nJ
Moving speed of the mobile sink	10m/s
Number of particles	100
Maximum number of iterations	1000
The constant θ	10
Data generated by nodes per round	128bit

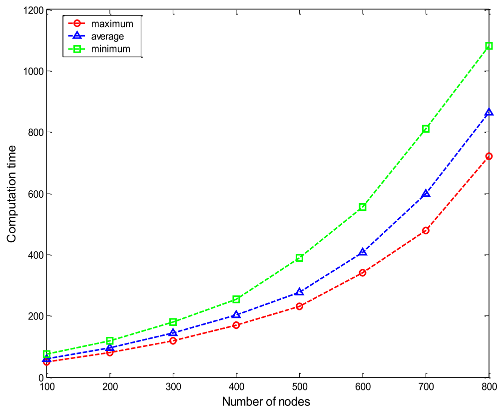

FIGURE 2. The computation time with different number of nodes.

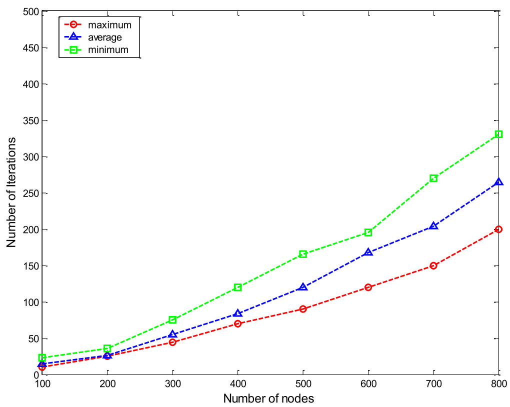

FIGURE 3. The number of iterations with different number of nodes.

Furthermore, we compare the network performance with DEPSS [40], RPS [41] and EPDS [42] mainly in following aspects: the mobile sink path length, the total hops, data gathering delay, network lifetime and the running time [43]. Figure 4 shows the comparison results of trajectory length of the mobile sink. In mobile sink mode, the path length can reflect the performance of real-time data transmission, and the mobility of sink will lead to the change of network topology and routing. If no reasonable global optimization strategy is adopted, it may lead to delay of data collection and deterioration of network lifetime. From the experimental results, the mobile route of EPDS algorithm is significantly higher than other algorithms. This is because it uses single

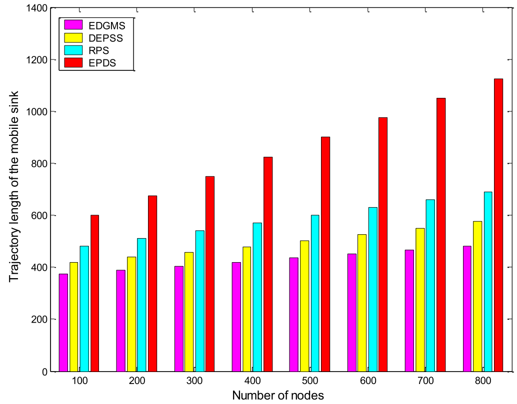

FIGURE 4. Comparison of trajectory length of the mobile sink with different number of nodes.

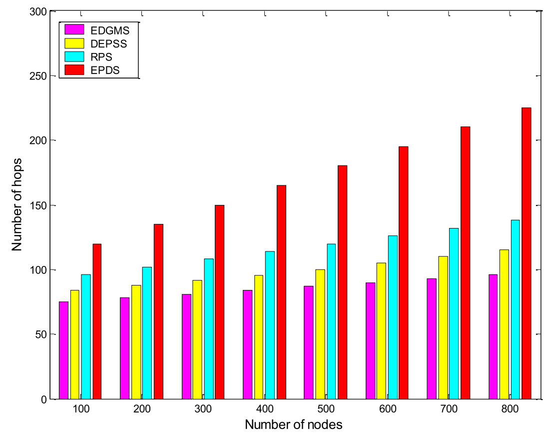

FIGURE 5. Comparison of the total hops with different number of nodes.

hop direct access, which will increase the delay of data collection, especially in the scenario of large-scale deployment of sensor nodes [44], [45].

Figure 5 shows the comparison of the total hops for different algorithms. With the given delay constraint, our proposed algorithm can obtain the shorter hops than other algorithms. In RPS, the cluster heads are randomly selected to weaken the influence of “hot spot” problem, but it is unable to optimize the path length from member nodes to corresponding cluster head. EPDS combines clustering and tree topology, and takes the node nearest to the mobile sink as the root node to dynamically construct the number of routes. This algorithm is suitable for distributed networks, but it still does not consider the path optimization problem from the child node to the sink node, and results in relatively large trajectory length of data collection. By employing steiner minimum tree, DEPSS can acquire the relatively shorter total hops than RPS and EPDS. However, the algorithm of DEPSS is complex, which will lead to high network maintenance cost and computational complexity.

Figure 6 shows the data gathering delay under different number of nodes. From the experimental results, with the increase of the number of sensor nodes, the data collection delay of each algorithm will increase. Comparatively, our proposed algorithm does not increase sharply and meets

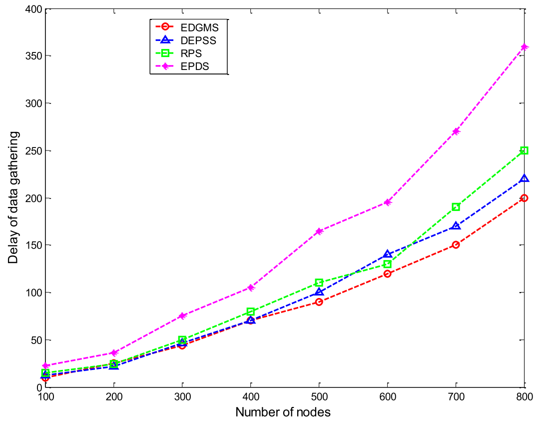

FIGURE 6. Comparison of the data gathering delay with different number of nodes.

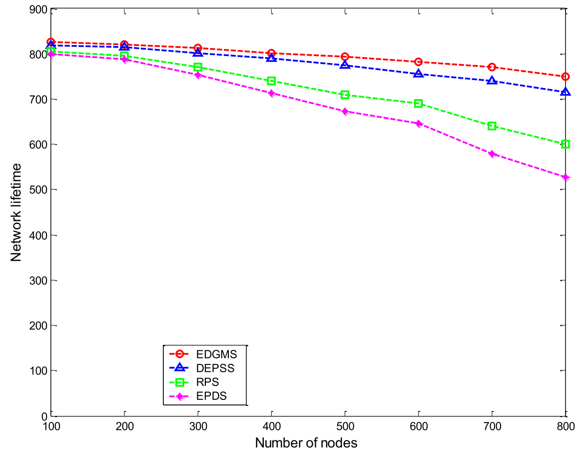

FIGURE 7. Comparison of the network lifetime with different number of nodes.

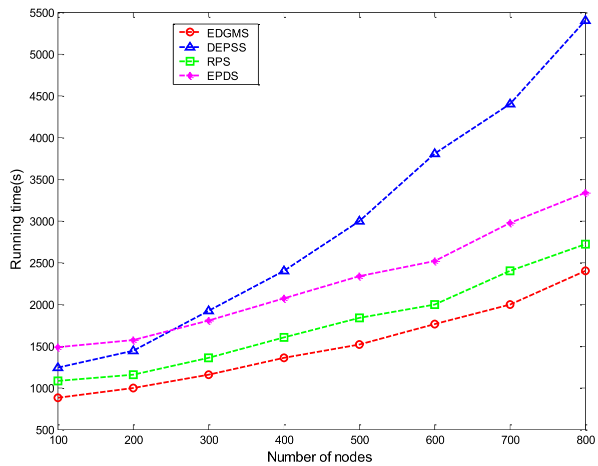

FIGURE 8. Comparison of the running time with different number of nodes.

the constraints. In this paper, the particle swarm optimization strategy with adaptive elite mutation improves the population diversity effectively and avoids falling into the local optimal solution prematurely. Also, it ensures that the data collection delay of mobile sink at each rendezvous point is minimized. Due to frequent movement of mobile sink and use single hop direct access for data collection activity, the overall delay of sink in DEPSS is significantly higher than that of the other three algorithms. In addition, it can be observed that RPS can obtain better data gathering delay as the number of nodes is small. However, the data gathering delay increases significantly as well as the number of sensor nodes. It indicates that the algorithm has poor scalability. The performance of DEPSS in data gathering delay is not good enough, that is because the collected data can not be transmitted until the sink stops moving and it may take a certain amount of time to reconstruct the routing tree.

The results in Figure 7 show the network lifetime of those algorithms, reflecting the ability in aspect of energy consumption balance. It can be seen from the experimental results that our proposed algorithm fully takes into account of the location and number of rendezvous points, as well as the minimization of the sum of hops for data relay. Therefore, the distribution of energy consumption of the sensor nodes is more uniform than other algorithms. In RPS, the cluster heads' selection adopts random way, which may lead to uneven distribution of the clusters and unbalanced energy consumption. Especially when the number of nodes in the network is large, it is easy to cause the hot-spot problem. By allowing sink to access the area with higher node density, EPDS can effectively avoid too large number of communication hops between the sensor nodes and the rendezvous points. However, that scheme will form long traversal path of mobile sink inevitably, and result in uneven node's energy consumption and affecting the network lifetime to a certain extent.

Figure 8 shows the running time with different number of sensor nodes. It can be seen from the figure that the algorithm proposed in this paper is basically equal to RPS and performs better than other methods, and the time complexity of DEPSS algorithm demonstrates obviously higher than other algorithms. The reason is that in DEPSS, the beacons should be required to inform the sensor of obtaining its current position during the movement of mobile sink. And then, the optimal route from all sensors to the sink will be updated step by step. In actual operation, each node needs to determine a latest route in time and updates frequently, which will results in large computational cost.

VI. CONCLUSION

In this paper, we propose an energy-aware data gathering mechanism for mobile sink in wireless sensor networks using particle swarm optimization. Firstly, the mathematical model is established according to the total network energy consumption and delay constraints in mobile sink data collection. Then, the optimal rendezvous points are selected to aggregate data originated from the source nodes through multi-hop relay, and the aggregation tree will be constructed for data transmission. The spanning tree is encoded into particles, and the random method is designed to generate the data collection spanning tree with constrain of tree height limit. Furthermore, a particle swarm optimization strategy with adaptive elite mutation is designed to improve the population diversity and avoid falling into the local optimal solution prematurely. The simulation results confirmed that our proposed mechanism outperforms the existing algorithms, regarding the average energy exhaustion, the network lifetime, and the running time.

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