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Sink Node Placement Strategies based on Cat Swarm Optimization Algorithm

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Abstract. *The wireless sensor network (WSN) is a system composed of a large number of sensor nodes, which are distributed in a designed coverage region for detecting specific interested events. The sensor nodes would pass the collected information back to the data collection center, which is called the sink node. In WSNs, the sink node is designed to play the role as the data processing and the control center; and the rest of sensor nodes are responsible for sensing the interested events and transmitting the related information back to the sink node. Therefore, where to place the sink node in the whole network in an important issue because the position of the sink node directly affects the data transmission efficiency and the distance from the terminal sensor node to the sink node. In this paper, we propose a sink node placement method by applying Cat Swarm Optimization algorithm (CSO) and use the greedy algorithm to create the data transmission paths. In addition, a newly designed fitness function is used in the operation to reduce the total energy consumption. Moreover, the sink node placement problem is solved by Particle Swarm Optimization algorithm (PSO) for further compare. Simulation results indicate that our proposed method presents good performance in reducing the total energy consumption, which can prolong the lifetime of network in an efficient way.*
Keywords: Wireless sensor network, Cat swarm optimization, Sink node placement.

1. **Introduction.** Along with the increasing development of WSNs, this technology has been embedded into our daily lives. The technology of WSNs have been used in monitoring the health conditions of person, tracking objects, and sensing specific targets such as the

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pollutant. The WSNs mentioned above are typically consist of a lot of common sensor nodes with limited energy source and one data collection center called the sink node. The sensor nodes transfer the detected meaningful events to the sink by cooperatively working with other nodes. In previous papers, if the common sensor nodes are uniformly deployed in a regular geometric region, e.g., a circular or a rectangular area, the sink node will be deployed at the relative center of the field. Sink node placement determined by P-Median Problem model [1, 2], which has been proved to present the characteristic of non-deterministic polynomial-time hard, is concluded that the center of the WSN's coverage area is the optimal position in the general WSNs. However, this conclusion is made without considering the regional barrier and the hot pot problem. Nowadays, there are many types of WSNs and the related application fields. In all kinds of WSNs, all deployed sensor nodes are responsible for detecting the interested events and transmitting the information back to the sink node. The most common and the familiar one is called the flat networks; and the sink node is in charge of processing/analyzing the collected information and sending control commands to the whole WSNs. If the distance between the terminal sensor nodes to the sink node is longer; the energy consumption costed by the transmission is larger. However, the interested events are usually not uniformly appear in the WSNs' coverage regions. It implies that the sensor nodes, which detect the interested events more frequently, would run out of energy much earlier than other sensor nodes. If the sink node is placed not on the center but on the proper position, the lifetime of the whole WSNs may be extended without increasing other costs. Therefore, the placement of the sink node plays an important role in WSNs. The optimal placement of the sink node is not only an advantage of the reduction of the time delay but is also a positive contribution to reduce the total energy consumption.

In this paper, we propose a sink node placement method by using Cat Swarm Optimization (CSO) [12, 4] to determine the location of the sink node in a single static sink node WSNs environment. Moreover, the greedy heuristic method [5, 6, 7] is employed to generate the data transmission paths for the sensor nodes to the sink after determining the location of the sink node. The generated result is used as the baseline for comparing to the results obtained by our proposed method.

The rest of the paper is structured as follows: the related works of sink node location determination with analytic results are briefly reviewed in section 2; our proposed method for finding the near best location of the sink node by CSO is introduced in section 3; the greedy algorithm for constructing the transmission path is described in section 4; the simulation results are presented in section 5, and the conclusions made in the last session.

2. **Related Work.** In order to extend the lifetime of WSNs, several strategies and models are proposed one after another. For example, Wang et al. [8], Oyman and Ersoy [9] proposed the WSNs model with multi sink nodes, single but mobile sink node, and the model contains fixed sensor nodes of which are capable to batch-upload information collected from the near by regions back to the sink node. Except modifying the number or type of the sink nodes, another way to extend the lifetime of WSNs is to carefully design the location for placing the sink node. The branch of sink node placement has attracted more and more researchers' eyes in recent years. For instance,Yang (2006) [10] uses Genetic Algorithm (GA) to determine the location of the sink node in WSNs. Zoltan et al. (2007) [11] propose a method to decide the location of the sink node by calculating the number of sensor nodes, whose data are relayed by a neighboring of a sink. However, this method would provide unstable results when the routing protocol is changed.

As the solid truth that the sink node location is an important issue in WSNs, more and more related research results are presented in recent years. For instance, Chai et al. (2012) [12] propose a design with genetic-algorithm-based quasi-optimal method to obtain equasi-optimal solutions at quadratic time for solving k-anonymity sink-location problems. This method requires at least k indistinguishable entities in the network to the nodes of which around the sink node for protecting the sink-location privacy. Chen and Li (2013) [14] analyze that the sink node placement problem and propose a set of strategies for finding the optimal placement location for the sink node in both the single-hop and the multi-hop WSNs environments, respectively. Their design adopts a routing-cost based ant routing algorithm to decide the location of the sink node. Hidehiro et al. (2010) [15] propose a method to solve the problem of allocating M sink nodes in a two dimensional space by the suppression particle swarm optimization algorithm. In the suppression particle swarm optimization algorithm, it has a suppression scheme by storing copies of the position vectors from particles with better evaluation results for controlling the excessive conversion of particle. The detail of the average delivery ration and the communication load effecting factors are revealed. However, only the sink node location issue is taken considered in this literature. The discussions on the residual energy and the health condition of the nodes are still remained blank. To carefully select the location for deploying the sink node in WSNs, both the residual energy and the health condition of the nodes are also considered in our design.

3. **Finding the Proper Location for the Sink Node by CSO.** Assume that all sensor nodes in the WSNs are randomly deployed and uniformly distributed in the coverage area. Every node is equipped with the same communication gear with the equal transmission distance; and the sensing range of the sensors equipped on the sensor nodes are also identical. To find the proper location for the sink node in WSNs, the residual energy equipped on the sensor nodes are assumed to be randomly distributed in a feasible range. CSO [12, 4] is employed in this paper for finding the near best location of the sink node under the assumptions mentioned above. In our design, every cat represents a potential location of the sink node, and the cat with the best fitness value is capable to determine the final location of the sink node in the WSNs. The procedure for achieving the goal with CSO is listed as follows:

Step 1. Initialization: Randomly distribute the cats into the solution space. Let cat_i represents a single artificial agent, where $\boldsymbol{i}$ is the index of the artificial agent. In this case, the solution space is composed of a 2-D plane. Hence, every artificial agent contains 2 dimensional vector to represent its coordinate, which is denoted by the second subindexes x and y, in the solution space. The initial range and the velocities for every dimension are designed to fit the minimum and the maximum boundary condition. Moreover, every artificial agent stores the coordinate (denoted by $cat_{i,best}$) corresponding to its personal best fitness value as the historical best solution.

Step 2. Evaluation: Calculate the fitness value (denoted by F_n) for every cat with the fitness function. Replacing the stored near best solution (denoted by cat_{best}) over the population if the fitness value is better than cat_{best}.

Step 3. Movement: Move the cats by taking the operations in the seeking mode or the tracing mode according to the statuses of the motion flags.

Seeking mode: Make *SMP* copys of the cat of which entered into the seeking mode. Using equations 1 and 2 to produce a slight shifting to the copies, where r is a random vector of which the value on every column is in the value set of *-1, 0, 1*. Different values of r results in different actions of the cats: the movement result of the cat on a single dimension is 20% less than the original coordinate when r is equal to -1; no movement is made on a single dimension when r is equal to 0; the movement distance on a single dimension is 20% greater than the original coordinate when r is equal to 1. The coordinates obtained after the movement should not exceed the border of the network field.

Calculate all fitness values by the formula listed as follows for the *SMP* copies after the movement.

$$x(t+1) = x(t) \times (1 + 0.2r), r \in [\text{-}1,\ 0,\ 1] \tag{1}$$

$$y(t+1) = y(t) \times (1 + 0.2r), r \in [\text{-}1,\ 0,\ 1] \tag{2}$$

Should any of the copy present better fitness value than the original cat, replace the cat by the newly found solution with better fitness value.

Tracing mode: The cat, which takes the tracing mode action should be moved based on its corresponding velocities by equations listed as follows:

$$v_{i,x}(t+1) = v_{i,x}(t) + r_1 \times c_1 \times (x_{i,t} - x_{best}) + r_2 \times c_2 \times (x_t - x_{i,history}) \tag{3}$$

$$v_{i,y}(t+1) = v_{i,y}(t) + r_1 \times c_1 \times (y_{i,t} - y_{best}) + r_2 \times c_2 \times (y_t - y_{i,history}) \tag{4}$$

$$x(t+1) = x(t) + v_{i,x}(t+1) \tag{5}$$

$$y(t+1) = y(t) + v_{i,y}(t+1) \tag{6}$$

where x_{best} and y_{best} denote the x and y value of cat_{best}, respectively, $x_{i,history}$ and $y_{i,history}$ are the coordinates x and y for cat_i of which presents the best fitness value in the historical data, $v_{i,x}(t)$ and $v_{i,y}(t)$ are the velocities on different dimensions for cat_i in the current iteration, $v_{i,x}(t+1)$ and $v_{i,y}(t+1)$ are the velocities in the next iteration; r_1, r_2, c_1, and c_2 are the random numbers.

Step 4. Termination Checking: Check whether the terminational condition is satisfied. If it is satisfied, output the coordinate of cat_{bset} to decide where to allocate the sink node; otherwise, go to step 2 and continue the evolution process.

The Fitness Function Design: The fitness function is an user defined criterion for determining the term of optimum. In this case, three factors are taken into the consideration in designing the fitness function. The first term defined is called TotalDis. It is used to represent the sum of the distances between sensor nodes to the cat, i.e., the sink node. The second one is called Energy_amount. It stands for the sum of the residual energy overall neighborhood nodes of the cat. The last term is Num_amount for representing the number of direct connection nodes of a cat. The designed fitness function is listed as follows:

$$F = \alpha_1 \times (\frac{TotalDis}{N}) + \alpha_2 \times (\frac{Energy\_amount}{Num\_amout}) + \alpha_3 \times Num\_amount \tag{7}$$

where N is the number of total nodes in the network, and the parameter setting is $\alpha_1 = -0.1$, $\alpha_2 = 0.01$, $\alpha_3 = 0.3$.

4. **Transmission Path Construction Using Greedy Algorithm.** The transmission paths of which the nodes select play the important roles in the WSNs. Properly designed transmission paths result in the less amount of energy consumption and the shorter transmission delay. The conventional solutions usually provided by the greedy algorithms such as the famous Dijkstra algorithm with the heuristic processes. The local optimal solution may be found in the earlier stage, and the outcome is shifted to the near best solution in the recursive processes. The Dijkstra algorithm is proposed to solve the traveling salesman problem.

To build the transmission path with the minimum connected dominating set problem using the greedy algorithm, the status of a node can be depicted in three status: Status 1 denotes that a node is yet joined in any path; Status 2 denotes that a node is joined in a path and serves as a forwarding node; Status 3 denotes that a node is joined in a path and it is the terminal node in the path. In addition, four sets, which are called the UnCovered set, the InCovered set, the Covered set, and the DownFind set, are defined in the path building process. The UnCovered set includes the nodes of which have not been collected into any path; the InCovered set includes the nodes that are right on the process for being collected into the paths; the Covered set includes the nodes been collected in the paths; and the DownFind set includes the nodes, which are latest collected into a path. The transmission paths are built level by level. The first level includes the nodes that can directly transmit the data to the sink node; the second and the rest of levels are distributed as the tree structure. The lower level can only transmit the data to its upper level. When processing a specific level, the nodes are put in the InCovered set; and the nodes in its lower level are put in the DownFind set.

Path Building Process A transmission path can be constructed by the process listed as follows:

Step 1: Set all nodes to Status 1 and collect them into the UnCovered set.

Step 2: Shift all neighborhood nodes of the sink node into the Covered set and the InCovered set and set these nodes to Status 3.

Step 3: Empty the DownFind set before shifting the nodes collected in the Incovered set to the DownFind set. Change the status to 2 for the nodes in the DownFind set under the condition that the one of the nodes has at least a neighborhood node is in status 1. Set the status to 1 for the neighborhood nodes of the nodes, which are collected in the DownFind set, and collect the neighborhood nodes into the InCovered set.

Step 4: Let a be one of the node in the InCovered set. Compute and find the shortest distance D_{tol} by the formula listed as follows from node a to the sink node via any of the nodes in the DownFind set. Mark the node in the DownFind set with the shortest distance as node a's next hop.

$$D_{tol} = D(a, n_1) + D(n_1, n_2) + D(n_2, n_3) + ... + D(n_n, sink) \tag{8}$$

where node a is in the InCovered set, node n_1 is in the DownFind set, and node n_2 is the next hop of node n_1, node n_3 is the next hop of node n_2, and node n_n denotes the last node on the path to the sink.

Step 5: Check whether all nodes are collected into the Covered set. If the result is positive, it implies that the InCovered set is empty. Thus the process can be terminated, otherwise go back to Step 3 and repeat the process till the termination condition is satisfied.

5. **Experiment.** Different number of sensor nodes including 100, 200, 300, 400, 500, and 600 nodes are used in our experiments. The sensor nodes are randomly deployed into a 2-D environment with the size of 200×200 square units. Our proposed algorithm is employed to decide the deployment location of the sink node, and the greedy algorithm is used to construct the transfer paths for the whole WSNs. Every sensor node is equipped with an identical communication module providing the equal communication and sensing distance. In our experiment, the communication radius is set to 40 units. Moreover, the energy consumption includes the energy provided for both transmitting and receiving the data. The consumed energy for receiving one package of the data is designed to be 40% less than transmitting. The energy carried on a sensor node is randomly set in the range of 1000 to 2000.

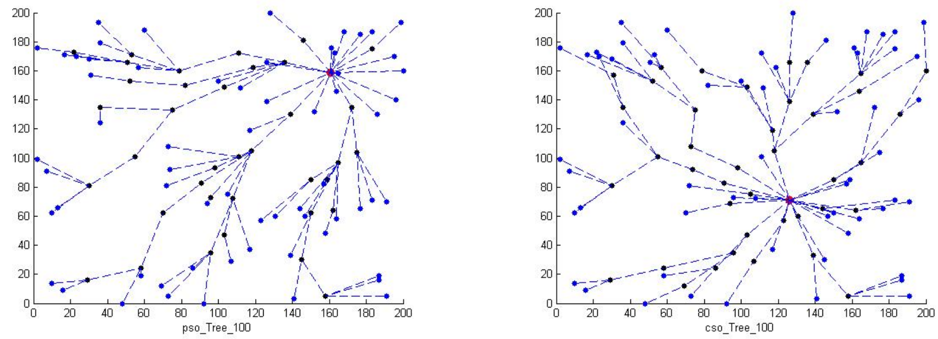
Our proposed strategy is compared with a sink node location determination algorithm based on the Particle Swarm Optimization (PSO) approach [16] proposed by Mohamed et al. in 2015. This algorithm aims to produce an energy-aware topology control protocol. For both CSO and PSO algorithms, the number of artificial agents is set to 16. The outcome of the experiment is a coordinate of the optimal option for deploying the sink node in the WSNs. Table 1 shows the total energy consumption of sending the same number of packages.

Table 1. Comparing PSO approach with CSO approach on Energy Consumption

		PSO [16]	CSO
No. of Nodes No. of Transmitted Packages	100 5.0×10^2	14.0338	10.7135
No. of Nodes No. of Transmitted Packages	200 1.0×10^3	20.8981	19.2287
No. of Nodes No. of Transmitted Packages	300 1.5×10^3	27.8352	26.8324
No. of Nodes No. of Transmitted Packages	400 2.0×10^3	40.3712	36.4622
No. of Nodes No. of Transmitted Packages	500 2.5×10^3	46.7464	46.6385
No. of Nodes No. of Transmitted Packages	600 3.0×10^3	61.8228	54.5633

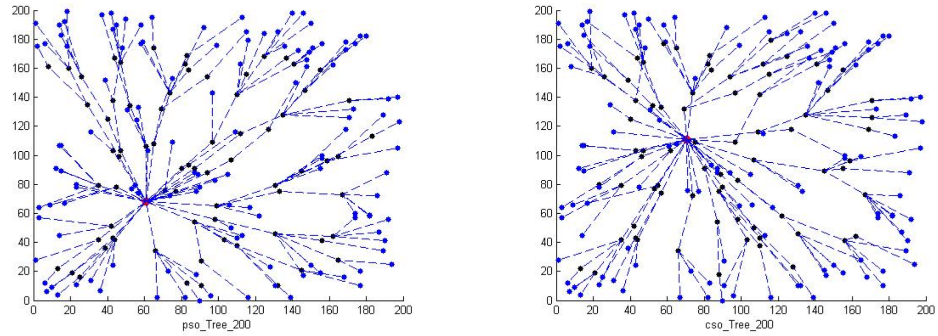
The number of nodes and the transmitted packages are given in every row, and the total power consumption of the WSNs with PSO and CSO approaches are given in the second and the third column. For example, the total power consumption with PSO and CSO approaches are 14.0338 and 10.7135, respectively, with 5.0×10^2 packages transmitted in the 100 nodes environment. Obviously, the total power consumption produced by CSO approach is less than by PSO appraoch in all test conditions.

Since the location of the sink node is decided by either CSO approach or PSO approach before applying the greedy algorithm to construct the transmission paths, the whole WSNs network with the deployed sink node and the transmitting paths with 100, 200, 300, 400, 500, and 600 nodes are revealed in Figure 1 to Figure 6 for comparing. Figure 1 reveals the 100 nodes WSNs with the sink node deployment strategy by PSO in (a) and the sink node deployment strategy by CSO in (b); Figure 2 shows the 200 nodes WSNs with the sink node deployment strategy by PSO in (a) and the sink node deployment strategy by CSO in (b); and so on so forth.



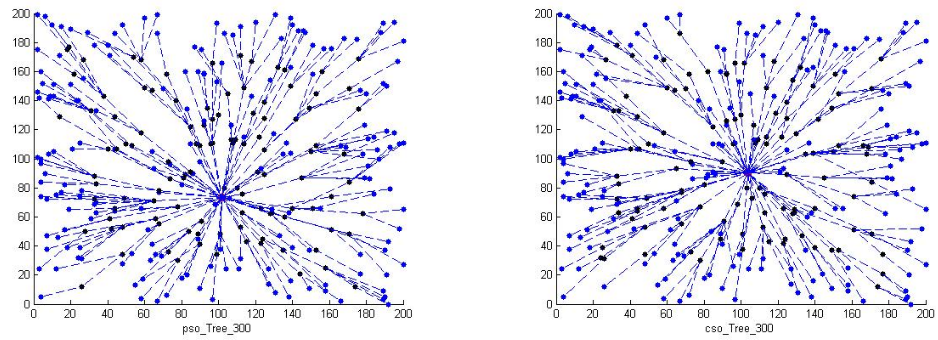
(a) (b)

FIGURE 1. 100 nodes WSNs with the sink node allocated by: (a) PSO approach and (b) CSO approach



(a) (b)

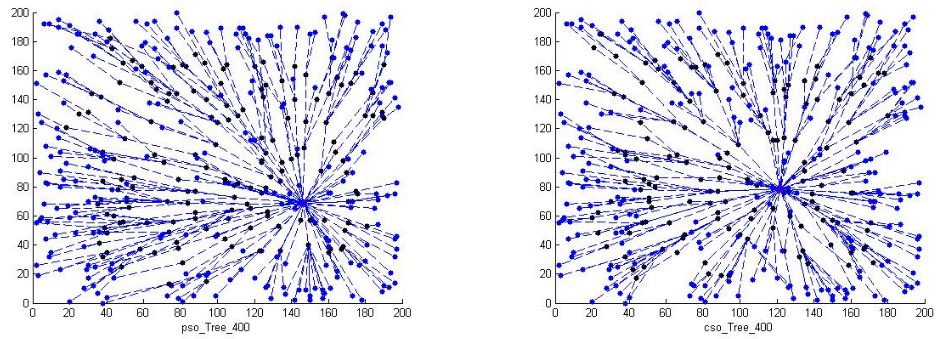
FIGURE 2. 200 nodes WSNs with the sink node allocated by: (a) PSO approach and (b) CSO approach



(a) (b)

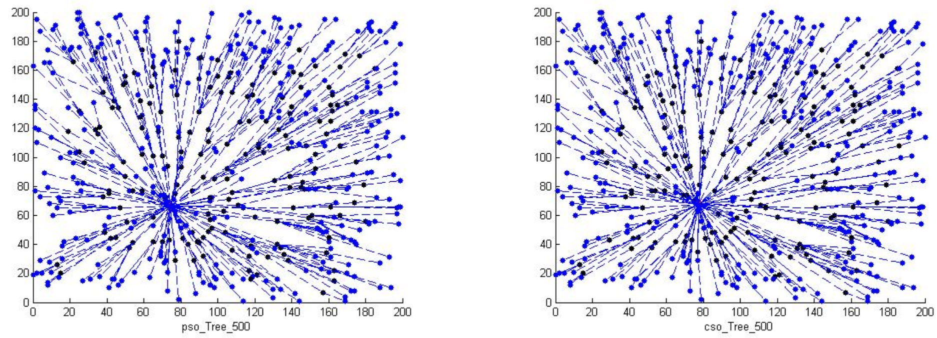
FIGURE 3. 300 nodes WSNs with the sink node allocated by: (a) PSO approach and (b) CSO approach

By observing the allocated sink node in Figure 1 and Figure 2, it is obvious that the sink node is allocated on different nodes by PSO and CSO approaches. The differences on the sink node location and the transmission paths result in different power consumption results.



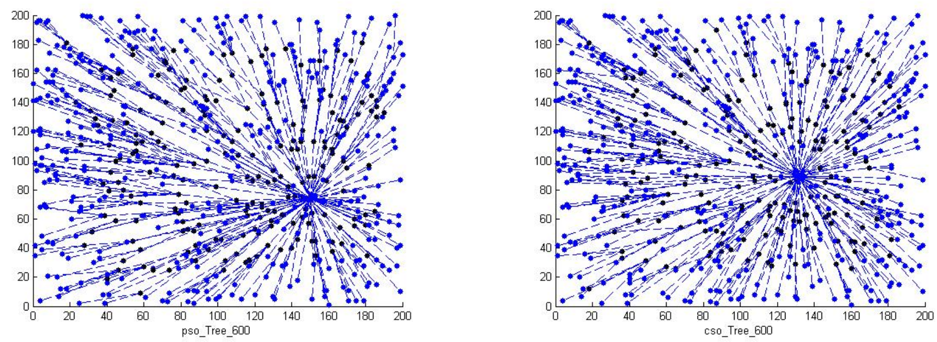
(a) (b)

FIGURE 4. 400 nodes WSNs with the sink node allocated by: (a) PSO approach and (b) CSO approach



(a) (b)

FIGURE 5. 500 nodes WSNs with the sink node allocated by: (a) PSO approach and (b) CSO approach



(a) (b)

FIGURE 6. 600 nodes WSNs with the sink node allocated by: (a) PSO approach and (b) CSO approach

6. **Conclusions.** In this paper, we propose a sink node placement method by applying CSO and use the greedy algorithm to create the data transmission paths. In addition, a newly designed fitness function is used in the operation to reduce the total energy consumption. Moreover, the sink node placement problem is also solved by PSO approach

with the transmission paths built by the greedy algorithm for the compare. The proposed method is tested with 6 different numbers of the sensor node environments. The results are compared on the power consumption with the sink node allocated by PSO approach. The experimental results indicate that our proposed method presents better efficiency on reducing the total power consumption in the whole WSNs.

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