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POWER SAVING MOBILE SENSOR NETWORKS BY DYNAMIC RELAY COMMUNICATIONS

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Abstract. *Mobile wireless sensor networks can perform state observation in wide area with a small number of nodes. Therefore, it is expected to collect data efficiently and flexibly in areas where it is difficult to add sensors and intrusion of human. Although the previous study has proposed the method using virtual rails, it cannot deal with the changes of state of observation area. In this study, we propose a new method based on Discrete binary Particle Swam Optimization (DPSO) to optimize the placement of virtual rails in mobile sensor networks. In the proposed method, both the number of virtual rails and placement can be determined according to the state of the observation area. In simulation experiments, the performance of the proposed method is investigated to verify its effectiveness.*

Keywords: Mobile wireless sensor networks, Amount of average residual power, DPSO, Virtual rail

1. **Introduction.** In recent years, there has been an increasing interest in Mobile Wireless Sensor Networks (MWSNs) with a moving function in sensor nodes [1,2]. MWSNs, which consist of Mobile Sensor Nodes (MSNs), have a wide range of applications, such as state observation of the disaster area and survey of the lunar surface. The problems of MWSNs include that constructing the topology occurs frequently and that the battery is finite. Hence, various methods using virtual rails have been proposed [3-5]. Also, dynamic data collection method [4] allows to collect data with less power consumption without knowing the positions of each other by relaying communication along the deployed virtual rails. However, there is a problem that the power consumption increases according to the number of virtual rails. This paper proposes a rail optimal placement method using Discrete binary Particle Swarm Optimization (DPSO) [6]. In the proposed method, both the number of virtual rails and placement can be determined according to the state of the observation area. In addition, we propose an objective function for evaluating virtual rails combination determined by DPSO. In simulation experiment, the performance of the proposed method is investigated to verify its effectiveness. The rest of the paper is organized as follows. Section 2 outlines dynamic data collection method. In Section 3, we describe the proposed virtual rails optimum placement method using DPSO and an objective function for evaluating virtual rails combination determined by DPSO. In Section 4, conditions of simulation and parameter setting are introduced. In Section 5, the experimental results are reported in detail. Finally, this paper closes with conclusions and ideas for further study in Section 6.

2. **Dynamic Data Collection Method.** The previous method consists of three phases of sensing phase, data transfer phase, and return phase.

2.1. **Sensing phase.** In the sensing phase, each sensor node performs sensing at a predetermined observation point.

2.2. **Data transfer phase.** In the data transfer phase, each sensor node sets the nearest virtual rail on its own virtual rail. After each sensor node gathers on the virtual rails, the transmission node moves to the point where it can communicate with the next sensor node. After that, the transmission of data to the next sensor node is started. Dynamic method is shown in Figure 1. In the case that the next sensor node is not within the communicable distance, the sensor node that received the data moves to the distance able to communicate with the next sensor node. After communication becomes possible to the next sensor node, the sensor node selects the data communication method and performs data communication. The drawing on the upper right side part of Figure 1 is the static communication method. This method is a method of transmitting data wirelessly from the place without moving. The drawing on the lower right side of Figure 1 is the dynamic communication method. This method moves from the received position information to the position of the next sensor node. After that, transmission is performed. In the previous method, out of two methods, one that reduces power consumption is selected and data is communicated.

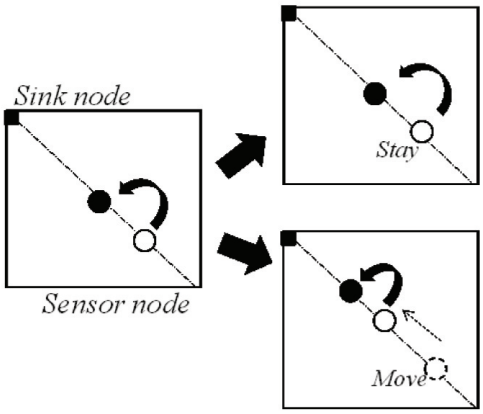

Figure 1. Dynamic method

2.3. **Return phase.** In the return phase, each sensor node moves to the original observation point. When all the sensor nodes return to the predetermined observation point, it is defined as the end of the cycle. After that, all sensor nodes shift to the sensing phase.

2.4. **Problems of previous method.** In the dynamic data collection method, each sensor node is randomly deployed in the observation area. Hence, optimal placement of deployed virtual rails is different depending on condition observation area. It seems necessary to re-experiment changing the number of deployed virtual rails. Observation area by previous method is shown in Figure 2. Figure 3 shows the amount of average residual power after 20 cycles obtained by 3 patterns using the previous method. In the previous method, the virtual rails are deployed at equal intervals, and in a sparse network, the power consumption of the sensor node increases. Therefore, the usage rate for each virtual rail is biased by the number of nodes and observation area. Moreover, it is considered that it cannot deal with the environment where the number of nodes and the node density change. Hence, this paper proposes a rail optimal placement method using DPSO. In the proposed method, both the number of virtual rails and placement can be determined according to the state of the observation area.

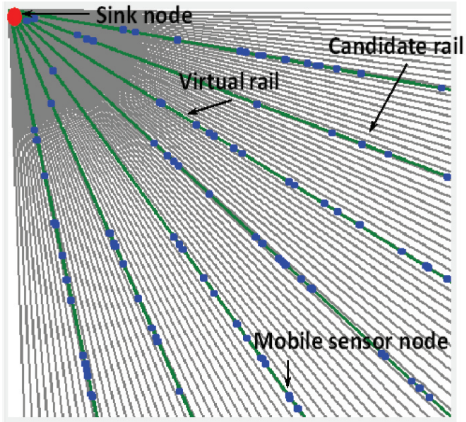

FIGURE 2. Observation area by previous method

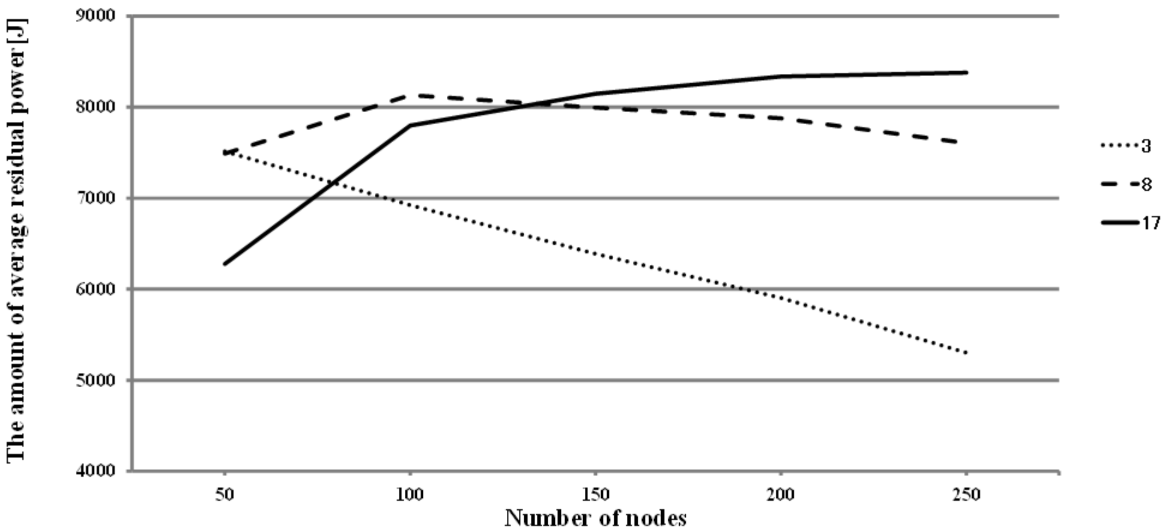

FIGURE 3. The amount of average residual power by previous method

3. **Proposed Method.** This paper proposes virtual rails optimum placement method using DPSO. In addition, we propose an objective function for evaluating virtual rails combination determined by DPSO. In the proposed method, it is possible to deploy optimal virtual rails according to the changes in the number of nodes and the condition of the observation area, and to reduce the power consumption of each node. DPSO is positively used as a promising combination optimization method because it is superior to the other methods on solving many difficult combination optimization problems. In the proposed method, candidate rails are set in the observation area where each sensor node is randomly deployed. DPSO is applied to the combination optimization problem which determines whether to place virtual rails on the candidate rails. In DPSO, each particle constituting a swarm searches for a solution until a predetermined iteration is reached using the personal best solution $\left(pbest_{id}^{k}\right)$ and the global best solution shared in the swarm found during the search process $\left(gbest^{k}\right)$. Each particle produces a new velocity vector $\left(v_{id}^{k+1}\right)$ by linearly coupling the previous velocity vector $\left(v_{id}^{k}\right)$, $pbest_{id}^{k}$, and $gbest^{k}$ before moving to the next position $\left(x_{id}^{k+1}\right)$. Assume an n-dimensional search space, and a swarm consisting of N particles. Superscript k indicates the number of iterations, subscript d $(d = 1, \ldots, n)$ represents the index of the variable, and subscript i $(i = 1, \ldots, N)$ represents the index of the particle. At the $k + 1$ iteration, the velocity vector $\left(v_{id}^{k+1}\right)$ and

position vector $\left(x_{id}^{k+1}\right)$ of the i-th particle are updated by the following equations

$$v_{id}^{k+1} = \omega \cdot v_{id}^{k} + c_1 \cdot r_1 \cdot \left(pbest_{id}^{k} - x_{id}^{k}\right) + c_2 \cdot r_2 \cdot \left(gbest^{k} - x_{id}^{k}\right) \tag{1}$$

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \tag{2}$$

where r_1 and r_2 are random numbers, uniformly distributed within the interval $[0, 1]$. ω is a parameter called the *inertial weight*. c_1 and c_2 are positive constants, which are referred to as the *cognitive* and *social* parameters, respectively.

Each element (variable) of the position vector of each particle is transformed from the variable of continuous type of the binary state variable, i.e., 0 or 1, according to the following rule

$$\begin{aligned} \text{if } \rho < sig\left(v_{id}^{k+1}\right) \quad & \text{then } x_{id}^{k+1} = 1; \\ & \text{else } x_{id}^{k+1} = 0 \end{aligned} \tag{3}$$

$$sig\left(v_{id}^{k+1}\right) = \frac{1}{1 + \exp\left(v_{id}^{k+1}\right)} \tag{4}$$

where $sig(\cdot)$ is the sigmoid function. ρ is a random number, uniformly distributed within the interval $[0, 1]$. The value of position vector $\left(x_{id}^{k+1}\right)$ is determined by comparing the results of the sigmoid function with ρ. In the proposed method, candidate rails are set in the observation area where each sensor node is randomly deployed, and it is decided whether or not to place the rail in this candidate rail. DPSO is applied to the combination optimization problem which determines whether to place virtual rails on the candidate rails. The objective function for evaluating the virtual rails combination determined by DPSO is the following Equation (5). The equation of the threshold value K is shown in (6).

$$F = \frac{C^{-mn}}{n - dn} \tag{5}$$

$$K = \frac{D}{Rail\_num} \tag{6}$$

where n is the number of sensor nodes, dn is the number of nodes whose travel distance to the virtual rails is shorter than the threshold value K, mn is the number of nodes where the distance to the next node on the virtual rail is further than communication distance. $Rail\_num$ is the number of virtual rails, D is fixed value. The threshold value K is calculated by dividing the fixed value D by deployed $Rail\_num$. Also, in the case when the number of virtual rails is large, the value of the threshold value K becomes small. Using objective function, it is possible to obtain a combination of a better virtual rails deployment.

4. **Conditions of Simulation and Parameter Setting.** Through the simulation experiments, we evaluated the effectiveness of the proposed method compared with previous method. Table 1 shows the conditions of simulation. Table 2 shows parameter settings on algorithms. Sensor nodes are randomly placed in the observation area of 400 × 400 [m], and a sink node is placed on the upper left corner of the observation area. The total electric energy of each node was set to 10,000 [J], the fixed value D was set to 100 [m]. The observation points randomly deployed within the observation area and there are no obstacles. The amount of power consumption depends on the communication distance, the amount of data, and the moving distance. The power consumption model was evaluated using Reference [7]. Each experiment was conducted for 20 cycles in these simulation environments. Also, the amount of average residual power of all nodes was measured and evaluated.

Table 1. Conditions of simulation

Observation environment	400×400 [m]
Number of sink nodes	1
Number of sensor nodes	50-250
Sensing data	50 [Mbit]
The amount of power consumption	1 [J/M]
Communication distance	50 [m]
Total power consumption	10,000 [J]

Table 2. Parameter settings on algorithm

particle size	100
ω	0.8
c_1, c_2	2.0

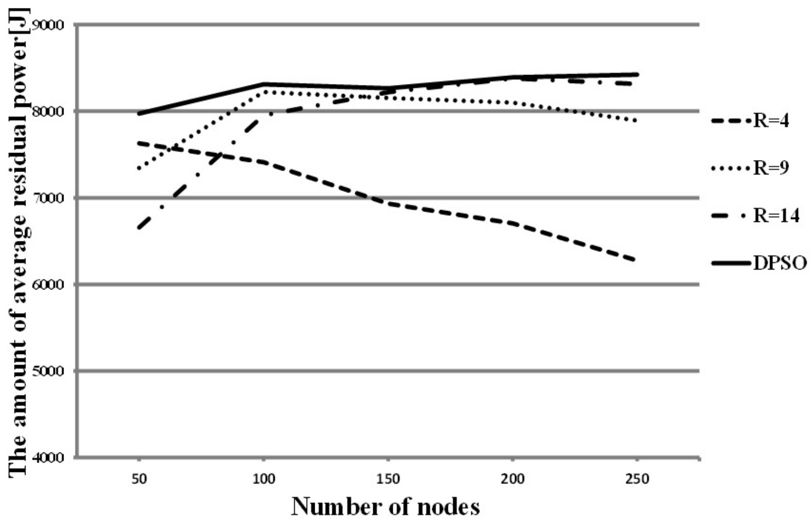

Figure 4. The amount of average residual power

Table 3. The amount of average residual power

Number of nodes	Number of virtual rails			
	4	9	14	DPSO
50	7629.8	7344.8	6657.6	7972.3
100	7411.5	8221.0	7952.1	8311.7
150	6933.8	8153.1	8219.7	8264.3
200	6705.1	8098.6	8378.7	8392.2
250	6275.6	7891.2	8313.9	8421.9

5. **Experimental Result.** Figure 4 and Table 3 show the results of the amount of average residual power of the previous method and the proposed method. The previous method sets the number of virtual rails of three patterns, where R represents the number of the deployed virtual rails by previous method. Also, Figure 5 shows observation area by the proposed method. In the previous method, it allowed to confirm that there is a difference in the amount of average residual power according to the state of observation area. On the other hand, in DPSO, the amount of average residual power keeps a high value even when the state of observation area is changed. In the previous method, when

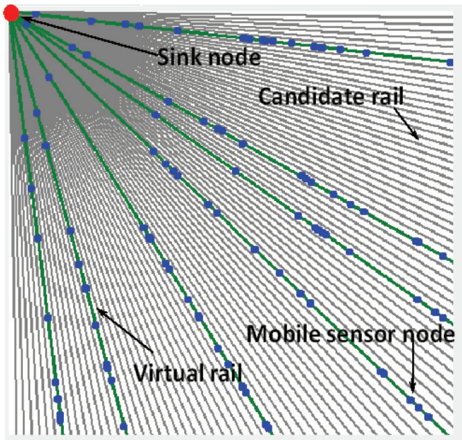

Figure 5. Observation area by proposed method

the number of nodes is small and the number of virtual rails is large, the power consumption increases since each node largely moves on the virtual rails. On the other hand, in case when the number of virtual rails is small and the number of nodes is large, the power consumption increases since each node largely moves in order to reach the virtual rail. Also, because the amount of data transmitted by each node on the virtual rail increases, the power consumption increases. In the proposed method, the optimum number of virtual rails and position are able to be calculated according to the number of nodes by DPSO. The proposed method has superiority compared with the previous method in the experiments.

6. **Conclusions.** In this paper, we have proposed a new method based on DPSO to optimize the placement of virtual rails in MSNs. In addition, we proposed an objective function for evaluating virtual rails combination determined by DPSO and have verified its effectiveness. Through the simulation experiments, we have confirmed that the proposed method can deploy optimal virtual rails according to the changes in the number of nodes and the condition of the observation area. Future work includes a detailed evaluation of the proposed method and mobile sensor applications.

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