Recharging Route Scheduling for Wireless Sensor Network Through Particle Swarm Optimization

Hengjing Zhang, Juan He, Runzhi Wang, Chuanxin Zhao(✉), Fulong Chen, and Yang Wang

School of Mathematics and Computer Science, Anhui Normal University, Wuhu 241000, China
zhaocx@ahnu.edu.cn

Abstract. Wireless rechargeable sensor network can effective prolong the network lifetime through energy replenishment. However, how to schedule the energy replenishment still need to be carefully designed. In this paper, we proposed a novel route scheduling method for wireless sensor network to maximize network utility. Experiments results indicate that our method can more effective replenish energy than the compared method.

Keywords: Wireless rechargeable sensor network · Network utility · Particle swarm optimization · TSP

1 Introduction

With the rapid development of science technology, Internet of Things have caused more and more people's attention, such as wireless sensor networks (WSNs). WSNs mainly in the applications of surveillance and monitoring including environment sensing, nature disaster, target- tracking, structural health monitoring, etc. [1–3]. The traditional sensors [4–6] are mainly powered by batteries, but their limited battery capacity limits the large-scale deployment of wireless sensor networks. In other words, wireless sensor networks in the transmission process could not continue operations. Although there have been proposed energy saving method on the sensor in the past decade years, wireless sensor networks still left some problems and encountered bottleneck in the real deployments of WSNs and in wireless data communications.

To alleviate the limited capacity problem, researchers proposed to the renewable energy technology, which enables sensors to harvest ambient energy from their surroundings such as solar energy, wind energy, etc. [7–9]. However, the temporally–spatially nature of renewable energy makes it difficult to predict sensor capture rates. For example, it is shown that the difference of energy generating rates in sunny, cloudy and shadowy days can be up to three orders of magnitude in a solar collection system [10]. Therefore, the sensor can be charged so that the sensor has a stable energy. The recent breakthrough in the wireless power transfer technique based on strongly coupled magnetic resonances has drawn plenty of attentions [11]. Wireless power transmission

F. Chen and Y. Luo (Eds.): Industrial IoT 2017, LNICST 202, pp. 11–23, 2017.
DOI: 10.1007/978-3-319-60753-5_2

technology is a promising technology to stable and high recharge rate wireless transmission power by Kurs et al. [12, 13].

Particle swarm optimization (PSO) is a population-based adaptive search optimization technique based on a simplified model of animal social behavior, first proposed by Kennedy and Eberhart in 1995. Such as fish school and bird populations. PSO was originally aimed at single-objective continuous optimization problem, it is a population-based optimization algorithm [14]. The basic principle of the PSO algorithm that each bird is abstracted as a particle, and the optimization results corresponding to the particle in space exploration position [14]. Therefore, the introduction of PSO algorithm can greatly improve the performance of WSN in the aspects of load balance, energy consumption and so on. PSO works with a population of particles. Particles move in the search space to find optimal solution. A particle adjusts its velocity before its movement according to some simple rules. Make use of the best position visited by each particle and the global best solution produced by the swarm to drive particles to a promising region.

In the paper, we propose multiple mobile wireless chargers to replenish sensors in a large scale WSN with wireless power transfer for a monitoring, making no sensor will run out of energy. We consider the flexibility of sensor energy charging mode, the sensor is charged by mobile Charger for on-demand routing and data routing and energy supplement. In order to avoid the termination of energy, we provide a method to transmission the energy from a mobile charger.

The rest of this paper is organized as follows. Section 2 reviews related work. Section 3 presents system model and notions. Section 4 proposes method. Section 5 evaluates the algorithm performance, and Sect. 6 concludes the paper.

2 Related Work

In order to prolong the service lifetime of the network, mobile chargers be used in wireless sensor networks. A few studies have been conducted to explore mobile chargers to replenish energy to sensors. Most existing studies considered sensor energy recharging and data collection routing jointly. For instance, Gu et al. [15] considered the problem of mobile strategy affects the survival time of direct network, which the author assumes the network is divided into several regions, and the cluster head is selected in the interior each area. The mobile node collects data directly from the cluster head. Its energy balance can be maintained by multi hop transmission. However, it will cause some data overflow and additional communication delay. Zheng et al. [16] designed a path selection probabilistic model and used the ACO algorithm to find the optimal path from the processing node to the destination node. But complexity of their proposed ACO algorithm is relatively high.

Guo et al. [17] proposed a framework for wireless energy supplements and mobile data collection based on the anchor point, considering that all kinds of capacity consumption and time vary with energy supplementation. In the energy balance, energy conservation and link capacity constraints, the problem of energy charge is considered to be the maximize utility. Zhao et al. [18] considered the combination of mobile data optimization and energy charging to achieve the energy complements range and latency data collection by using mobility. They have developed a charging and data collection problem as a way to adjust the data rate, flow routing, and link scheduling issues to achieve maximum network utility.

Similarly, Yang et al. [19] proposed a sleep multi-path routing protocol to save energy in directional diffusion by using desired path success and path dependency requirements to limit the number of active alternative paths. To improve the energy efficiency by reducing the length of the alternative paths, Ganesan et al. [20] proposed the braided multi-path protocol. In this protocol, rather than building completely disjoint paths, partially disjoint paths are constructed. In this protocol, instead of building a complete disjoint path, a partially disjoint path is constructed, which is a path-based failure that may fail on the edge while other edges are still available. Liu et al. [21] proposed topology control method for a multichannel multi-radio wireless network using directional antennas.

There are a few recent works using on-demand sensors to supplement the energy. Xu et al. [22] proposed a method to schedule K mobile chargers to add energy. The maximum charge time in the K charger is minimized for live sensors. Ren et al. [23] have recently investigated the deployment of a single mobile charger to charge under distance-constrained sensors. Approximate algorithm for the minimization of network utility [24] is proposed by Liang et al. By means of a charging sensor, under the energy constraints of each moving vehicle, moving vehicles are used to charge a set of charged sensors. For our work, we also take into accounted to minimize the total travel multiple mobile charger to maintain the permanent operation of the sensor network.

3 Problem Statement

How to schedule the charging vehicle to replenish the network directly affects the service life of the whole wireless sensor network. When there is only one charging vehicle in the entire network, it needs to traverse all sensor nodes in the network and add energy to them. Therefore, it is very important to choose the best path to traverse the network. We first assume that all sensors have reached the threshold of energy consumption, and they need for additional. And then we also assumed that the charging vehicle with infinite energy to support it to traverse all nodes and charge them, such as in Fig. 1. Through the above assumptions, the charging problem of wireless sensor network can be converted into Traveling Salesman Problem. Finally, the algorithm for dealing with this problem is proposed.

We can consider this problem as optimization problem. Let $S = \{s_1, s_2, \ldots, s_N\}$ be the set of sensors. We define a graph $G = (V, E)$ to represents the network, where V refers to the set of sensors and the base station (v0) and E denotes the paths between those sensors. There is an edge (i, i + 1) between sensors i and sensor i + 1, $\forall i \in V$.

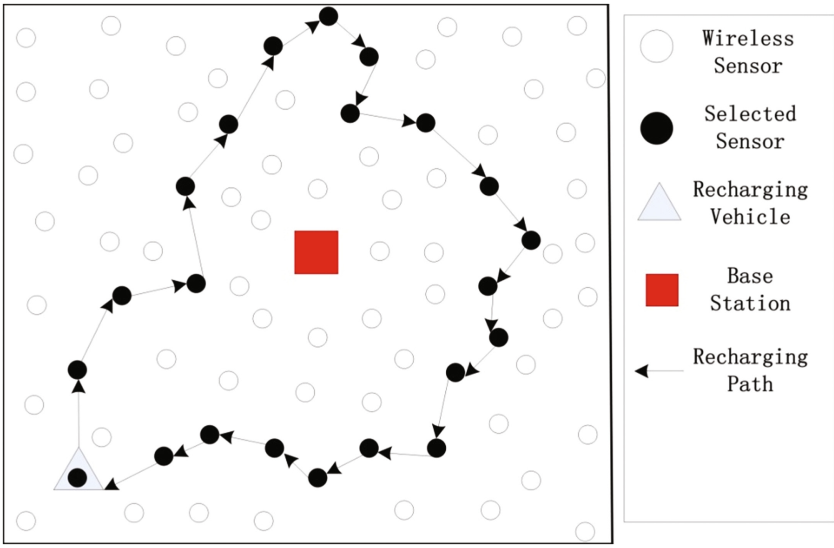

Fig. 1. Scheduling of recharging route for a wireless sensor network

Energy required by sensor node i is defined as e_i. $p_{i,i+1}$ is the energy consumed by a charging vehicle while move from sensor node i to sensor i + 1. Binary variable a_i equals 1 if sensor node i is recharged by charging vehicle; otherwise, it is 0. And binary variable $b_{i,i+1}$ equals 1 if the charging vehicle is move from sensor i to sensor i + 1; otherwise, it is 0. We define the total energy consumption of charging car during a charging tour as E_c. Table 1 lists the definitions of all notations.

Table 1. The parameters of network

Parameter	Value
Number of sensors *N*	20, 40, 60, 80, 100
The Upper limit of Iteration times	5000
Inertia weight *w*	0.5 f
Side length of sensing field *L*	200
Supply voltage	3 V
Charge threshold *Ec*	30
Consumption of Recharging Vehicles Em	0.56 J/m
Speed of Recharging Vehicles Vr	1 m/s
Magnification of $\sum 1/\mathbf{RE}$	500

We aim to find the maximum charging efficiency of the charging vehicle under the premise of ensuring the normal operation of sensor network, i.e., the ratio of the total energy demand of sensors to energy capacity of charging vehicle.

Maximize:

$$\sum_{i=0}^{N} a_i e_i / E_c \tag{1}$$

Subject to:

$$\sum_{i=0}^{N} b_{i,i+1} p_{i,i+1} > 0, \forall i \in s \tag{2}$$

$$\sum_{i=0}^{N} a_i e_i + \sum_{i=0}^{N} b_{i,i+1} p_{i,i+1} \le E_c, \forall i \in s \tag{3}$$

$$a_{i,i+1} \in \{0, 1\}, \forall i \in s \tag{4}$$

$$b_{i,i+1} \in \{0, 1\}, \forall i \in s \tag{5}$$

In the above statement, constraint (2) shows that the charging vehicle moves at least once during a charging cycle. Constraint (3) ensures that the capacity of charging vehicle should not be depleted. Constraints (4) and (5) indicates that a_i and $b_{i,i+1}$ are all binary variables.

4 Proposed Method

4.1 Particle Swarm Optimization Algorithm

Particle swarm optimization has been used to solve resource assignment and network deployment [25, 26]. In the PSO, particle swarm search in an n dimensional space. In this space, each particle's position represents a solution to the problem. Particles search for new solutions by adjusting the position X. Every particle can remember their best solution, denoted as P_{id}. The best position of the particle swarm passed which is also the optimal solution to the current search, denoted as P_{gd}. Each particle has a velocity, denoted as V.

$$V_{id}^{'} = \omega V_{id} + \eta_1 rand()(P_{id} - X_{id}) + \eta_2 rand()(P_{gd} - X_{id}) \tag{6}$$

The V_{id} means the velocity of the i particle at the d dimension. ω is the inertia weight. η_1, η_2 is the important parameters to adjusting P_{id} and P_{gd}. rand() is a random number generating function. In this way, we can get the next position of the particle.

$$X_{id}^{'} = X_{id} + V_{id} \tag{7}$$

4.2 Charging Utility

We consider a modified PSO algorithm in this situation that there is only one recharging vehicles charging for the whole sensor cluster. For simplicity, we assume that all sensors have got the threshold of energy consumption so they all need additional energy. The recharging vehicle must pass all nodes to charge for all sensor nodes. In addition, it is assumed that the recharging vehicle has unlimited energy, it has enough energy to support itself to travel all nodes and charge all nodes. So the wireless charging sensor network can be converted into the TSP traveling salesman problem.

As the remaining energy of each sensor is different and the distance is also different. When recharging vehicle moves, it needs consume energy. Therefore, we define a charging utility criterion to measure the charging utility:

$$f(i) = \partial \frac{1}{RE_i} - e_m \times D_{i,j}, i,j = 0, 1, 2, \cdots, n, i \neq j \quad (8)$$

RE_i is the residual energy of sensor. e_m is the energy consumption when recharging vehicle drives one unit meters. $D_{i,j}$ is the pseudo Euclidean distance between sensor i and sensor j. ∂ is the constant coefficient.

When RE_i is small, the energy of sensor i is lower. As the result, the $\frac{1}{RE_i}$ is bigger, so the charging priority of the sensor i is higher and the charging utility is better. When $D_{i,j}$ is smaller, the energy the recharging vehicle consumes when it is moving is also less. In the contrary, the charging utility is better. Therefore, the standard can be well described for the charging utility.

We know the charging utility function of each sensor. According to this function, the fitness of each particle can be obtained:

$$fitness(k) = \sum (\partial \frac{1}{RE_i} - e_m \times D_{i,i+1}), i = 0, 1, 2, \cdots, n, k = 0, 1, 2, \cdots n \quad (9)$$

4.3 Improved PSO Algorithm

Because we have got the fitness, what we also need to know is the speed of particles. The speed determines the direction and distance they fly. Then the particles will follow the current optimal particle to search the best solution. We iterate this step to update the particle until we find the optimal solution or up to upper limit of the iteration. However, the basic PSO algorithm is used to solve the continuous problem. But we can't directly use formula (7) in the TSP problem. Therefore, we improved the PSO algorithm and introduced the exchange order to construct a special PSO algorithm. So we can use it to solve the traveling salesman problem. We introduce the following new speed formula.

$$V_{id}^{'} = V_{id} \times \alpha(p_{id} - X_{id}) \times \beta(p_{gd} - X_{id}) \quad (10)$$

The α, β is the random number between 0 and 1.$\alpha(P_{id} - X_{id})$ means the basic exchange sequence $(P_{id} - X_{id})$ is retained at the probability α. $\beta(P_{gd} - X_{id})$ means the basic exchange sequence $(P_{gd} - X_{id})$ is retained at the probability β. So we can get this conclusion: when α is bigger, $(P_{id} - X_{id})$ is larger, the effect of P_{id} is bigger. Similarly, when β, $\left(P_{gd} - X_{id}\right)$ is larger, the effect of P_{gd} is bigger.

Next, we will describe the algorithm. First, we input the location and residual energy of each sensor nodes. We initial P_{id} and P_{gd} and randomly generated N particles. Each particle means a path to traverse all nodes. Next, according to the particle fitness function, we calculate the fitness of each particle. Then we start to iterate: we randomly change the path sequence and generate a new path and we calculate the fitness again. We compare it to the fitness of the best position of P_{id} the particle experiences. If better, we update P_{id}. Then, we also compare it to the fitness of the best position of P_{gd} the group experiences. If better, we update P_{gd}. If we can find the enough good position or up to the maximum number of iterations. We say we meet the ending conditions to end the cycle. Otherwise, continue to iterate. The flow chart of the algorithm is as Fig. 2:

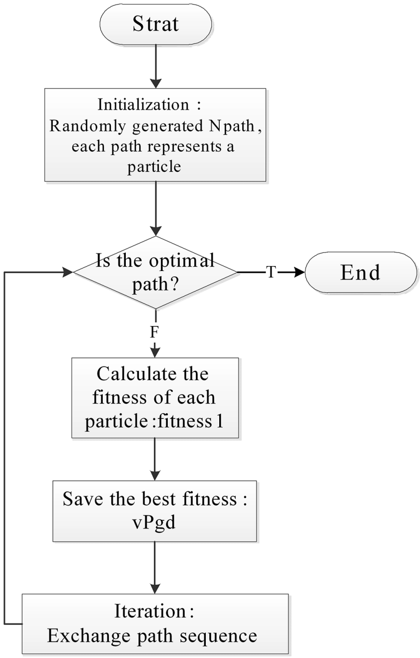

Fig. 2. The flowchart of method

5 Experiment and Simulation

In our simulation experiment, we laid N sensors at random in a square area whose side length L is 200. We laid a base station to receive sensor signal. Each sensor is equipped with CC2530 communication module and PIR to detect the target. The average current is 10 mA under 3 V voltage when the sensor is activated. It consumes 27 mA when they send or receive data package. The supply voltage range is between 2.0 V and 3.6 V, and we use 3 V in this experiment. Each sensor produces data package at constant speed, and each data package measures 20 bytes. During spare time the average current is 170 μA. We set the threshold value of the sensor is half of the whole power capacity. Recharging vehicle runs constantly at 1 m/s which consumes 0.56/m.

We realize the algorithm through Java and illustrate the result of the algorithm by diagram. We set these two auto-charging cars for two kinds of algorithms with same initial coordinates. Also, we set the initial coordinate of sensors randomly. We compare the results of CRSA and PSO: setting 5 sensor groups, and the sensor node numbers of these groups are 20, 40, 60, 80, 100, respectively.

5.1 Utility Evaluation

First of all, we evaluate the charging utility of the two algorithms. We compare the charging utility of the recharging vehicle under two algorithms. In the former condition, recharging vehicle charges the sensor through the charging path given by PSO. Meanwhile, recharging vehicle charges the sensor by the path given by CRSA in the second condition.

The comparison of charging utility within two algorithms that recharging vehicles charge all the sensors' nodes by the given paths is showed in Fig. 1 as below. The abscissa of the chart is the number of the sensors while the ordinate of the chart is the charging utility.

It illustrates by the Fig. 3 that when the scales of the sensors are 20, 40, 60, 80, 100, charging utilities of PSO are all larger than the corresponding ones of CRSA. In addition, with the scale of sensors enlarging the utility gap between these two algorithms becomes wider and wider. When the sensor's scale is small, the paths and given paths from PSO intelligent algorithm are less, when the sensor scale is 20, PSO algorithm only improves the charging utility by 37.2%. When the sensor scale is 40, the utility increases by 44.6%, while the scale is 60, it increases by 52.3%. Additionally, when the scale is 80 or 100, the utility is improved by 73.8% or 75.4% respectively. It demonstrates that the larger the scale is the better charging utility planned by PSO algorithm.

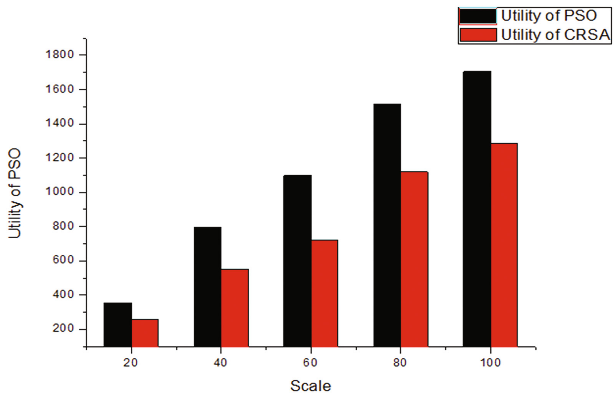

Fig. 3. The compared result of two algorithms for 5 networks

5.2 Convergence Analysis

Then, we will analyze the convergence of PSO. As followed, we compare these convergences in 5 different scales.

The Fig. 4 shows the convergence of PSO algorithm when sensor scale is 20. We can see from the graph that algorithm converges rapidly at 39th generation with a constant rate: 394.8.

As for the sensor group whose scale is 40, its algorithm convergence is shown by Fig. 5. The utility converges at 919th generation. Additionally, before the final convergence the utility convergent briefly for three times. At last, it finds a new best particle and converges. After the convergence, the utility maintains at 767.3.

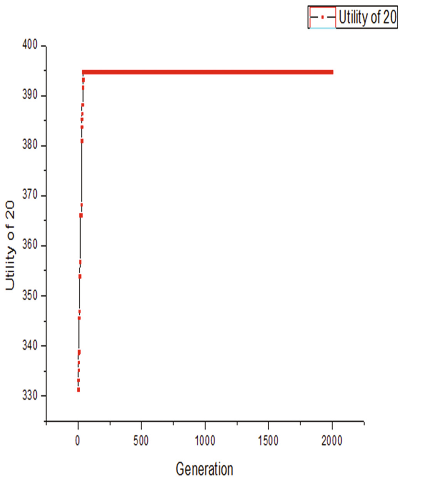

Fig. 4. The fitness of PSO with 20 sensors

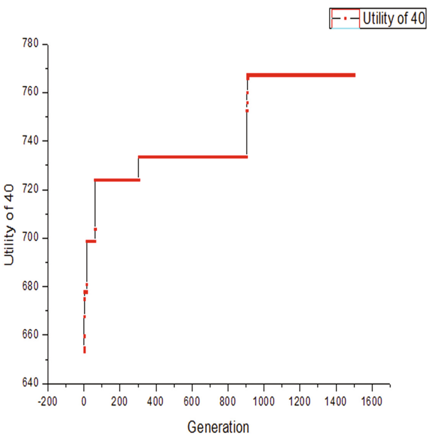

Fig. 5. The fitness of PSO with 40 sensors

As for the sensor group whose scale is 60, its algorithm convergence is shown by Fig. 6. The utility converges at 1781th generation. After the final convergence, the utility maintains at 1032.1. Additionally, before the final convergence the utility convergent briefly for five times. At last, it finds a new best particle and converges.

As for the sensor group whose scale is 80, its algorithm convergence is shown by Fig. 7. The utility converges at 2472th generation. After the final convergence, the utility maintains at 1395.2. Additionally, before the final convergence the utility convergent briefly for nine times. At last, it finds a new best particle and converges.

As for the sensor group whose scale is 100, its algorithm convergence is shown by Fig. 8. The utility converges at 419th generation. After the final convergence, the utility maintains at 1664.1. Additionally, before the final convergence the utility convergent briefly for three times. At last, it finds a new best particle and converges.

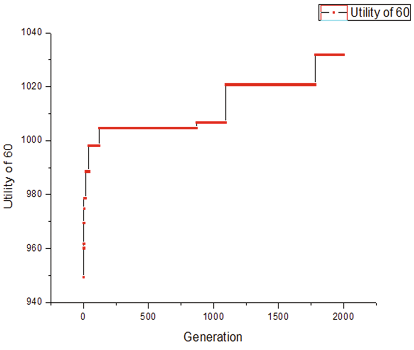

Fig. 6. The fitness of PSO with 60 sensors

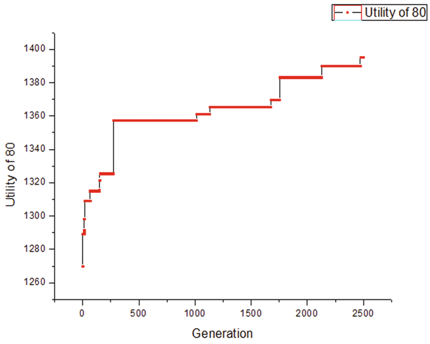

Fig. 7. The fitness of PSO with 80 sensors

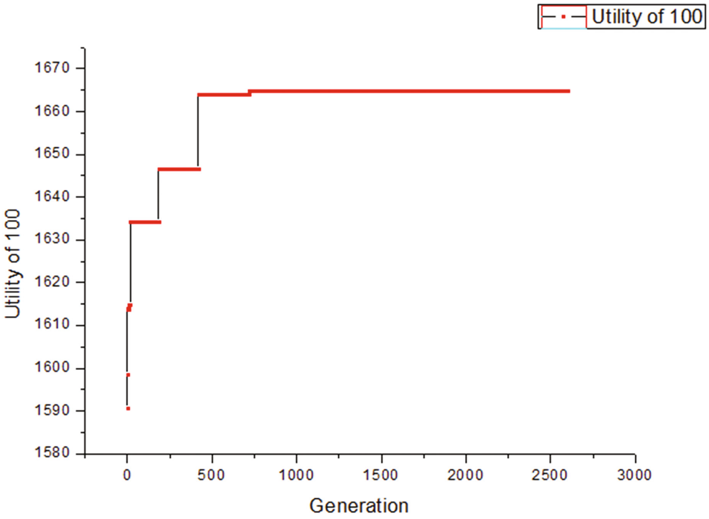

Fig. 8. The fitness of PSO with 100 sensors

5.3 Shortest Distance Assessment

We evaluate the shortest moving distance for sensors which is provided by recharging vehicles of two algorithms. We compare the shortest distances when sensor scale is 20, 40, 60, 80, 100 of two algorithms, respectively. Under the first circumstance, recharging vehicles plan the charging path and calculate the shortest distance by PSO algorithm. While under the second circumstance, recharging vehicles plan the charging path and calculate the shortest distance by CRSA algorithm.

It can be shown by Fig. 9 that with the sensor scale extending the distance for recharging vehicles need to move increases. However, it is not linear increase. When sensor scale increases from 60 to 80, the shortest moving distance for recharging vehicle increases apparently slower. When sensor scale is 20, the shortest distance planned by CRSA algorithm is 793 while it planned by PSO algorithm is 423. The shortest moving distance optimizes and improves by 87.5%. When sensor scale is 40, the shortest distance planned by CRSA algorithm is 1544 while it planned by PSO algorithm is 598. The shortest moving distance optimizes and improves by 158.3%. When sensor scale is 60, the shortest distance planned by CRSA algorithm is 2597 while it planned by PSO algorithm is 1145. The shortest moving distance optimizes and improves by 126.8%. When sensor scale is 80, the shortest distance planned by CRSA algorithm is 2971 while it planned by PSO algorithm is 1448. The shortest moving distance optimizes and improves by 105.2%. When sensor scale is 100, the shortest moving distance planned by CRSA algorithm is 4154 while it planned by PSO algorithm is 2546. The shortest moving distance optimizes and improves by 63.1%.

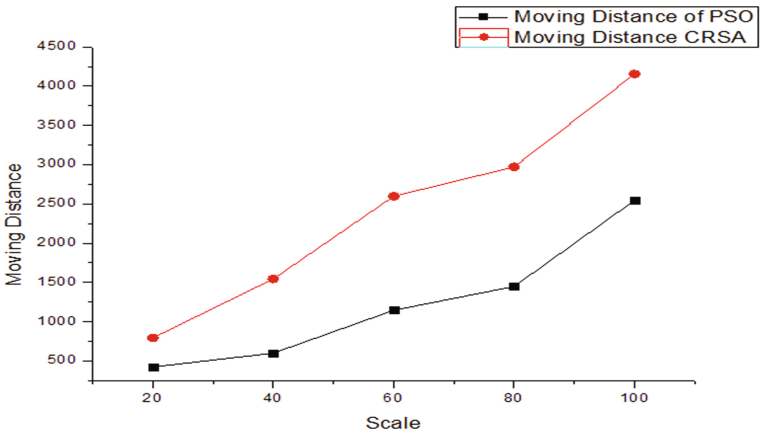

Fig. 9. The moving distance of 2 Algorithm

6 Conclusion

In this paper, we proposed a novel route scheduling method based on particle swarm optimization for wireless sensor network to maximize network utility. Experiments results indicate that our method can more effective replenish energy than compared method. Next, we will relax the assumption of energy to study the more real recharging scheduling for wireless network.

References

1. Yick, J., Mukherjee, B., Ghosal, D.: Wireless sensor network survey. Comput. Netw. **52**, 2292–2330 (2008)
2. Yick, J., Mukherjee, B., Ghosal, D.: Wireless sensor network survey. Comput. Netw. Int. J. Comput. Telecommun. Netw. **52**(12), 2292–2330 (2008)

3. Akyildiz, I.F., Su, W., Sankarasubramaniam, Y., Cayirci, E.: Wireless sensor networks: a survey. Comput. Netw. **38**(4), 393–422 (2002)
4. Zahmati, A.S., Abolhassani, B., Beheshti Shirazi, A., Bakhtiari, A.S: An energy efficient protocol with static clustering for wireless sensor networks, Int. J. Electron. Circuits Syst. **69** (2007)
5. Younis, O., Fahmy, S.: HEED: a hybrid, energy-efficient, distributed clustering approach for ad hoc sensor networks. IEEE Trans. Mob. Comput. **3**(4), 366–379 (2004)
6. Wei, D., Jin, Y., Vural, S.: An energy-efficient clustering solution for wireless sensor networks. IEEE Trans. Wireless Commun. **10**(11), 3973–3983 (2011)
7. Liang, W., Ren, X., Jia, X., Xu, X.: Monitoring quality maximization through fair rate allocation in harvesting sensor networks. IEEE Trans. Parallel Distrib. Syst. **24**(9), 1827–1840 (2013)
8. Kansal, A., Hsu, J., Zahedi, S., Srivastava, M.B.: Power management in energy harvesting sensor networks. ACM Trans. Embed. Comput. Syst. **6**(4), 32 (2007)
9. Ren, X., Liang, W., Xu, W.: Use of a mobile sink for maximizing data collection in energy harvesting sensor networks. In: Proceedings of 42nd international conference on parallel processing (ICPP), pp. 439–448. IEEE (2013)
10. Rahimi, M., Shah, H., Sukhatme, G., Heideman, J., Estrin, D.: Studying the feasibility of energy harvesting in a mobile sensor network. In: Proceedings of international conference on robotics and automation (ICRA), vol. 1, pp. 19–24. IEEE (2003)
11. Kurs, A., Karalis, A., Moffatt, R., Joannopoulos, J.D., Fisher, P., Soljacic, M.: Wireless power transfer via strongly coupled magnetic resonances. Science **317**, 83–86 (2007)
12. Lin, Z., Zhang, H., Wang, Y., Yao, F.: Energy-efficient routing protocol on mobile sink in wireless sensor network. Adv. Mater. Res. **787**, 1050–1055 (2013)
13. Gu, Y., Ji, Y., Li, J., Zhao, B.: ESWC: efficient scheduling for the mobile sink in wireless sensor networks with delay constraint. IEEE Trans. Parallel Distrib. Syst. **24**(7), 1310–1320 (2013)
14. Liang, Y., Yu, H.: PSO-based energy efficient gathering in sensor networks. In: Jia, X., Wu, J., He, Y. (eds.) MSN 2005. LNCS, vol. 3794, pp. 362–369. Springer, Heidelberg (2005). doi:10.1007/11599463_36
15. Zheng, W., Liu, S., Kou, L.: Dynamic mobile agent routing algorithm in sensor network. Control Decis. **25**(7), 1035–1039 (2010)
16. Guo, S., Wang, C., Yang, Y.: Mobile data gathering with wireless energy replenishment in rechargeable sensor networks. In: Proceedings of INFOCOM, pp. 1932–1940. IEEE (2013)
17. Zhao, M., Li, J., Yang, Y.: Joint mobile energy replenishment and data gathering in wireless rechargeable sensor networks. In: Proceedings of 23rd international tele-traffic congress (ITC), pp. 238–245. IEEE (2011)
18. Yang, O., Heinzelman, W.: Sleeping multipath routing: a trade-off between reliability and lifetime in wireless sensor networks. In: Proceedings of the 30th IEEE Conference on Global Telecommunications, GLOBECOM 2011, pp. 1–5 (2011)
19. Ganesan, D., Govindan, R., Shenker, S., Estrin, D.: Highly-resilient, energy-efficient multipath routing in wireless sensor networks. ACM SIGMOBILE Mob. Comput. Commun. Rev. **5**(4), 11–25 (2001)
20. Liu, Q., Jia, X., Zhou, Y.: Topology control for multi-channel multi-radio wireless mesh networks using directional antenas. Wirel. Network **17**, 41–51 (2010). doi:10.1007/s11276-010-0263-1
21. Xu, W., Liang, W., Lin, X.: Approximation algorithms for min-max cycle cover problems. IEEE Trans. Comput. (2013, to appear)
22. Ren, X., Liang, W., Xu, W.: Maximizing charging throughput in rechargeable sensor networks. In: Proceeding of ICCCN. IEEE (2014)

23. Liang, W., Xu, W., Ren, X., Jia, X., Lin, X.: Maintaining sensor networks perpetually via wireless recharging mobile vehicles. In: Proceeding of LCN. IEEE (2014)
24. Wang, C., Li, J., Ye, F., Yang, Y.: Multi-vehicle coordination for wireless energy replenishment in sensor networks. In: Proceeding of IPDPS. IEEE (2013)
25. Chuanxin, Z., Fulong, C., Ruchuan, W., Cheng, Z., Yonglong, L.: Multi-objective channel assignment and gateway deployment optimizer for wireless mesh network. J. Comput. Res. Dev. **52**(8), 1831–1841 (2015)
26. Zhao, C.-X., Wang, R.-C., Huang, H.-P., Sun, L.-J.: Cross-layer power allocation for multi-radio multi-channel Ad Hoc network. Syst. Eng. Electron. **33**(4), 894–899 (2011)