Journal of Information Hiding and Multimedia Signal Processing ©2021 ISSN 2073-4212
Ubiquitous International Volume **12**, Number **1**, March **2021**

Solar Wireless Sensor Network Routing Algorithm Based on Multi-Objective Particle Swarm Optimization

Jian Wu[1], Ming Xu[2], Fei-Fei Liu[1], Miao Huang[2], Long-Hua Ma[2*] and Zhe-Ming Lu[3]

[1]School of Electrical Engineering and Automation
Jiangxi University of Science and Technology
Ganzhou 341000,China
wujian_322@163.com

[2]School of Information Science and Engineering
Ningbo Institute of Technology
Zhejiang University
Ningbo 315100, China
*Corresponding Author: lhma_zju@zju.edu.cn

[3]School of Aeronautics and Astronautics
Zhejiang University
Hangzhou 310027, P. R. China
zheminglu@zju.edu.cn
Received September 2020; revised November 2020

Abstract. *With the development of information technology, wireless sensor networks have been widely used in agricultural irrigation management, military intrusion monitoring, industrial control and other fields. How to reduce the node energy consumption and maintain energy balance has been a hot topic in wireless sensor network research. This paper proposes a multi-hop data forwarding algorithm for wireless sensor networks powered by solar cells and batteries, and presents a multi-objective decision-making model for data forwarding node selection of next hop. The Pareto optimal solution set is obtained by using multi-objective particle swarm optimization algorithm. The characteristics of solar energy acquisition are analyzed, and a solar energy supply model is designed. The simulation results show that the data forwarding algorithm can adapt to the change of network energy, and reduce network energy consumption and network delay.*
Keywords: Wireless sensor network, Solar energy, Data forwarding, Multi-objective particle swarm optimization

---

1. **Introduction.** Wireless Sensor Network (WSN) consists of a number of sensor nodes placed in the monitoring area. These sensor nodes cooperate with each other to collect monitoring information to the base station. With the development of information technology, wireless sensor networks have been widely used in agricultural irrigation management, military intrusion monitoring, industrial control and other fields. How to reduce the node energy consumption and maintain energy balance has been a hot topic in wireless sensor network research[1]. With the development of energy acquisition technology, it is possible for the network to run indefinitely by equipping nodes with energy collection devices such as solar cells and thermoelectric cells[2]. Compared with the traditional

energy-constrained wireless sensor networks, the energy-harvesting wireless sensor networks will no longer reduce the residual power of the nodes due to the additional energy supply, but will fluctuate according to the energy replenishment characteristics. When the power of the node is exhausted, the node no longer dies permanently but falls asleep, and can resume operation after the energy is replenished.

At present, the research on energy-harvesting WSN is mainly divided into three categories, i.e., node hardware design[3], energy management and routing algorithms. There are few researches on routing algorithms, most of which are based on wireless sensor networks powered by solar cells. Solar Aware-LEACH[4] extends the network lifetime by sending the information of residual energy and solar energy status of each sensor node to the base station so that the node with solar cells is selected as the cluster head node first. Islam et al.[5] improved SLEACH and extended the network lifetime by 19.58%. ZHANG et al. [6] analyzes the characteristics of solar energy supply, defines three states according to the residual energy of the network: energy consumption period, energy storage period and stable period, and selects the best cluster head according to different states. Cao et al. [7] proposed an EHR routing protocol, which takes energy collection as the main factor in routing design, introduces a hybrid routing metric that combines residual energy and energy collection rate, and proposes an update mechanism that allows each node to grasp the energy information of its neighbors. And then select the optimal next hop node based on hybrid metric and neighbor node energy information. There are also other schemes in recent years[8-15]. In this paper, we proposes a multi-hop data forwarding routing algorithm for wireless sensor networks powered by solar cells and batteries. By partitioning the network monitoring area and the node communication area, using the MOPSO algorithm to solve the Pareto solution with minimum energy consumption and minimum delay and selecting the next hop from the appropriate area according to the current state of the network nodes to trade-off between energy consumption and delay.

Compared with random clustering routing such as LEACH and its improved protocol, the algorithm proposed in this paper does not require excessive computation of nodes, nor does it have a cumbersome interaction process when clustering, and has the advantage of easy accurate calculation without knowing the specific location information of all nodes. It can be optimized according to different needs.

2. **System Model.**

2.1. **Solar energy harvesting model.**

Solar energy has a significant diurnal periodicity, because there is no light at night, there is no energy acquisition, after sunrise energy acquisition efficiency gradually increased, and reached the maximum at noon, then gradually reduced. Therefore, we use trapezoidal model [8] as a solar energy harvesting model. The relationship between the solar power and time collected by a node during the day is as follows:

$$Esolar(t) = \begin{cases} b(t-t_0) & t_0 \le t < t_1 \\ E_{max} & t_1 \le t < t_2 \\ E_{max} - b(t-t_2) & t_2 \le t < t_3 \\ 0 & \text{others} \end{cases} \tag{1}$$

E_{max} is the maximum power of solar energy, b is the slope,t_1 and t_2 are the time when the acquisition rate in the energy acquisition model rises to the highest and starts to fall from the highest, t_0 and t_3 are the time of sunrise and sunset respectively. Considering the location of each node and the weather changes, the energy obtained from different dates may be different, and the level of energy obtained from each node may be slightly different. Fig.1 is a solar energy acquisition model within 5 days. This model simulates the solar energy acquisition by using random function. The specific parameters will be set in the simulation.

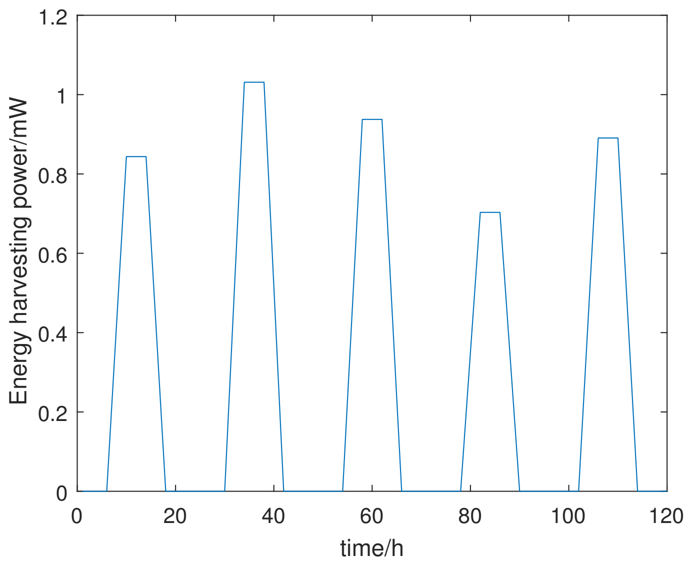

FIGURE 1. Solar energy harvesting model

2.2. **Network and energy consumption model.** In this paper, we assume that 100 nodes are randomly distributed in an 800m square area and the base station is located at the midpoint of the square side. We also assume that the wireless sensor network has the following properties:

1. All nodes are randomly distributed in the square area, and the location of nodes will not change after deployment.
2. All nodes can measure the amount of their remaining energy.
3. Each node has the same communication capability and the transmission power can be adjusted.
4. All nodes have unique ID.
5. If the transmitting power of the data transmitter is known, the receiver can calculate the approximate distance from the transmitter to itself according to the RSSI of the received signal strength.
6. All nodes have the same initial energy Eo and can be supplemented by solar cells. The energy upper limit of the nodes is Em.
7. The energy of the base station is not limited, and has strong storage and computing power.

Radio energy dissipation model adopted in this paper is consistent with that in reference [9]. As shown in Fig.2, the model is divided into three parts: transmitting circuit, amplifying circuit and receiving circuit.

The energy consumed by transmitting L-length data to a node with a distance of d consists of transmitting circuit loss and power amplification loss, and it is given by:

$$E_{TX}(L,d) = \begin{cases} L \times E_{elec} + L \times \epsilon_{fs} \times d^2 & d < d_0 \\ L \times E_{elec} + L \times \epsilon_{mp} \times d^4 & d \geq d_0 \end{cases} \quad (2)$$

E_{elec} is the energy consumed by processing one bit data in the transmitting or receiving circuit, d is the transmission distance, and when the transmission distance d is less than d_0 the power amplification loss adopts the free space model with the value of ϵ_{fs}; when the

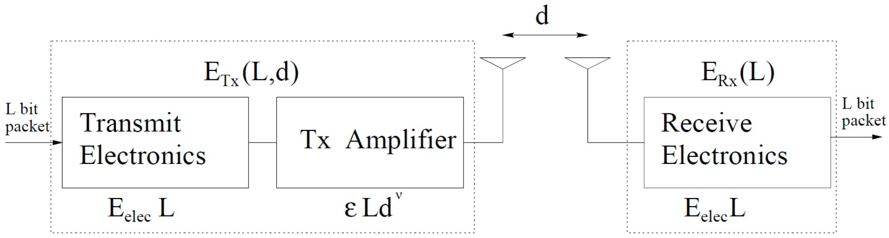

FIGURE 2. Radio energy dissipation model

transmission distance is greater than or equal to d_0, the power amplification loss adopts the multi-channel attenuation model with the value of ϵ_{mp}. d_0 is a distance threshold with a value of $d_0 = \sqrt{\frac{\epsilon_{mp}}{\epsilon_{fs}}}$. The energy consumed by nodes with L-length is:

$$E_{RX} = L \times E_{elec} \tag{3}$$

Obviously, the energy consumption of the received data is less than the energy consumption generated by the transmitted data. When data length is fixed, $L \times E_{elec}$ is a constant. It can be considered that $L \times E_{elec}$ is the minimum energy consumption when nodes work. Taking into account the second part of the energy consumption formula when data is transmitted, the value of $L \times \epsilon_{fs} \times d^2$ cannot be less than $L \times E_{elec}$[10]. Consequently, we conclude that the minimum transmission distance $d_{min} = \sqrt{\frac{E_{elec}}{\epsilon_{fs}}}$.It can be understood as the range of signal coverage when the transmission power is minimum.

The delay of transmitting information from node to base station is:

$$Delay = (qd + td + pd) \times NF \tag{4}$$

Its value mainly depends on NF, the number of intermediate forwarders between node and sink. qd is the average queuing delay of each intermediate forwarding node, td is the average transmission delay, pd is the average propagation delay.

3. **Routing Algorithm.** The routing algorithm proposed in this paper is divided into three stages: 1. network initialization stage; 2. data forwarding node selection stage; 3. data transmission stage.

3.1. **Network Initialization Stage.** We use the base station as the center and $R_i(i = 1, 2, 3 \cdots)$ as the radius to generate a series of circles to partition the network monitoring area. $R_i = i \times d_{min}(i = 1, 2, 3 \cdots)$. These concentric circles divide the network monitoring area into several circular regions and label them by C. The monitoring area partition is shown in Fig.3.

The base station is represented by X in Fig.3. Firstly, the base station broadcast partition confirms the packet, and other nodes in the network calculate their approximate distance from the base station by the received signal strength RSSI, so as to determine their own partition.

In order to better select data forwarding nodes, we also partitioned the communication scope of each node. Each node takes its location as the center,and takes $R(k) = k \times d_{min}(k = 1, 2, 3 \cdots \frac{r}{d_{min}})$ as radius, divide the communication ranges into $\frac{r}{d_{min}}$ concentric rings. R is the maximum communication scope of nodes. k can be understood as the transmit power level of nodes. This partitioning method can avoid the nodes communicating with the nearer nodes with higher transmitting power. Each node confirms the neighbor node's location in its own communication range by sending HELLO packets with

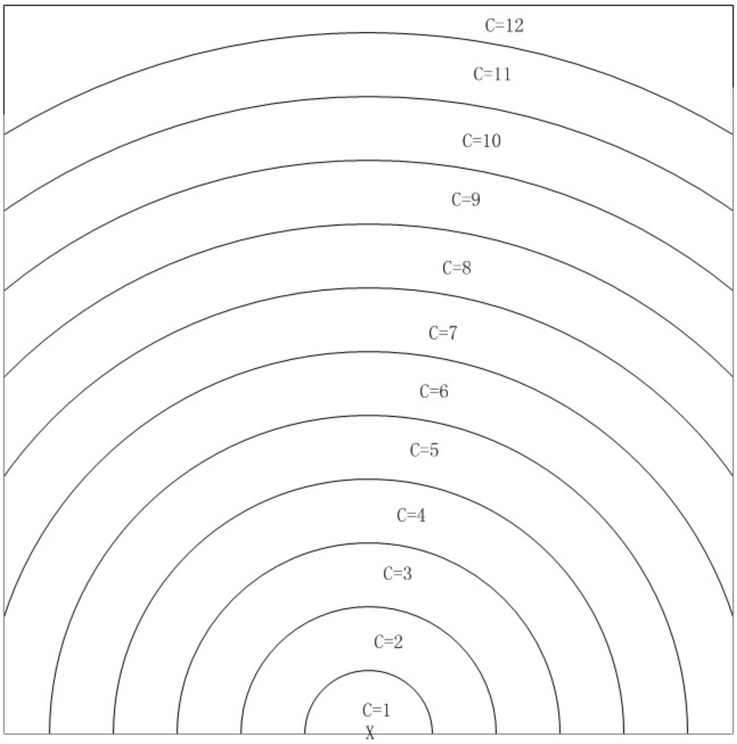

FIGURE 3. Partition of network monitoring area

different power level k. Neighbor node j which located at node i's k ring and C_j less than or equal to $C_i - k + 1$ is the potential next hop forwarding node when the node transmit power is k. The node records all potential next-hop node ID numbers corresponding to different transmit power levels and sends them to the base station.

Take the red node(C=10) in Fig.4 as an example. When $k = 3$, the shaded part of Fig.4 is the candidate area of proxy forwarding node.

Obviously, choosing the forwarding node from the first ring can ensure the minimum energy consumption, but it may increase the number of forwarding information to the base station, thus increasing the information delay, while other nodes will consume more energy. If the node chooses the forwarding node from the outer loop, it will reduce the delay, but it will consume more energy. The algorithm proposed in this paper balances the energy consumption of the network by choosing the ring number k of the information forwarding node reasonably, so that the network performance is optimal under the premise of sustainable operation.

3.2. **Data Forwarding Node Selection Stage.** After initialization, the base station will get the following information of all nodes: the distance from the base station $dtoBS$, the area code Ci of node i, the current residual energy Ei of each node. At the same time, the base station will store the candidate node ID corresponding to different k values of node i in $CPF[i, k_i]$.

The base station determines the k value for each node to select the next hop. Obviously, if the base station has the lowest cost to communicate directly with the base station in the candidate area. The value range of k with different C values is different, for example, the nodes of $C = 1$ can only take $k = 1$. In addition, a k value may correspond to multiple candidate nodes, at this time the node with high residual energy is preferentially selected; when there is no node in the candidate region, this value should be forbidden for this node. When the k value of all nodes is confirmed, the base station generates the

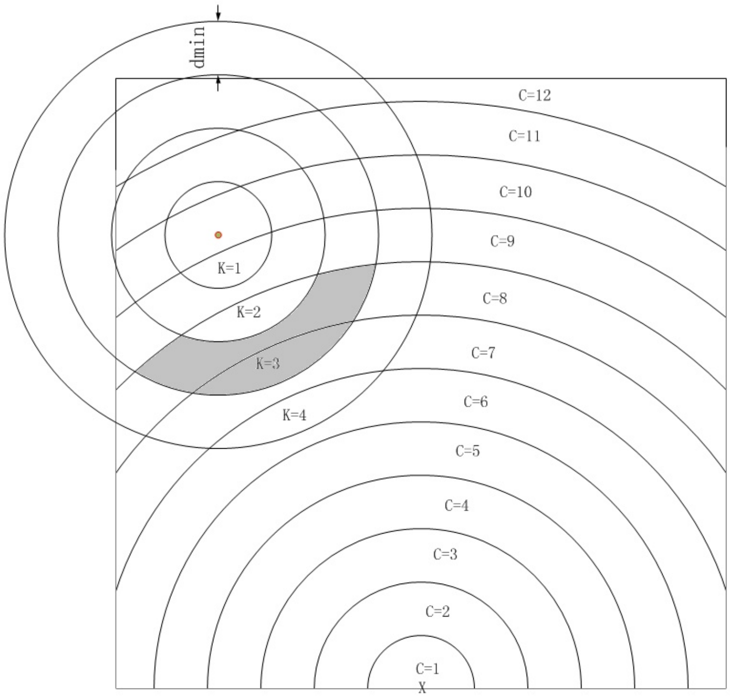

FIGURE 4. Schematic diagram of forwarding node selection

data transmission link and sends the link down to each node in the network. The base station counts the number of sub-nodes T_i for each node and the number of transfers of information from each node to the base station NF_i.

In order to make the network stable and durable, the energy consumption of the entire network should be as small as possible. In order to ensure real-time information, the network delay can not be too high. According to these two requirements, the objective function is as follows:

$$f1 = E_{total} = L\sum_{i=1}^{n}[E_{elec} + \epsilon(k_i \times d_{min})^v + T_i \times (E_{elec} + Eda)] \tag{5}$$

$$f2 = D = \frac{1}{n}\sum_{i=1}^{n}[(qd + td + pd) \times NF_i] \tag{6}$$

$$\begin{cases} \epsilon = \epsilon_{fs} & k_i \times d_{min} < d_0 \\ \epsilon = \epsilon_{mp} & k_i \times d_{min} \geq d_0 \\ v = 2 & k_i \times d_{min} < d_0 \\ v = 4 & k_i \times d_{min} \geq d_0 \end{cases} \tag{7}$$

The target $f1$ is the total energy consumption of the network, the target $f2$ is average delay. Eda is the processing(data aggregation) cost of a bit Determination of constraint conditions:

1. The range of the transmit power level of node i:

$$1 \leq k_i \leq k_{max}, k_i \in N \tag{8}$$

2. The transmit power level of node i is less than the area code C:

$$1 \leq k_i \leq C_i \tag{9}$$

3. When the transmit power of node i is k, the corresponding candidate node can not be empty:

$$CPF[i, k_i] \neq \emptyset \tag{10}$$

3.3. **Data Transmission Stage.** After each node selects the forwarding node, the base station broadcasts the path information and allocates the information transmission slot layer by layer. In the data transmission phase, the outer node sends the collected data to the relay node. The relay node fuses the collected data with the data to be forwarded, and then sends it to the next hop relay node until the information is sent to the base station. The base station redistributes the k value of each node according to the residual energy of each node every certain time, and then carries on the data transmission.

4. **Using MOPSO to solve k values of nodes.** PSO algorithm is a swarm intelligence evolutionary computation method proposed by KENNEDY in 1995. As an efficient parallel optimization algorithm, PSO algorithm can be used to solve a large number of nonlinear, non-differentiable and multi-peak complex optimization problems. Based on the improved multi-objective particle swarm optimization algorithm based on maximin fitness function[11], we restrict the evolution of particles in integer space by making the initial position and velocity of particles integer.

The algorithm flow is as follows:

1. Load the network initialization data and set the parameters of the multi-objective particle swarm optimization algorithm, in which the number of particles $PG = 100$, the learning factor $C1 = C2 = 0.5$, the inertia weight ω from 0.9 to 0.4, the dominant value $\epsilon = 0.01$, the maximum number of iterations is 1000, the external document size is 100.

2. Population initialization: the initial position of each particle is given randomly. For particles that do not meet the constraints, the initial velocity of each particle is 0.

3. According to formula (11) (12), we calculate the function values of two targets of each particle in the solution set.

$$f_1(x_i) = \frac{f_1(x_i) - min(f_1(x_i))}{max(f_1(x_i)) - min(f_1(x_i))} \tag{11}$$

$$f_2(x_i) = \frac{f_2(x_i) - min(f_2(x_i))}{max(f_2(x_i)) - min(f_2(x_i))} \tag{12}$$

According to Eq.(13), the fitness function of each particle is calculated, the particles with fitness less than zero are stored in the external document, and the fitness function of the particles in the external document is calculated again according to Eq.(13) to eliminate the bad solution.

$$f_{maximin}(x_i) = max_{j \neq i}\{min\{f_1(x_i) - \frac{f_1(x_j)}{1+\epsilon}, f_2(x_i) - \frac{f_2(x_j)}{1+\epsilon}\}\} \tag{13}$$

4. Iterative compute particles in dominant solution sets. Select the first 20% of the non-dominant particles from the external documents and select a particle as the global extreme PG by roulette method. If the particle is better than the current particle, then replace it.;

5. Update the velocity and position of each particle. For particles that do not satisfy the constraints, update the velocity and position again until the constraints are satisfied, and the updated particles are stored in the dominant set.

6. If the maximum number of iterations is reached or the external document is full, output the external document and terminate the program, otherwise go to step 3.

5. **Simulation and result analysis.** We use MATLAB as the simulation platform to carry out the experiment, the monitoring area is 800m*800m square, randomly distributed 100 nodes with the same initial energy, node distribution as shown in Fig.5. The base station is located at the middle point of the bottom edge and is represented by X. The simulation time is 3 days. The parameters are shown in Table 1.

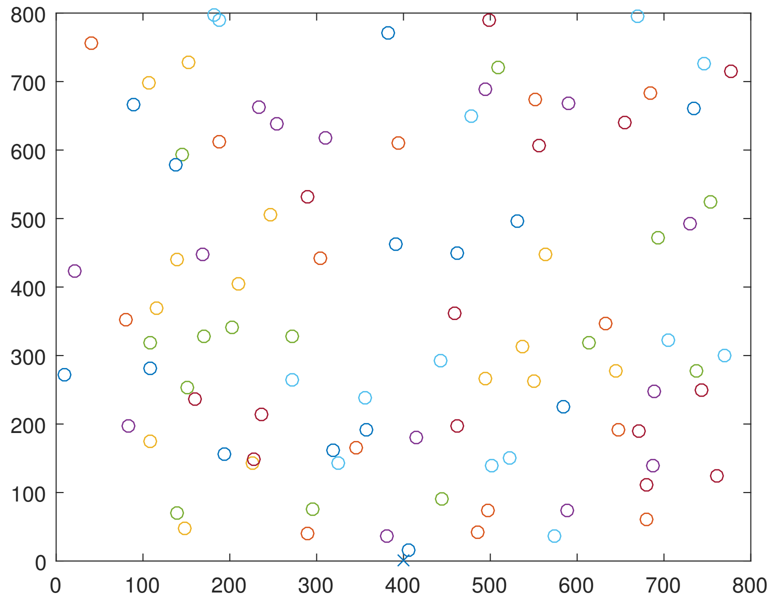

FIGURE 5. A wireless sensor network

TABLE 1. Simulation Parameters

parameters	value	parameterd	value
Eo	$0.4J$	ϵ_{mp}	$0.0013pJ/bit/m^4$
Em	$0.5J$	ϵ_{fs}	$10pJ/bit/m^2$
L	$100bit$	$qd + td + pd$	0.01
E_{elec}	$50nJ/bit$	E_{max}	$0.1J/h$
Eda	$5nJ/bit$	n	100

Fig.6 is the Pareto front obtained from 1000 iterations.

f1 denotes network energy consumption, f2 denotes the average delay of the network. The decision maker can choose the optimal solution according to the requirements of the usage scenario and the current state of the network.

We selected several sets of solutions from Pareto's frontier to simulate its performance. Firstly, without considering solar energy as energy supplement, the network lifetime is simulated in four modes (corresponding to G, E, C, A) with minimum delay, small delay, small energy consumption and minimum energy consumption, as shown in Fig.7. In the latter three working modes, the number of death nodes is significantly less than that of LEACH algorithm.

Then we simulate the average residual energy of the network working at A, B, D and F under the condition of solar cells as energy supplement. In the simulation, we assume that the sunrise time is 6 a.m. and the sunset time is 6 p.m. and the energy acquisition

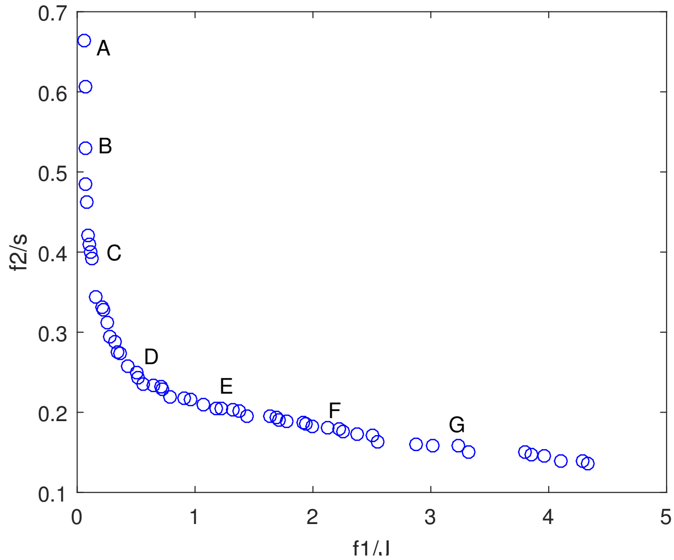

FIGURE 6. Pareto front

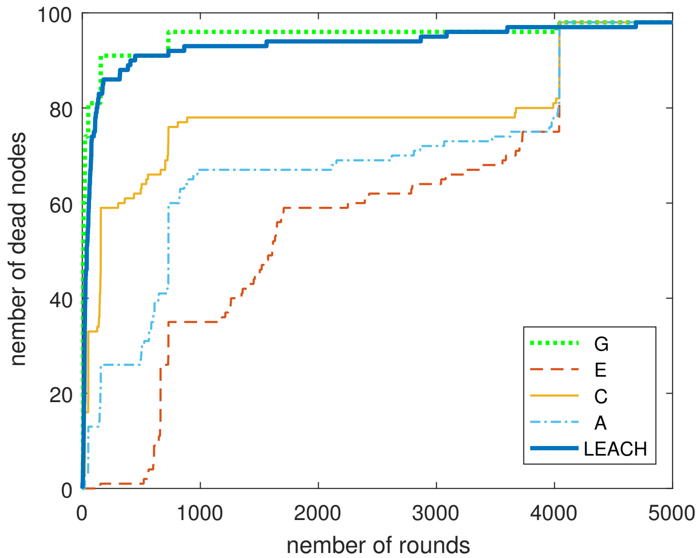

FIGURE 7. Comparison between LEACH and our solution

efficiency reaches the peak value of E_{max} from 10 o'clock to 14 o'clock. All nodes upload the monitoring data every three minutes, and the average residual power of the network nodes under different operating modes is compared as shown in Fig.8.

Combined with the characteristics of solar energy replenishment, in order to avoid the node power consumption, we make the node change its working mode according to the amount of its remaining power, so that the node can improve the network performance by increasing energy consumption and reducing the delay when there is more residual energy. When the remaining power of nodes is low, sacrificing delay performance to reduce energy consumption and avoid nodes entering sleep mode. In order to simulate the effects of bad weather conditions, we set the energy obtained on the second day to 80% of the first day, 60% on the third day, and 20% on the fourth day. The average residual energy and average delay of all nodes in the network changed with time is shown in Fig.9.

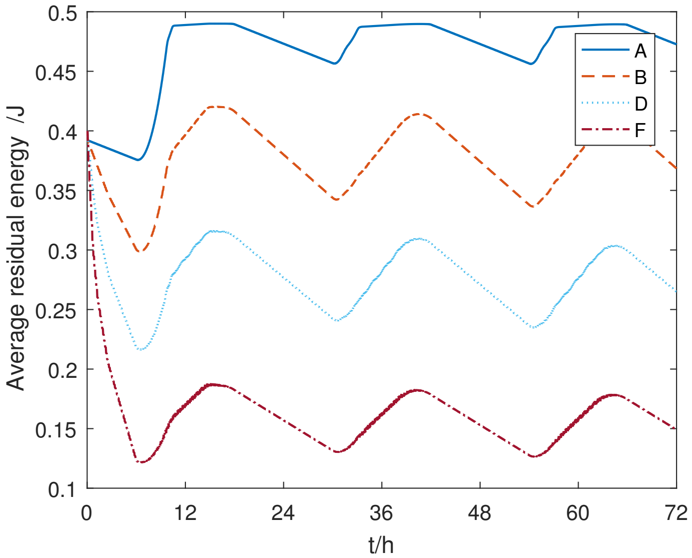

FIGURE 8. Comparison between A,B,D,F

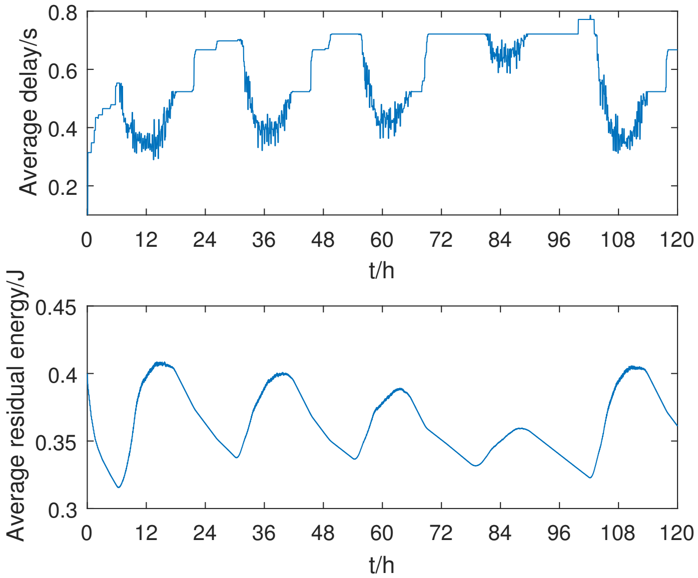

FIGURE 9. The average residual energy and average delay

As we can see from Fig.9, as the node energy drops, the rate of decline slows down and the network can operate in an energy-efficient manner. When the lighting is adequate, the network performance can also be improved. On the fourth day when the weather was not ideal, after a day of operation, the network's remaining energy before the next sunrise was not much different.

6. **Conclusions.** This paper presents a data forwarding routing algorithm for wireless sensor networks powered by solar cells and storage batteries, analyzes the characteristics of solar energy acquisition, and establishes a solar energy acquisition model. The multi-objective particle swarm optimization algorithm is applied to the optimization of energy consumption and delay in wireless sensor networks. By choosing the next hop forwarding node for each node, more satisfactory solutions are obtained at one time. By changing

the transmission power level according to the node power, the network performance can be improved and the network delay can be reduced when the energy is sufficient, and the energy overhead can be reduced when the energy is insufficient. MATLAB simulation results show that the proposed routing algorithm is suitable for solar-powered wireless sensor networks, can make full use of the energy obtained, and its performance is better than LEACH protocol.

Acknowledgment. This work is supported by the National Nature Science Foundation of China under Grant number 61633019, 61272020 and 61673268; Science Fund for Creative Research Groups of the National Natural Science Foundation of China under Grant Number 61621002; Zhejiang Provincial Natural Science Foundation of China under Grant number LZ15F030004 and LY16F010061; Research Programs of Educational Commission Foundation of Zhejiang Province of China under Grant number Y201636903; Shanghai Sailing Program under Grant number 17YF1413100 and 17YF1428300.

REFERENCES

[1] N. Sabor, M. Abo-Zahhad, S. Sasaki, S. M. Ahamed, *An unequal multi-hop balanced immune clustering protocol for wireless sensor networks*, Applied Soft Computing, vol. 43, pp. 372-389, 2016.

[2] S. Sudevalayam, and P. Kulkarni, *Energy harvesting sensor nodes: survey and implications*, IEEE Communications Surveys and Tutorials, vol.13, no.3, pp.443-461, 2008.

[3] Y. Gao, G. Sun, W. Li, Y. Pan, *Wireless sensor node design based on solar energy supply*, IEEE International Conference on Power Electronics and Intelligent Transportation System, pp.203-207, 2009.

[4] T. Voigt, A. Dunkels, J. Alonso, H. Ritter, and J. Schiller, *Solar-aware clustering in wireless sensor networks*, IEEE International Symposium on Computers and Communications, pp. 238-243, 2004.

[5] J. Islam, M. Islam, and N. Islam, *A-sLEACH: An advanced solar aware leach protocol for energy efficient routing in wireless sensor networks*, IEEE International Conference on Networking, pp.1-4, 2007.

[6] Y. J. Zhang, X. P. Fan, S. Q. Liu, Z. J. Chen, and Z. H. Qu, *Research of clustering routing of wireless sensor network based on solar power supplying situation*, Application Research of Computers, vol. 29, no. 1, pp. 260-262, 2012.

[7] Y. Cao, X. Y. Liu, L. Kong, M. Y. Wu, and M. K. Khan, *EHR: Routing protocol for energy harvesting wireless sensor networks*, IEEE International Conference on Parallel and Distributed Systems, pp. 56-63, 2007.

[8] H. J. Chen, J. H. Han, L. Liu, *Research on clustering ambient for energy harvesting routing algorithm in wireless sensor network*, Computer Engineering, vol. 42, no.3, pp.143-147, 2016.

[9] W. B. Heinzelman, A. P. Chandrakasan, and H. Balakrishnan, *An application specific protocol architecture for wireless microsensor networks*, IEEE Transactions on Wireless Communication, vol.1, no.4, pp.660-670, 2002.

[10] H. M. Ammari, *On the energy-delay trade-off in geographic forwarding in always-on wireless sensor networks: A multi-objective optimization problem*, Computer Networks, vol.57, no.9, pp.1913-1935, 2013.

[11] M. Xu, X. Shen, L. H. Ma, Y. J. Huang, J. Hu, J. P. Gu, H. Q. Jin, and J. X. Qian, *Research on modified multi-objective particle swarm optimization*, Control and Decision, vol. 24, no.11, pp.1713-1634, 2009.

[12] J. S. Pan, L. Kong, T. W. Sung, P. W. Tsai, and W. Snasel, *α-fraction first strategy for hierarchical wireless sensor networks, Journal of Internet Technology*, vol. 19, no. 6, pp. 1717-1726, 2018.

[13] J. S. Pan, L. Kong, T. W. Sung, P. W. Tsai, and V. Snášel, *A clustering scheme for wireless sensor networks based on genetic algorithm and dominating set*, Journal of Internet Technology, vol. 19, no. 4 , pp. 1111-1118, 2018.

[14] J. S. Pan, Z. Meng, S. C. Chu, and H. Xu, *Monkey king evolution: an enhanced ebb-tide-fish algorithm for global optimization and its application in vehicle navigation under wireless sensor network environment*, Telecommunication Systems, vol. 65, no. 3, pp. 351-364, 2017.

[15] Z. Meng, J. S. Pan, and L. Kong, *Parameters with adaptive learning mechanism (PALM) for the enhancement of differential evolution, Knowledge Based Systems*, vol. 141, pp. 92-112, 2018.