



Contents lists available at ScienceDirect

Journal of Network and Computer Applications

journal homepage: www.elsevier.com/locate/jnca

The path planning scheme for joint charging and data collection in WRSNs: A multi-objective optimization method



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ARTICLE INFO

Keywords:

Wireless rechargeable sensor network
Joint energy replenishment and data collection
Path planning
Multi-objective optimization

ABSTRACT

Considering the limited energy of the mobile wireless charging equipment (WCE) in wireless rechargeable sensor networks (WRSNs), strategies for energy replenishment and data collection are proposed. A novel path planning model for the mobile WCE based on multi-objective optimization is constructed to both replenish energy and collect data, as well as to maximize the total energy utility of the mobile WCE and minimize the average delay of data transmission. An algorithm of multi-objective ant colony optimization (ES-MOAC) based on the elitist strategy is proposed to determine the Pareto set, so that the state transition strategy and the pheromone updating strategy improve. How the parameter settings of the ant colony algorithm affect the proposed algorithm is analyzed. The results of 50 groups of numerical simulation experiments show that the average of the Pareto set of the ES-MOAC algorithm is 27.8% higher than that of the NSGA-II algorithm.

1. Introduction

The data collection is one of the most important tasks in Wireless Sensor Networks (WSNs) and the related research on energy problem is a hot topic. Sensor nodes in the traditional WSNs transmit data through a multi-hop, which often leads to energy shortage (Lian et al., 2006; Olariu and Stojmenovic, 2006). The longer the distance between the sensor nodes and the fixed base station is, the more tasks for relaying data and the higher communication load for the sensor nodes are. Thus, some sensor nodes will die early because of energy shortage. To solve this problem, there are three methods. The first attempt is to reduce consumption. A mobile sink is introduced into the network to collect data and reduce energy consumption. A second method is to increase income. Mobile charging equipment is used to replenish energy for sensor nodes. The third is a combination of two previous ideas. Wireless Charging Equipment (WCE) is not only used to replenish energy for the sensor nodes but also collects data for them. Mobile WCE performs (Hu et al., 2016) for sensor nodes in two ways, simultaneously charging the simple sensor node (Xu et al., 2014) and the multiple sensor nodes (Fu et al., 2013). In addition, there are many researches on WCE, such as

the mobility of WCE (Chen et al., 2018) and different types of WCE based on the underlying terrain (Pang et al., 2014), etc.

To reduce energy consumption, the mobile sink in a WSN traveling throughout the whole network, both collects data from the nearby sensor nodes and reduces the communication load of the sensor nodes. Therefore, the lifespan of the network is prolonged. In (Guo et al., 1953), a data collection strategy based on a mobile sink in WSNs was proposed to calculate the shortest Hamilton Circuit consisting of all the collection points traversed by the mobile sink through the Quantum Genetic Algorithm (QGA). As a result, the load of sensor nodes balanced and the lifespan of the network increased. The same method was applied to (Lu and Wang, 2014). A mobile sink moves around the whole network to collect data for a limited time. Chang et al. (Chang and Shen, 2016) proposed a strategy of energy conservation based on the tree to reduce energy consumption, in which a mobile sink was used to collect data to balance the network load. Considering the large-scale WSNs in the wild, Iwata et al. (2017) proposed a data collection strategy for the mobile sink to reduce energy consumption of the sensor nodes near to the fixed sink to avoid energy shortage.

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<https://doi.org/10.1016/j.jnca.2020.102565>

Received 5 August 2019; Received in revised form 13 January 2020; Accepted 5 February 2020

Available online 8 February 2020

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To increase income, the wireless charging technology (Xie et al., 2013) is applied to WSNs, in which the wireless charging equipment (WCE) travels around the whole network to replenish energy for sensor nodes. Such a network is Wireless Rechargeable Sensor Network (WRSN) (Yang and Wang, 2015). Shi et al. (2012) assumed that the mobile WCE carried infinite energy and demonstrated that the charging along the Hamilton Circuit perpetually prolonged the lifespan of the whole network. In (He et al., 2013, 2015), the mobile WCE provides energy by demand according to the queuing theory. Xu et al. (2017) proposed a charging strategy based on balancing the remaining lifespan of sensor nodes in the network, which targets to minimize the total energy consumption of the mobile WCE and prolong the lifespan of the whole network through the study on the charging path of the mobile WCE and the charging time for sensor nodes. Based on (Xu et al., 2017), a periodic charging strategy of the mobile WCE with the limited energy was proposed in (Chen et al., 2017), which tended to maximize the charging cycle and minimize the total energy consumption of the mobile WCE as well. The optimization problem is solved by the chaotic particle swarm algorithm.

Few researchers try both to reduce consumption and increase income. Xie et al. (2015) proposed a joint framework of mobile charging and data collecting, which studies the traveling path of the mobile WCE for charging and data collecting to improve the network performance if the lifespan of the network remained unaffected. Wang et al. (2016) proposed a dispatching strategy for the mobile WCE and data collection equipment to balance energy consumption and reduce data transmission delay. Additionally, Guo et al. (2013) regarded the WCE as a mobile sink. The mobile WCE travels throughout the whole network to charge and collect data and then returns to the base station to upload the data collected from sensor nodes. To solve this problem, a distributed strategy was proposed to optimize the network performance. In (Zhao et al., 2014), Zhao et al. also assumed that the WCE was equipped with data collection module to avoid imbalanced energy distribution brought by the fixed base station. Single optimization objective has been studied in the literature above-mentioned: some researches on how to improve the performance of data transmission in the permanent working network being secured; others focus on how to prolong the lifespan of the network with the secured performance of data transmission.

Based on the previous studies, this paper examines the path planning of mobile WCEs with the strategy of joint mobile charging and data collection strategy based on the multiple objectives to figure out the traveling path and the charging time for each sensor node. With limited traveling energy, the mobile WCE charges sensor nodes and collects data. Thus, the traveling path of the mobile WCE has an effect on not only the network lifespan but also on the performance of the data transmission. To solve this problem, a multi-objective optimization model is established to maximize the total energy efficiency of the mobile WCE and minimize the average delay of data transmission of sensor nodes, which prolongs the network lifespan and improve the performance of data transmission. A multi-objective ant colony optimization algorithm (ES-MOAC) based on the elitist strategy is also proposed to obtain the Pareto set. Two main contributions of this paper are:

- 1) To the best of our knowledge, this is the first attempt to establish a multi-objective optimization model on the basis of a multi-objective optimization model on the basis of strategies for both mobile charging and data collection. There are two optimization objectives: to maximize the total energy utility of the mobile WCE and to minimize the average delay of data transmission. The influence of the traveling path of the mobile WCE and charging time for each sensor node on the optimization objectives greatly are studied.
- 2) An algorithm for multi-objective ant colony optimization algorithm (ES-MOAC) based on the elitist strategy is proposed. The state transition strategy and the pheromone updating strategy are modified as the algorithm for ant colony optimization (ACO) performs.

The rest of this paper is organized as follows. Section 2 discusses the related work. Section 3 describes the structure of WRSNs and problem statement. Section 4 demonstrates the multi-objective optimization model and two objective functions. Section 5 proposes the ES-MOAC with the modified state transition strategy and pheromone updating strategy. Section 6 describes the simulation experiments and results, showing the advantages of the proposed algorithm. Section 7 presents the conclusion.

2. Related work

The relevant literature in path planning explains two categories of schemes: separate charging scheme; combinative charging and data collection scheme. Swarm intelligence algorithms for path planning is elaborated.

Separate charging scheme. With the development of wireless rechargeable sensor network technology, the charging scheme has the hot issue in this research field (Hu et al., 2016). The design of a charging scheme depends on WCE properties including the number, the charging range, the charging capacity constraints of and, etc. According to the size of networks, there are charging schemes based on single-WCE (Peng et al., 2010; Fu et al., 2016a; Wang et al., 2017); according to the number of WCE, there are charging schemes based on multi-WCE (Peng et al., 2012; Zhang et al., 2015). This paper examines a single-WCE charging scheme working for a small-scale network. According to charging range of WCE, there are two categories of charging technology, namely one to one charging technology (Ren et al., 2014; Dai et al., 2013) and one to many charging technology (Fu et al., 2013, 2016b; Tong et al., 2010). Due to the limited charging range of WCE and the sparse distribution of sensor nodes in our network, this paper claims one to one charging technology for WCE. In addition, according to the charging capacity constraints of WCE, there are schemes of charging as a whole (Shi et al., 2012, 2014) and schemes of charging on demand (He et al., 2013; Xu et al., 2017; Fu et al., 2016c). On the basis of (Xu et al., 2017), the charging strategy for balancing lifespan to prolong the network lifespan is optimized.

Combinative charging and data collection scheme. WCE path planning for combinative charging and data collection scheme has become increasingly important to wireless rechargeable sensor networks. WCE is not only responsible for charging sensor nodes, but also for collecting data generated by sensor nodes. Liu et al. (2019) proposed a novel dynamic clustering based mobile-to-cluster (M2C) scheme. Given the random traveling path of WCE, then the energy consumption of being a cluster head is estimated. The sensor nodes with residual energy close to the estimation are actively elected as head nodes. Most visited head nodes are those of residual energy, reducing the travel distance and increasing energy efficiency of charging. An energy replenishment and data collection algorithm for WRSNs was proposed in (Han et al., 2018). The network is divided into multiple clusters based on the K-means algorithm. The proposed algorithm effectively replenish energy for the network. Hu et al. (Hu and Wang, 2016) examined the mobile charger that did not maintain full operation of the WRSN and proposed the balance flow scheme to maximize the utility of data collection. Most research concerns charging demand of sensor nodes, which fulfills a single focused objective. For instance, energy constraints carried by the WCE and the distance between the nodes and the WCE determine the traveling path of the WCE. The charging strategy and data collection strategy of WCE are designed according to the constraints such as the traveling path, the data flow among the sensor nodes, to maximize the network energy (Xie et al., 2015; Wang et al., 2016; Guo et al., 2013; Zhao et al., 2014; Liu et al., 2019; Han et al., 2018; Hu and Wang, 2016). In contrast, this paper discusses both charging and data collection for path planning of WCE. The detailed explanation is available in the following sections.

Swarm intelligence algorithms. According to (Xu et al., 2017), WCE path planning is a combinatorial optimization problem, which is part

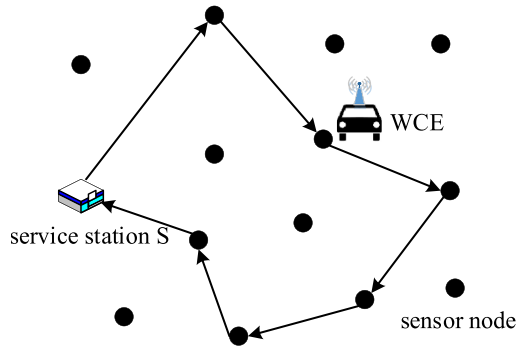


Fig. 1. Diagram of a WRSN with a mobile WCE and a service station.

of NP-hard. Swarm intelligent algorithms are available for natural combinatorial optimization. Lyu et al. (2019) proposed a hybrid particle swarm optimization genetic algorithm for the periodic charging planning. Xu et al. (2017) proposed a max-min ant algorithm for the WCE path planning. Ant colony algorithm is a meta-heuristic optimization algorithm simulating the foraging behaviors of ants in nature to find the optimal path. Compared with particle swarm optimization and genetic algorithm, it is more effective in the path planning. This paper presents a novel ant colony optimization algorithm for both charging and data collection. Integrated with a strategy for leveraging elite ants, the transition probability and pheromone updates are refined. Simulation experiments are conducted to compare the proposed algorithm with the classical swarm intelligence algorithm called NSGA-II (Deb et al., 2002).

3. Network structure and problem statement

3.1. The structure of a WRSN

N sensor nodes, denoted as $SN = \{s_1, \dots, s_i, \dots, s_N\}, i \in \{1, 2, \dots, N\}$, are deployed over a 2-D monitored area in a WRSN. The positions of nodes are fixed. In addition, a mobile WCE with data collection module and a fixed service station are deployed in the WRSN shown in Fig. 1. It is assumed that there is no fixed base station in the network. Instead, the mobile WCE is served as a mobile base station to collect data. All the sensor nodes are powered by wireless rechargeable batteries which share the same capacity. The capacity of each battery is denoted as E_{max} . To keep sensor nodes working properly, the minimum energy level of each battery is denoted as E_{min} . In the beginning, the energy level of the battery is E_{max} . The energy carried by the mobile WCE is limited and is divided into two parts: the limited traveling energy and the charging energy. The initial traveling energy and the initial charging energy is denoted as E_{max}^{tra} and E_{max}^{ch} , respectively. The mobile WCE sets off from service station S , travels through the network to replenish energy for sensor nodes, collects data simultaneously and then returns to service station S to replenish energy for itself when its traveling energy or charging energy is insufficient. The mobile WCE stays at service station S for maintenance when it completes all the tasks.

3.2. Problem statement

All the sensor nodes are homogeneous in the WRSNs, but the consumption power of each sensor node is different due to the rate of data generated by each sensor node itself and the amount of data forwarded by each sensor node. Therefore, different sensor nodes typically have different demands for energy. When the WCE reaches a sensor node, it charges and collects data for only one sensor node at a time. The charging time of sensor node s_i is τ_i^{ch} and the time to collect data is τ_i^{cd} . The charging efficiency of the WCE is much lower than that of

the data collection efficiency. The order of magnitude is not twice, and the charging time τ_i^{ch} is much longer than the data collection time τ_i^{cd} , namely $\tau_i^{ch} \gg \tau_i^{cd}$. Relative to the charging time of each sensor node, the data collection time is negligible. Therefore, the stay time of the WCE at each sensor node depends on the charging time. The sequence of the WCE accessing different sensor nodes affects the delay of data transmission in the WRSNs.

This paper assumes that the initial traveling energy and the charging energy carried by the mobile WCE are limited and separated. Therefore, the following three points should be taken into account.

- 1) Because of the limited traveling energy and the sparse distribution of the sensor nodes in the WRSN, the mobile WCE may not have enough energy to visit all the sensor nodes in one cycle.
- 2) Because of the limited charging energy, the mobile WCE only tries its best to replenish energy for the sensor nodes to prolong the lifespan of the network and improve the energy efficiency. In other words, the mobile WCE may not keep the network working perpetually.
- 3) In this study, the mobile WCE not only charges sensor nodes but also collects data generated by the nodes. Therefore, the path planning for the mobile WCE with mobile charging and data collecting strategy demonstrates the traveling path and the charging time of each node. Two optimization objectives, to maximize the total energy efficiency of the mobile WCE and to minimize the average delay of data transmission among sensor nodes, are established to prolong the network lifespan and improve data transmission on the basis of balancing the rest lifespan of the sensor nodes. In addition, to describe the problem clearly, two definitions are introduced before establishing and analyzing the multi-objective optimization.

Definition 1. Working Round

The mobile WCE sets off from service station S , travels to several sensor nodes only once to charge and collect data, and returns to service station S to replenish energy for itself due to the limited traveling energy and the limited charging energy. This process is defined as a working round, which is denoted as τ_r^c ($r = \{1, 2, \dots, R\}$).

Definition 2. Working Cycle

As shown in Fig. 2, the mobile WCE starts from the service station S , conducts several working rounds, and returns to service station S , which is defined as a working cycle that is denoted as T ($T \in \{T_1, T_2, \dots, T_Z\}$). In a working cycle, each sensor node is visited by the mobile WCE only once. Because the WCE cannot ensure if the network is perpetually working. Z is an uncertain positive integer.

The energy replenishment time for the mobile WCE in service station S can be neglected because the energy replenishment is realized by replacing batteries quickly between two working rounds. As a result, the duration of a working cycle only includes several working rounds.

The mobile WCE returns to service station S to have a break after a working cycle, which is defined as the docking time. The docking time

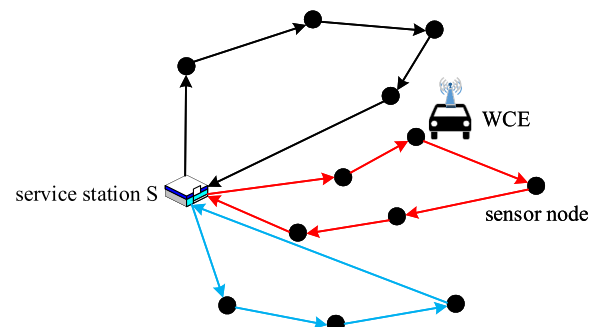


Fig. 2. Diagram of the traveling path of the mobile WCE during a working cycle.

is denoted as τ_{vac} . The docking time for the mobile WCE is relatively longer than a working cycle and different working cycles share the same docking time.

4. Model construction

4.1. Data flow and energy consumption power

In this paper, the energy model in (Shi et al., 2012) is adopted. It is assumed that sensor node s_i ($i \in 1, 2, \dots, N$) generates data at a constant rate of R_i (bit/s). g_{ij} (bit/s) is the rate of data transmission between sensor node s_i and s_j . g_{iW} (bit/s) is the rate of data transmission between sensor node s_i and the mobile WCE. From the view of the data flow, sensor node s_i must satisfy the following equation.

$$\sum_{a \in N}^{a \neq i} g_{ai} + R_i = \sum_{j \in N}^{j \neq i} g_{ij} + g_{iW} \quad (1)$$

During the working cycle, the energy consumption power of sensor node s_i is $p_i(W)$ and the receiving data energy consumption rate of each sensor node is θ (J/bit). The transmitting data energy consumption rate between sensor node s_i and s_j is denoted as θ_{ij} (J/bit) and the transmitting data energy consumption rate between sensor node s_i and the mobile WCE is denoted as θ_{iW} (J/bit). Besides, $\theta_{ij} = \eta_1 + \eta_2 D_{ij}^4$, of which D_{ij} is the Euclid distance between sensor node s_i and s_j , η_1 is the constant unrelated to D_{ij} and η_2 is the constant related to D_{ij} . At any time, the power of sensor node s_i satisfies Equation (2).

$$p_i = \theta \sum_{a \in N}^{a \neq i} g_{ai} + \sum_{j \in N}^{j \neq i} \theta_{ij} g_{ij} + \theta_{iW} g_{iW} \quad (2)$$

in which $\theta \sum_{a \in N}^{a \neq i} g_{ai}$ is the energy consumption power of sensor node s_i generated by receiving data from other sensor nodes, $\sum_{j \in N}^{j \neq i} \theta_{ij} g_{ij}$ is the energy consumption power of sensor node s_i which is generated by transmitting data to other sensor nodes, and $\theta_{iW} g_{iW}$ is the energy consumption power of sensor node s_i which is generated by transmitting data to the mobile WCE.

It is assumed that the data transmission is completed instantly, so the transmission time is neglected. In this paper, the static routing protocol is adopted, so the energy consumption power of a sensor node s_i is a constant.

4.2. The traveling path and time of the mobile WCE

The mobile WCE sets off from service station S , replenishes energy for sensor nodes and collects data, and then returns to service station S to be maintained. After R ($R \in \mathbb{Z}$) working rounds, all the sensor nodes in the network have been replenished with energy and the data have been collected only once. The traveling path of the mobile WCE in a working cycle T is Q . According to Definition 1, traveling path Q_r in a working round is

$$Q_r = (\pi_0, \pi_1, \dots, \pi_m, \pi_0) \quad (3)$$

where π_0 is service station S and π_i ($1 \leq i \leq m$) is the i th sensor node in the traveling path. The traveling distance of the mobile WCE in a working round satisfies

$$D_Q^r = \sum_{i=0}^{m-1} d_{\pi_i, \pi_{i+1}} + d_{\pi_m, \pi_0} \quad (4)$$

where d_{π_i, π_j} (m) is the distance between the neighbor sensor nodes or between the sensor node and service station S . A working cycle consists of R working rounds, so the traveling distance D_Q in a working cycle satisfies Equation (5).

$$D_Q = \sum_{r=1}^R D_Q^r \quad (5)$$

The mobile WCE starts from service station S and then moves in the traveling path Q at the speed v (m) with traveling energy consumption power $p_{tra}(W)$. The charging time for sensor node s_i is denoted as τ_i (s). It is assumed that the data transmission from sensor node s_i to the mobile WCE is completed instantly, so the transmission time is neglected. That is to say, the charging time equals to the duration when the mobile WCE stays at sensor node s_i . Thus, the duration of a working round denoted as τ_r^c , satisfies Equation (6).

$$\begin{aligned} \tau_r^c &= \sum_{i=0}^{m-1} \tau_{\pi_i, \pi_{i+1}} + \tau_{\pi_m, \pi_0} + \sum_{i=1}^m \tau_i \\ &= \sum_{i=0}^{m-1} \frac{d_{\pi_i, \pi_{i+1}}}{v} + \frac{d_{\pi_m, \pi_0}}{v} + \sum_{i=1}^m \tau_i \\ &= \frac{D_Q^r}{v} + \sum_{i=1}^m \tau_i \end{aligned} \quad (6)$$

τ_{π_i, π_j} (s) is the traveling time of the mobile WCE traveling between two neighboring sensor nodes or between a sensor node and service station S . According to Definition 2, a working cycle that is denoted as T , satisfies Equation (7).

$$T = \sum_{r=1}^R \tau_r^c \quad (7)$$

In addition, a working cycle T also equals the sum of the total traveling time of the mobile WCE and the total charging time. Specifically, the total traveling time is D_Q/v in a working cycle and the charging time for all the sensor nodes is $\sum_{i=1}^N \tau_i$. Therefore, T also satisfies Equation (8).

$$T = \frac{D_Q}{v} + \sum_{i=1}^N \tau_i \quad (8)$$

4.3. The charging strategy for the mobile WCE

In order to prolong the lifespan of the network, a charging strategy based on the energy balancing is proposed. Specifically, the mobile WCE chooses the suitable sensor node to charge to balance the rest lifespan of all the sensor nodes to minimize the variance. The rest energy of sensor node s_i at any time t is denoted as $e_i(t)$ (J) which satisfies Equation (9).

$$E_{min} < e_i(t) < E_{max} \quad (9)$$

Therefore, the rest lifespan of sensor node s_i at time t is denoted as $T_{life}^i(t)$, which satisfies Equation (10).

$$T_{life}^i(t) = \frac{e_i(t) - E_{min}}{p_i} \quad (10)$$

It is assumed that the mobile WCE arrives at sensor node s_i at time t , and the charging power is denoted as U (W) and the charging time is denoted as τ_i . After sensor node s_i is charged, its rest lifespan should be denoted as $T_{life}^i(t_i + \tau_i)$ as its rest lifespan, which satisfies Equation (11).

$$\begin{aligned} T_{life}^i(t_i + \tau_i) &= \frac{e_i(t_i + \tau_i) - E_{min}}{p_i} \\ &= \frac{U \tau_i + e_i(t_i) - p_i \tau_i - E_{min}}{p_i} \end{aligned} \quad (11)$$

According to (10) and (11), the average rest lifespan of all the sensor nodes in WRSNs can be calculated according to Equation (12).

$$\overline{T_{life}^N(t_i + \tau_i)} = \left[T_{life}^i(t_i + \tau_i) + \sum_{j \in N}^{j \neq i} T_{life}^j(t_i + \tau_i) \right] / N \quad (12)$$

Moreover, the variance of rest lifespan of all the sensor nodes $S_{life}^2(t_i + \tau_i)$ is shown as follows.

$$S_{life}^2(t_i + \tau_i) = \frac{1}{N} \left\{ \left[\tau_{life}^i(t_i + \tau_i) - \overline{\tau_{life}^N(t_i + \tau_i)} \right]^2 + \sum_{j \neq i} \left[\tau_{life}^j(t_i + \tau_i) - \overline{\tau_{life}^N(t_i + \tau_i)} \right]^2 \right\} \quad (13)$$

However, the variance only reflects the fluctuation of the rest lifespan of all the sensor nodes and fails to indicate their average rest lifespan. Though the variance is low, the average rest lifespan of all the sensor nodes may decrease continuously, which is dangerous to the whole network. Therefore, the rest lifespan of all the sensor nodes before and after replenishment for the sensor nodes by the mobile WCE should satisfy Equation (14).

$$\overline{T_{life}^N(t_i + \tau_i)} - \overline{T_{life}^N(t)} \geq 0 \quad (14)$$

According to (13), the variance $S_{life}^2(t_i + \tau_i)$ is a quadratic function, including only one independent variable τ_i . The charging time τ_i can be calculated by minimizing the variance. The introduction of constraint (14) adjusts the rest lifespan of the network to avoid the decrease of the total energy described above. However, if τ_i is unsolved by minimizing the variance, the sensor node is charged to E_{max} and the charging time of the WCE at sensor node s_i satisfies $\tau_i = (E_{max} - e_i(t_i)) / (U - p_i)$. When the mobile WCE sets off from service station S , its initial traveling energy and initial charging energy are denoted as E_{max}^{tra} and E_{max}^{ch} , respectively. It tends to realize the balanced rest lifespan of all the sensor nodes to prolong the lifespan of the whole network, maximizing the energy efficiency of the mobile. Total energy efficiency Φ is defined as the ratio of the energy consumption in a working cycle and total energy. Additionally, the energy consumption in a working round denoted as $E_{consume}^r$, consists of two parts—the traveling energy $p_{tra} \cdot (\sum_{i=0}^{m-1} \tau_{\pi_i, \pi_{i+1}} + \tau_{\pi_m, \pi_0})$ and the charging energy $U \cdot \sum_{i=0}^m \tau_i$. Thus, $E_{consume}^r$ in a working round satisfies the following energy constraint.

$$E_{consume}^r = p_{tra} \cdot \left(\sum_{i=0}^{m-1} \tau_{\pi_i, \pi_{i+1}} + \tau_{\pi_m, \pi_0} \right) + U \cdot \sum_{i=0}^m \tau_i \quad (15)$$

Moreover, total energy efficiency Φ of the mobile WCE is shown in Equation (16).

$$\Phi = \frac{\sum_{r=1}^R E_{consume}^r}{R (E_{max}^{tra} + E_{max}^{ch})} \quad (16)$$

During a working cycle, one of the optimization objectives is to maximize total energy efficiency Φ of the mobile WCE, denoted as $\min \frac{1}{\Phi}$, which is greatly related to the traveling path and the charging time of the mobile WCE in every working round.

4.4. The data collecting strategy of the mobile WCE

The mobile WCE not only charges sensor nodes but also collects data generated by sensor nodes when visiting all the sensor nodes in networks. Therefore, the reduction in the delay of the data transmission among sensor nodes should be considered to improve data transmission.

Because the docking time for the mobile WCE at a service station is relatively long, it is possible for the mobile WCE to receive requests to upload data from all the sensor nodes. The request sequence of all the sensor node is denoted as $\{t_q^1, t_q^2, \dots, t_q^i, \dots, t_q^N\}$, of which t_q^i is the request time of sensor node s_i . This paper assumes that the data transmission delay is allowed in the network, so the mobile WCE is used to travel throughout the network to collect data. Using the single-hop, data transmission from sensor node s_i to the mobile WCE is assumed to be completed instantly, so the transmission time is neglected when the

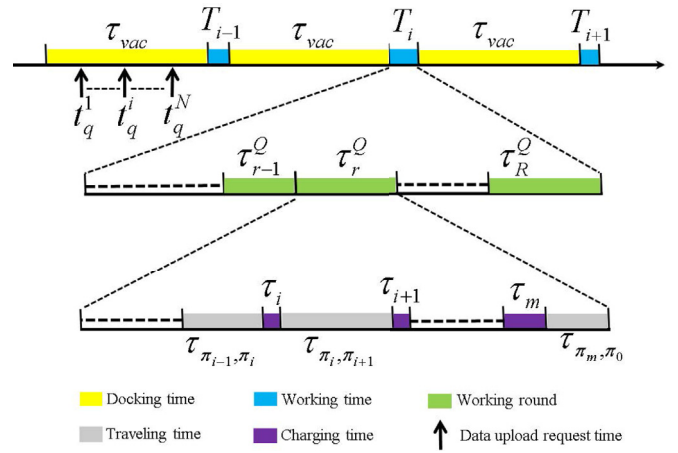


Fig. 3. Time axis of the working flow for the mobile WCE.

mobile WCE arrives at sensor node s_i at time t_i , denoted as Equation (17).

$$\Delta \tau_i = t_i - t_q^i \quad (17)$$

$\Delta \tau_i$ is the delay of data transmission that equals to the duration between the request time from sensor node s_i and the time when the mobile WCE receives data from sensor node s_i . $\Delta \tau_i$ is related to the traveling path of the mobile WCE before its arrival at sensor node s_i and the charging time for the previous sensor nodes.

$$\overline{\Delta \tau} = \frac{1}{N} \sum_{i=1}^N (t_i - t_q^i) \quad (18)$$

According to (18), the average delay of the data transmission among all the sensor nodes is denoted as $\Delta \tau$, which is related to the traveling path of the mobile WCE and the charging time for sensor nodes in a working round.

4.5. Multi-objective optimization model

According to the above description, the time axis of the whole working flow for the mobile WCE is shown in Fig. 3.

The mobile WCE not only charges sensor nodes but also collects data. Therefore, the traveling path of the mobile WCE and the charging time of the sensor nodes affects not only the rest lifespan of the sensor nodes but also data transmission. In the view of energy, it is necessary to maintain a balance of the rest lifespan of the sensor nodes, and then to prolong the lifespan of the network by maximizing the total energy efficiency of the mobile WCE. On the other hand, reducing the average delay, data transmission better performs. Multi-objective optimization is demonstrated by the traveling path and the charging time to secure the maximum energy efficiency and the minimum average transmission delay, which is shown as follows.

$$Obj : \arg \min_{Q, \tau_i} F = \left\{ \frac{1}{\Phi}, \overline{\Delta \tau} \right\}$$

$$s.t. : (4), (6), (8) \sim (10), (13) \sim (16), (18)$$

4.6. Problem hardness

To prove the NP-completeness of the multi-objective optimization of path planning, this paper discusses the traveling salesman problem(TSP). The decision version of the path planning and the TSP is stated as follows.

The decision Version of the multi-objective optimization problem of path planning is that given a set of sensor nodes SN deployed in a 2-D

plane, each node $s_i \in SN(i \in 1, 2, \dots, N)$ is of battery capacity E_{\max} . The consumed power of each node s_i is P_i , and the constant energy consumption rate of each node s_i is R_i . The WCE traverses each node once from the service station S in multiple work rounds in a working cycle. Is there a path to keep all the sensor nodes alive in a working cycle, which keeps the total energy utilization of the WCE high and the average delay of data transmission small?

Theorem. The Decision Version of the multi-objective optimization problem of Path Planning is NP-Complete.

Proof. Given a path $Q = \{S, \pi_1, \dots, \pi_i, S, \dots, \pi_N, S\}$, the working cycle is of R working rounds. The stay time of the WCE at each sensor node s_i is τ_i . The stay time of the WCE at service station S is zero. Therefore, the moment t_i when the WCE arrives at sensor node s_i is calculated. So is the energy consumption of each node and the energy to be charged in a working cycle. After the energy of each node cancels out, the remaining energy is not lower than E_{\min} . $O(N + R)$ is the time complexity to verify whether the path planning route meets the conditions, therefore, the multi-objective optimization problem of path planning is an NP problem.

Reduction from the TSP in polynomial time is conducted. Any instance of the TSP is denoted as $(G' = (V', E'), D)$; any instance of the multi-objective optimization problem of path planning is denoted as $(G = (V, E), S, R, \tau(\cdot), U, p_{tra}, v, E_{\max}^{tra}, E_{\max}^{ch}, t_i^q)$ $\tau(\cdot)$ is a group of the stay time when the WCE arrives at each sensor node and service station S . The instance of the multi-objective optimization of path planning from the instance of the TSP is constructed. $G = G', R = 1, V = V' \cup S, \tau(\cdot) = 1, U = 1, p_{tra} = 1, v = 1, E_{\max}^{tra} = 1, E_{\max}^{ch} = 1, \text{ and } t_i^q = 0$. If $Q' = (S, \pi'_1, \dots, \pi'_i, \dots, \pi'_N, S)$ is a tour of TSP, which covers all the nodes in V' and has a maximum length D . A path of the WCE is $Q = (S, \pi_1, \dots, \pi_i, \dots, \pi_N, S) = (S, \pi'_1, \dots, \pi'_i, \dots, \pi'_N, S) = Q'$. The following equations demonstrate the above description.

$$D = \sum_{i=1}^{N-1} \left(\frac{d_{\pi'_i, \pi'_{i+1}}}{v} \right) + \frac{d_{S, \pi'_1}}{v} + \frac{d_{\pi'_N, S}}{v}$$

$$D_Q = \sum_{i=1}^{N-1} \left(\frac{d_{\pi_i, \pi_{i+1}}}{v} \right) + \frac{d_{S, \pi_1}}{v} + \frac{d_{\pi_N, S}}{v}$$

$$E_{\text{consume}}^r = D + |V'| + 1 = D + |V|$$

$$\Phi = \frac{\sum_{r=1}^R E_{\text{consume}}^r}{R(E_{\max}^{tra} + E_{\max}^{ch})} = \frac{D + |V|}{2}$$

The delay of data transmission is $\Delta \tau_i = t_i$, which denotes the time when the WCE arrives at sensor node s_i . Given the travel route of the WCE and the stay time, the arrival time can be easily calculated in polynomial time. The time complexity to compute the average delay $\Delta \tau$ of data transmission is $O(D + |V|)$. TSP is an NP-complete problem, therefore the multi-objective optimization problem of path planning is also an NP-complete problem.

5. ES-MOAC algorithm

The multi-objective optimization problem of path planning is an NP-complete problem. Generally speaking, the swarm intelligence algorithm is used to solve this kind of problems, which includes ant colony optimization algorithm (ACO), particle swarm optimization (PSO), genetic algorithm (GA), etc. Ant colony optimization algorithm is an algorithm that simulates the foraging behavior of ants to find the optimal path.

In this study, the solution to the above multi-objective optimization problem is to figure out the path planning for the mobile WCE. In other words, the traveling path and the charging time of each sensor node are to be determined. Therefore, the ES-MOAC algorithm is proposed.

The key point of the ES-MOAC algorithm is to design the state transition strategy of ants and the pheromone updating strategy. The

state transition strategy of ants depends on the pheromone concentration, the distance between two sensor nodes and the rest lifespan of the sensor nodes in specific conditions. Otherwise, a sensor node that has not been visited is randomly chosen, so that partial optimal solutions are evitable. When it comes to the pheromone updating strategy, the pheromone updating in a working round depends on the rest pheromone from the previous working rounds after volatilization and the pheromone generated by the elitist ants corresponding to the Pareto set. This pheromone updating strategy is a revised elitist strategy, which contributes to obtain the optimal Pareto set.

5.1. The state transition strategy of ants

Corresponding to the ES-MOAC algorithm, ants can be viewed as the mobile WCE. The total number of ants is denoted as A . Ant k ($k = 1, 2, \dots, A$) sets off from the service station and chooses different traveling paths at the initial moment. After visiting sensor node s_i , ant k choose a second sensor node s_j to visit. Under the constraints of the limited rest traveling energy and the limited charging energy, the following conditions also should be considered to make decisions.

- 1) The higher the pheromone concentration along the path between sensor node s_i and a second sensor node s_j is, the more likely ant k is to choose a sensor node s_j to visit.
- 2) The shorter the distance between sensor node s_i and the next sensor node s_j is, the more likely the ant k is to choose a sensor node s_j to visit.
- 3) The shorter the rest lifespan of a second sensor node s_j is, the more likely ant k is to choose a sensor node s_j to visit.

In summary, the specific state transition strategy for ant k moving from sensor node s_i to sensor node s_j is shown as follows,

$$j = \begin{cases} \arg \max_{j \in ad_k} \left\{ [\sigma_{ij}(t)]^\alpha [\eta_{ij}(t)]^\beta [\varphi_{ij}(t)]^\gamma \right\}, & \text{if } q \leq q_0 \\ j \in ad_k, & \text{else} \end{cases} \quad (19)$$

α, β, λ are the weight coefficients; q_0 ($q_0 \in (0, 1)$) is a constant; q ($q \in (0, 1)$) is a random number; ad_k represents the set of sensor nodes that ant k has not been to, and $\sigma_{ij}(k)$ is the pheromone concentration on the path between sensor node s_i and a second sensor node s_j . $\eta_{ij}(t) = 1/d_{ij}\eta_{ij}(t)$, of which d_{ij} is the Euclid distance between sensor node s_i and a second sensor node j . $\varphi_{ij}(t) = 1/\tau_{life}^{ij}(t)$, of which $\tau_{life}^{ij}(t)$ is the rest lifespan of sensor node j when the ant just arrives at sensor node j after visiting sensor node i . Specifically, $\tau_{life}^{ij}(t) = (e_j(t_i + \tau_i) - p_j \cdot d_{ij}/V - E_{\min})/p_j \in ad_k$, which means random choice of sensor node s_j from ad_k .

5.2. The pheromone updating strategy

To avoid diluting the inspiration information with too much rest pheromone, the rest pheromone updates in round $(t + 1)$ after all the ants have been to all the sensor nodes in round t . Therefore, the pheromone concentration on the path between sensor node s_i and a second sensor node s_j in round $(t + 1)$ is updated by Equation (20).

$$\sigma_{ij}(t + 1) = (1 - \rho) \sigma_{ij}(t) + \sum_{k \in U_{BP(t)}} \Delta \sigma_{ij}^k(t) \quad (20)$$

ρ ($\rho \in (0, 1)$) is a volatility coefficient and BP is the Pareto set concluded by comparing the total energy efficiency and the average delay of data transmission after all the ants visited all the sensor nodes. $U_{BP(t)}$ is the set of elitist ant corresponding to the Pareto in t th working round.

The pheromone updating in a working round depends not only on the unvolatilized pheromone in the previous rounds but also on the pheromone generated by the elitist ants corresponding to the Pareto set. Therefore, the following three points matter.

- 1) The higher the energy efficiency Φ_{ij}^k is, the higher the pheromone concentration is. The lower $\overline{\Delta\tau}_k$ is, the higher the pheromone concentration is.
- 2) The less the elitist ant k returns to service station S is, the higher the pheromone concentration in a working round is. R_k indicates how many times the elitist ant k travels in a working round.
- 3) The shorter the traveling path in a working cycle is, the higher the pheromone concentration is.

To sum up, the pheromone generated by the elitist ant k in path (s_i, s_j) is shown in Equation (21),

$$\Delta\sigma_{ij}^k(t) = \begin{cases} \frac{\xi \cdot \Phi_k}{\overline{\Delta\tau}_k \cdot R_k \cdot D_Q^k}, & \text{if the } k\text{th ant pass the path } (s_i, s_j) \\ 0, & (\textit{else}) \end{cases} \quad (21)$$

of which Q is a regulator.

5.3. Algorithm statement

Based on the above state transition strategy of ants and pheromone updating strategy, traveling paths and the charging time can be determined according to the proposed ES-MOAC algorithm. In accordance with the ES-MOAC algorithm, the Pareto set turns out in a working cycle, and the steps are as follows (see Algorithm 1).

Algorithm 1 ES-MOAC algorithm

Input: Partial parameters of the network, charging system, and ant colony system.

Output: A Pareto set including two target values, the corresponding charging path and charging time.

- 1: Initialization: BP is empty, the maximum round of iterations is M , the number of ants is A , the iteration $t = 1$, initial pheromone $\sigma_{ij}(0) = 0$ and the other related parameters.
- 2: **while** $t \leq M$ **do**
- 3: **for** $k \leftarrow 1$ to n **do**
- 4: Calculate and obtain a traveling path for ant k according to formula (19).
- 5: Calculate and obtain a charging path for ant k : according to the traveling path of ant k , $E_{max}^{tra} \geq (D_{ij} + D_{js}) \cdot p_{tra}$ and $E_{max}^{ch} \geq \tau_i \cdot U$ should be satisfied when ant k will transfer sensor node s_j at sensor node s_i , otherwise, a service station should be set between sensor node s_i and sensor node s_j .
- 6: Calculate two target values corresponding ant k .
- 7: Update the Pareto set BP by comparing the solution of ant k and the previous Pareto solution.
- 8: **end for**
- 9: Update Pareto set $BP(t)$ in the t th working round: compare two objective values generated by all the ants in the t th working round.
- 10: Updated the pheromone concentration according to formula (20) and formula (21).
- 11: $t = t + 1$
- 12: **end while**
- 13: Obtain the Pareto set BP and the corresponding charging path Q and charging time τ_i .

6. Experimental results

6.1. Experimental settings

Twenty sensor nodes are randomly deployed over a 1000 m \times 1000 m square area, in which a service station is located at (0 m, 0 m). According to (Shi et al., 2012) and (Xu et al.,

2017), simulation parameters are shown as follows. $E_{max} = 10.8$ KJ, $E_{min} = 540$ J, $E_{tra} = 20$ KJ, $E_{ch} = 20$ KJ, $V = 8$ m/s, $U = 10$ W and $p_{tra} = 100$ W. The energy consumption power $p_i(W)$ is a random number from 0.1 to 1. The simulation platform is MATLAB R2016a.

What to analyze includes effects of the iterations, the number of ants A , adjustment factors q_0 in accordance with the State Transition Strategy of Ants and the pheromone volatilization coefficient ρ in accordance with the pheromone updating strategy derived from the ES-MOAC algorithm of certain fixed system parameters and comparison of ES-MOAC algorithm and NSGA-II (Deb et al., 2002).

In this section, we compare the proposed ES-MOAC with a state-of-the-art multi-objective method, namely NSGA-II algorithm. NSGA-II algorithm is one of the most popular multi-objective algorithms, which reduces the complexity of non-inferior ranking genetic algorithms and has the advantages of fast operation speed and good convergence of solution set. Furthermore, NSGA-II algorithm has become the benchmark for the performance of other multi-objective optimization algorithms. NSGA-II algorithm is improved based on non-dominated sorting genetic algorithm. These four new innovations are as follows– a fast non-dominated sorting procedure, a fast-crowded distance estimation procedure, a simple crowded comparison operator, and an elitist-preserving approach. The procedure of NSGA-II algorithm can be summarized as follows. Firstly, a combined population $R_t = P_t \cup Q_t$ is formed. Population R_t is of size $2H$. Then, population R_t is sorted according to non-domination, which generates a series of non-dominated sets Z_i and the crowded degree is calculated. Since both the offspring and the parent individuals are contained in population R_t , after the non-dominated sorting, the individuals contained in non-dominated set Z_1 are the best in population R_t . Therefore, the individuals of non-dominated set Z_1 are firstly put in a new parent population P_{t+1} . If the size of P_{t+1} is less than H , population P_{t+1} is filled with the individuals of the next-level non-dominated set Z_2 . The size of the population does not exceed H until the individuals of Z_3 is added. The crowded comparison operator is used for the individuals in set Z_3 , which make the individual number of the population P_{t+1} add up to H . Then, a new offspring population Q_{t+1} is generated by genetic operators, namely selection, crossover, mutation, etc.

6.2. Analysis of simulation

6.2.1. The influence of the parameters in the ant system of the ES-MOAC algorithm

According to Fig. 4, $\alpha = 1$, $\beta = 5$ and $\gamma = 4$. The Maximum iterations M is 150, and 50 groups of contrastive experiments are conducted. 10 ants, 15 ants, 20 ants and 25 ants are involved, respectively. As a result, the average number of the Pareto optimal solutions varies as the 50 groups of contrastive experiments iterate. The average number of the Pareto optimal solutions approaches to a specific constant value if the algorithm iterations are more than 120. If the number of ants is not less than 15, the number of ants rarely affects this algorithm.

According to the above experiments, as shown in Fig. 5, the maximum iteration M is 150, the number of ants A is 20, q_0 varies from 0 to 1, and the other ant system parameters remain unchanged. The curve of the average number of Pareto optimal solutions in 50 groups of contrastive experiments changes in accordance with the change of q_0 . If q_0 is between 0.6 and 0.9, the algorithmic results are ideal. Similarly, the maximum iteration M is 150, the number of ants A is 20, q_0 is 0.8, volatility coefficient ρ varies from 0 to 1 (see Fig. 6), and the other ant system parameters remained unchanged. The curve of the average number of Pareto optimal solutions in 50 groups of contrastive experiments changes in accordance with the change of ρ . If ρ is set between 0.2 and 0.5, the algorithmic results are ideal.

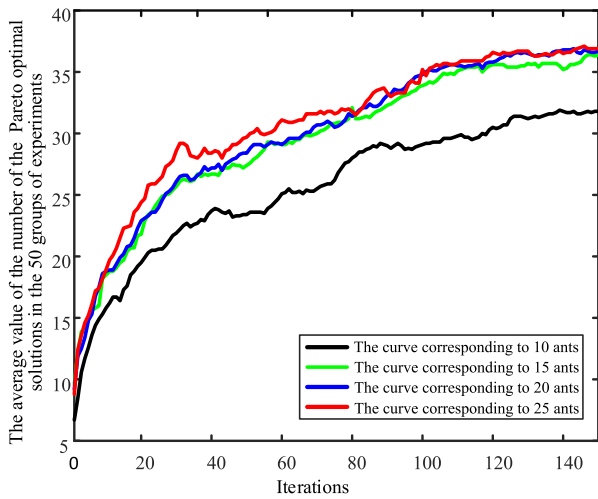


Fig. 4. Influence of iteration towards the number of Pareto optimal solution of the algorithm with different numbers of ants.

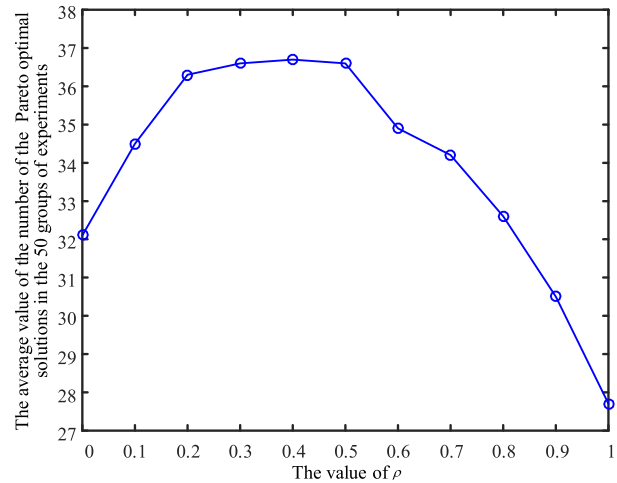


Fig. 6. Influence of pheromone volatilization coefficient ρ on the algorithm.

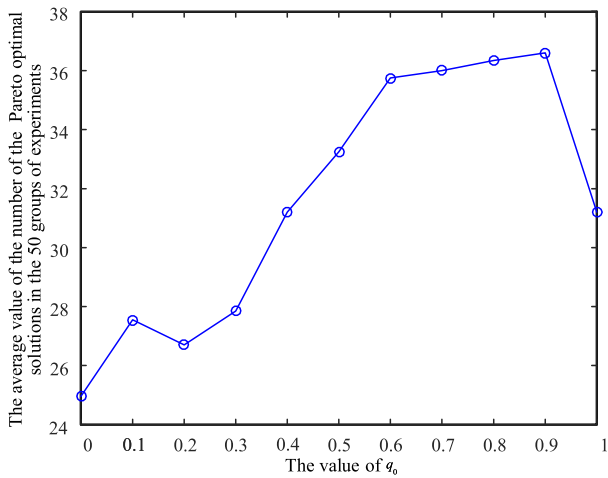


Fig. 5. Influence of adjustment factors q_0 on the algorithm.

Table 1

Position coordinates of 20 sensor nodes in the network.

Node No.	Coordinate/m	Node No.	Coordinate/m
1	(342,112)	11	(609,579)
2	(198,192)	12	(827,504)
3	(758,119)	13	(757,734)
4	(921,320)	14	(287,643)
5	(946,742)	15	(253,922)
6	(854,847)	16	(103,777)
7	(680,979)	17	(559,490)
8	(656,769)	18	(277,396)
9	(128,490)	19	(54,489)
10	(486,813)	20	(465,280)

the energy consumption of the mobile WCE in a working cycle with the highest total energy efficiency of the mobile WCE and the lowest average delay of data transmission in the network is shown in Table 2 and Table 3. Comparing Table 2 with Table 3, the number of working rounds corresponding to the lowest average delay of data transmission in a network within a working cycle is less than that of the solution with the highest total energy efficiency of the mobile WCE. Therefore, the mobile WCE spends less time in the path. The average delay of data transmission in the network is relatively low. The solution with the highest total energy efficiency of the mobile WCE has conducted more

6.2.2. Analysis of the results of ES-MOAC

According to the experiments above, the parameters of the algorithm are as follows: the maximum iteration M is 150, the number of ants A is 20, the adjusting factor q_0 in accordance with ant state transfer strategy is 0.8, and the volatilization coefficient of pheromone ρ in accordance with pheromone updating strategy is 0.4. In this section, the specific position coordinates of 20 sensor nodes in the network are shown in Table 1. The other network parameters are the same as those of the previous experimental settings. Then, shown in Fig. 7, the ES-MOAC algorithm is adopted to solve the Pareto frontier of the problem under different iterations. Rarely change under 120 iterations. On the other hand, the total energy efficiency of the mobile WCE and the average delay of data transmission in different conditions can be calculated.

All the red circles in Fig. 7 form the Pareto optimal solutions set. Decision-makers can choose a solution in the Pareto optimal solutions set to solve particular problems. If less delay in data transmission is required, decision-makers should choose the solutions formed by red circles in the lower right corner of Fig. 7. If the higher total energy utilization of the WCE is required, decision-makers should choose the solutions formed by red circles in the top left corner of Fig. 7. If a balance of the previous two is required, decision-makers should choose the solutions formed by red circles in the middle of Fig. 7. In addition,

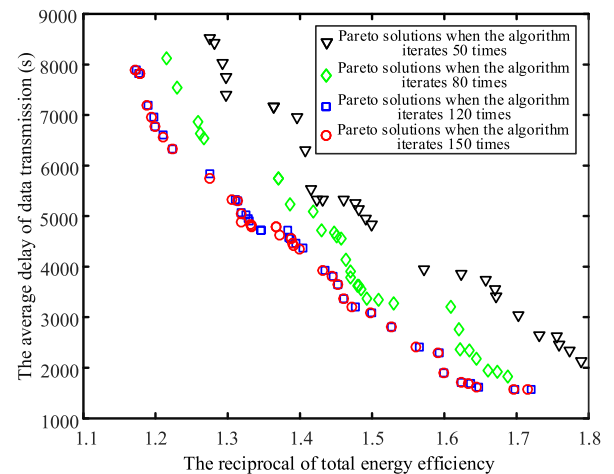


Fig. 7. Pareto frontiers under different iterations by using ES-MOAC.

Table 2
Energy consumption during a working cycle for the mobile WCE (highest total energy efficiency).

Traveling path in a round	Traveling energy/J	Charging energy/J
0-1-13-4-12-0	18098.38	13574.76
0-2-20-17-11-8-0	18469.46	15462.04
0-18-16-10-7-0	18783.94	16601.46
0-3-6-5-0	17503.66	16945.39
0-19-9-14-15-0	17462.01	17492.82

Table 3
Energy consumption during a working cycle for the mobile WCE (lowest average delay of data transmission).

Traveling path in a round	Traveling energy/J	Charging energy/J
0-19-9-16-15-10-14-18-2-0	19982.67	5487.37
0-1-20-17-11-8-7-0	19540.78	5647.44
0-3-4-12-5-6-13-0	19734.08	5555.05

working rounds, in which the energy cost is high and the time spent in a working cycle is long. To balance the rest energy of the sensor nodes in the network, the cost of charging energy is high and so is the total energy efficiency. Thus, the lifespan of the whole network is prolonged.

In (Shi et al., 2012), the battery energy of each sensor node is charged to E_{max} . The charging strategy is localized in the proposed algorithm called ES-MOAC. 50 experiments are conducted, following the proposed charging strategy in (Shi et al., 2012). In Fig. 8, y_1 and y_2 represent the number of the Pareto solutions calculated according to the charging strategies. The number of Pareto solutions obtained by this proposed scheme is much higher, compared to those obtained by the charging strategy in (Shi et al., 2012). The number of Pareto solutions obtained by this proposed scheme is much more than those obtained by the charging strategy in (Shi et al., 2012). The battery energy of each sensor node is charged to E_{max} , which makes it difficult to keep the other sensor nodes alive in the network. The proposed scheme is to minimize the variance of the remaining life of all the sensor nodes, which ensures that the remaining energy of all the sensor nodes is balanced and the network lifespan is prolonged.

Comparison of the Pareto frontiers by using the charging strategy in our paper and literature (Shi et al., 2012) is shown in Fig. 9. The figures show that the solutions obtained by the proposed scheme are more than those in accordance with the charging strategy in (Shi et al., 2012) to

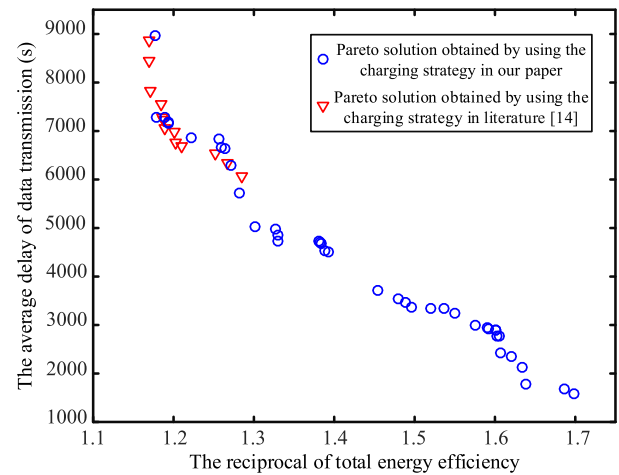


Fig. 9. Comparison of the Pareto frontiers by using the charging strategy in our paper and in literature (Shi et al., 2012).

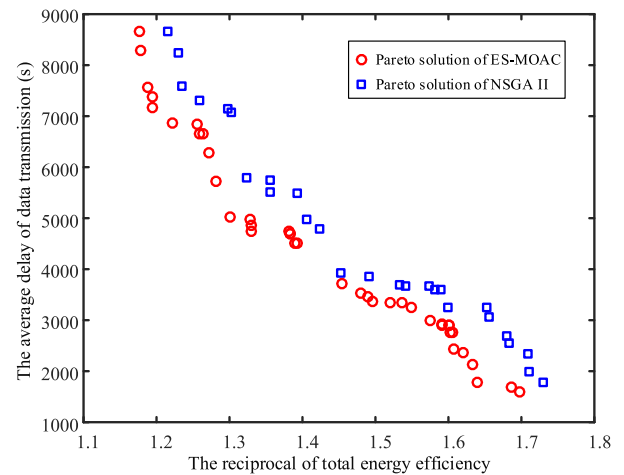


Fig. 10. Comparison of the Pareto frontiers by using ES-MOAC and NSGA-II.

be provided for the decision-makers. Decision-makers have options to better solve practical problems.

6.2.3. Comparisons of ES-MOAC and NSGA-II

According to the experiments mentioned above, the parameters of the algorithm can be set as follows: the maximum iteration M is 150, the number of ants A is 20, the adjusting factor q_0 in accordance with ant state transfer strategy is 0.8, and the volatilization coefficient of pheromone ρ in accordance with pheromone updating strategy is 0.4. Applying ES-MOAC and NSGA-II, 50 groups of experiments are conducted to compare. As shown in Fig. 10, the Pareto frontier generated by ES-MOAC is better than that generated by NSGA-II. As shown in Table 4, Φ is the total energy efficiency and $\Delta\tau$ is the average delay of data transmission. Φ and $\Delta\tau$ are the two optimization objectives in this study. RN is the number of Pareto optimal solutions. SP indicates the distribution range of Pareto optimal solutions in the objective space. M_3^* measures the distribution range of Pareto optimal solutions around its frontier. According to the statistic of comparative tests, ES-MOAC algorithm is better than NSGA-II, of which the total energy efficiency is up to 86.19%. Furthermore, the delay of data transmission obtained by the ES-MOAC algorithm is shortened by 11.67% when compared with NSGA-II. As shown in Fig. 11 and Table 4, the distribution of solutions obtained by ES-MOAC is more concentrated and the number of solutions is more than that obtained by NSGA-II. The average of RN in

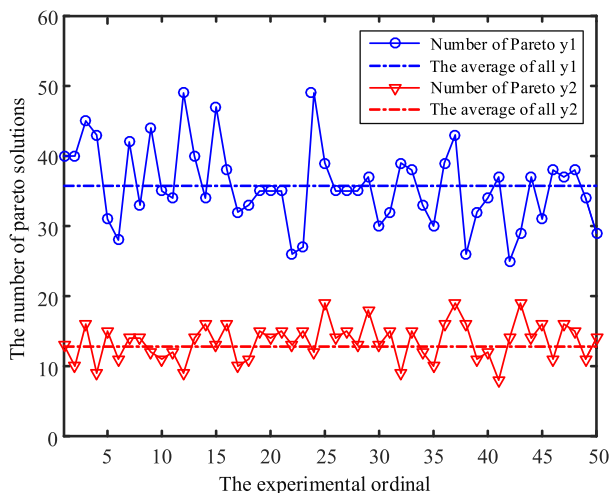


Fig. 8. The number of Pareto solutions obtained in each experiment under the two schemes and the average value.

Table 4
Comparison of the solutions obtained by ES-MOAC and NSGA-II.

Index		Statistic			
		Best value	Worst Value	Average	Median
$\Phi/\%$	ES-MOAC	86.19	56.02	71.28	71.43
	NSGA-II	85.42	52.21	68.19	67.28
$\overline{\Delta\tau}/s$	ES-MOAC	1380.42	8971.85	4404.85	4411.43
	NSGA-II	1541.12	9341.52	4642.56	4566.49
RN	ES-MOAC	49	25	36	35
	NSGA-II	34	15	26	26
SP	ES-MOAC	2416.57	25.41	765.86	487.96
	NSGA-II	2845.11	60.43	1025.25	833.30
M_3^*	ES-MOAC	5655.37	8.98	382.88	121.83
	NSGA-II	6520.66	9.82	539.42	129.01

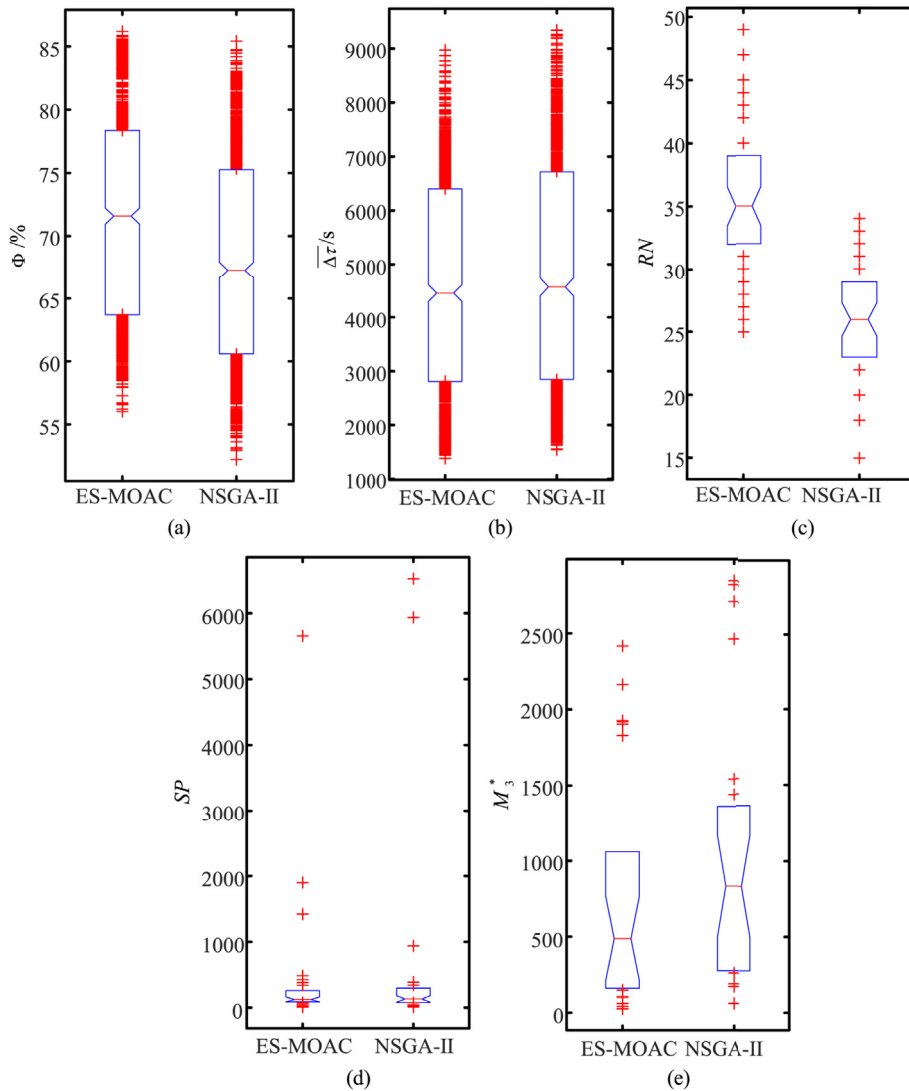


Fig. 11. Comparison of box plots of indexes obtained by ES-MOAC with NSGA-II.

accordance with the ES-MOAC is 27.8% more than with NSGA-II.

7. Conclusion

Considering the limited traveling energy and the charging energy, a multi-objective path planning model is proposed to both charge and collect data. As the balanced energy of the network is secured, there are the rules of charging path for the mobile WCE to maximize the total

energy efficiency of the mobile WCE and minimize the average data transmission delay. Consequently, data transmission improves in the network and the network lifespan extends. This paper proposes a multi-objective ant colony algorithm based on the elitist strategy. The ant colony transition strategy and pheromone updating strategy of the ES-MOAC algorithm are designed, and the Pareto set of the multi-objective optimization is derived, which provides decision-makers with different solutions. This study tests parameters including the maximum iterations

in the ant system, the number of ants, the adjustment factors in the ant state transition strategy and pheromone volatilization coefficient in accordance with pheromone updating strategy. The paper examines the algorithmic results of the ES-MOAC applied to a specific network, and verifies the model. 50 groups of experiments of the appropriate parameters are conducted in the same circumstance to compare the algorithms of ES-MOAC and NSGA-II. The simulation results demonstrate that the ES-MOAC algorithm is more effective than the other.

CRedit authorship contribution statement

Zhenchun Wei: Conceptualization, Methodology. **Chengkai Xia:** Data curation, Writing - original draft. **Xiaohui Yuan:** Supervision, Writing - review & editing. **Renhao Sun:** Software, Data curation. **Zengwei Lyu:** Software, Validation. **Lei Shi:** Resources. **Jianjun Ji:** Writing - review & editing.

Acknowledgment

The authors would like to thank the anonymous reviewers and editors for their valuable comments. The material presented in this paper is based on work funded by National Key Research Development Program of China (2018YFC0604404), China; Key Research and Development Project in Anhui Province (201904a07020030), China; Fundamental Research Funds for the Central Universities (PA2019GDPK0079), China.

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