Charging Route Planning for Wireless Rechargeable Sensor Networks

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Abstract

Wireless Sensor Network (WSN), as one of the important means of obtaining contemporary information, has attracted extensive attention from all walks of life. How to supply continuous energy to sensor network to make it run normally is a problem that has long puzzled people. This paper mainly studies the charging mode which uses the mobile charger to replenish the energy of the sensor battery. In order to ensure the real-time operation of the sensor and reduce the energy loss of the mobile charger on the road, we believe that the charging route planning is of great significance. At present, path planning for wireless sensor networks is usually treated as TSP and MTSP problems, and heuristic algorithm is used to analyze and solve the problems. However, the efficiency of a single heuristic algorithm is often limited, and it is difficult to balance the accuracy and efficiency in the face of more data. In this paper, using the known geographic coordinate data of longitude and latitude of each node, genetic algorithm and simulated annealing algorithm are used for comparative research and analysis to plan the shortest moving path when sending out a single mobile charger. The results show that the two algorithms have some advantages and disadvantages: the genetic algorithm is easy to fall into the local optimal solution, and the simulated annealing algorithm has a slower convergence speed. Therefore, we establish a hybrid algorithm to solve the shortest path planning route, and effectively improve the computing efficiency under the condition of ensuring a certain accuracy. We apply this hybrid algorithm to the path planning of multiple mobile chargers, and its high efficiency verifies the speed and reliability of our algorithm.

Keywords

TSP; MTSP; Genetic algorithm; Simulated annealing algorithm.

1. INTRODUCTION

Wireless Sensor Network is an important front-end component of the Internet of Things and Information Cyber-Physical System (CPS). Wireless sensor networks collect information from the environment, such as temperature, light, sound, vibration, and energy, and send the data to a data center, which analyzes the data and sends back control information. The wireless rechargeable sensor network refers to the use of mobile chargers to replenish energy for the battery of the sensor on a regular basis, so as to provide stable energy for the normal operation of WSN, so as to avoid the disadvantages caused by unstable energy absorption from the environment.

Wireless rechargeable sensor network consists of three parts: a Data Center DC, several Sensors, and one or more Mobile Charger MC. The data center and several sensors are distributed in a two-dimensional space. When the power of a sensor falls below a threshold,

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normal information collection cannot be carried out. In order to make WRSN work normally, the mobile charger needs to charge the sensor regularly to avoid its power falling below the threshold.

The mobile charger starts from the data center, passes through each sensor in turn at a fixed speed, stays at each sensor for a period of time and charges the sensor at a fixed charging rate until it returns to the data center after charging all the sensors. The energy consumption of the mobile charger is the normal energy consumption caused by charging the sensor nodes. On the other hand, the energy consumption of the mobile charger is on the way to charging the sensor. In order to reduce the energy consumption of mobile charger on the road, it is very important to plan the charging route of mobile charger reasonably.

2. COMPARISON AND ANALYSIS

2.1. Simplified Model

Considering the path planning problem of a single mobile charger, it can be simplified to a single traveling salesman problem (TSP) [1], that is, how a traveling salesman chooses the path to make its traveling distance the shortest.

When the longitude and latitude of each sensor position is known, we use Miller projection, which is similar to Mercator projection, to transform the earth's longitude and latitude coordinates into plane Cartesian coordinates, and convert the longitude and latitude into two-dimensional coordinate data.

The transformation is performed according to the following formula, where Jin represents longitude, Wei represents latitude, and Me =2.3.

$$\begin{cases} L_e = 6381372 * 2 * \pi \\ X_e = L \\ Y_e = \frac{L}{2} \\ x = \frac{X_e}{2} + \frac{X_e}{2*\pi} * Jin * \frac{\pi}{180} \\ y = \frac{Y_e}{2} + \frac{Y_e}{2*me} * 1.25 * \log_{10}[\tan 0.25 * \pi + 0.4 * Wei * \frac{\pi}{180}] \end{cases} \tag{1}$$

The relative projected position remains unchanged, and the relative positions of the data center and the sensor can be obtained after the change of the equal ratio as shown in the figure below:

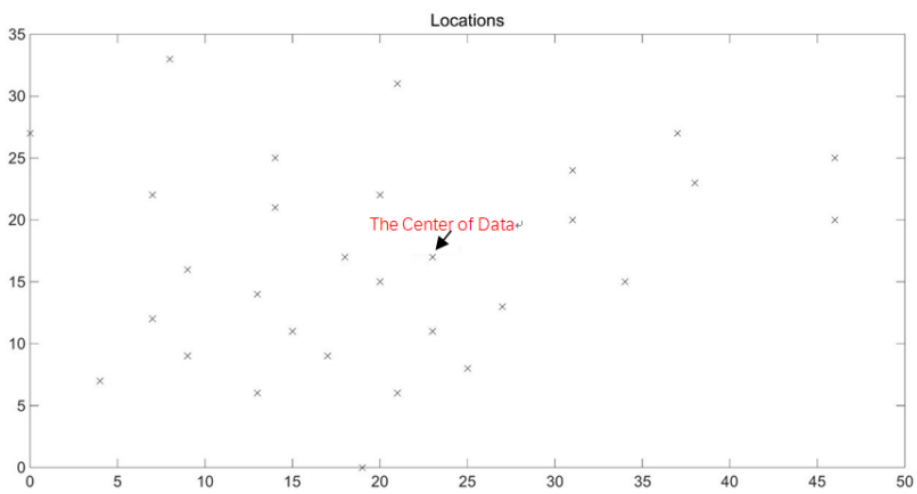

Figure 1. The data points figure

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From the longitude and latitude data, we use the Python-Geopy library to get the distance matrix:

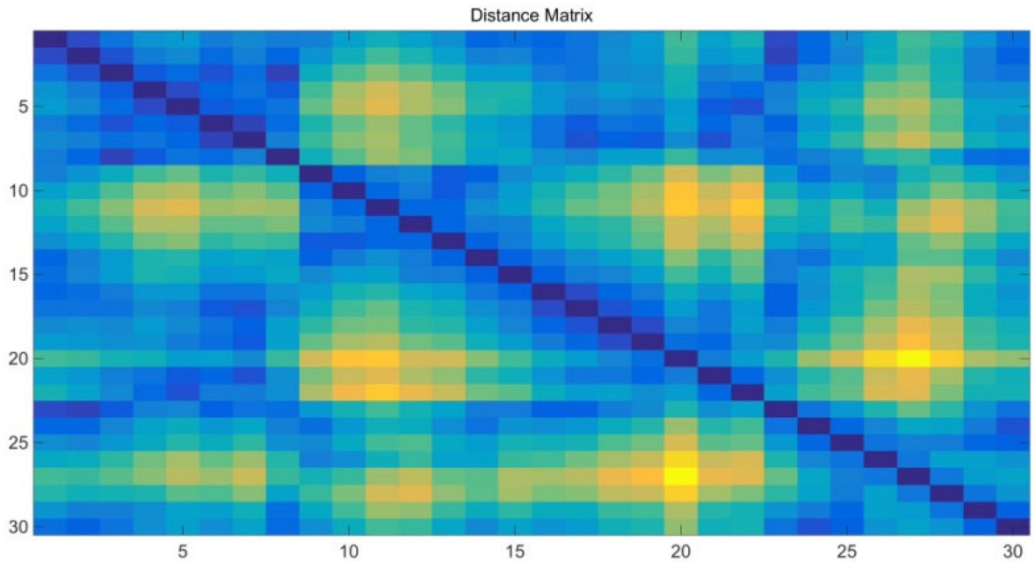

Figure 2. Distance matrix diagram

2.2. Genetic Algorithm Solution

For example, the code of 1, 5, 6, 3, 2, 9, 1 is defined as 1→5→6→3→2→9→1, and it is defined as "individual", where the data center code is 1, and the code of other sensors is added 1 according to the given data [2].

We first code the $\boldsymbol{Num}$ individuals to generate the initial population.

We adopted integer permutation coding method [3], and made the moving path as a one-dimensional vector, which was used as the coding of the individual to facilitate later operation. With only a single mobile charger, you only need to search for the shortest path to minimize energy consumption on the road. We take the total path length $\boldsymbol{S_i}$ as the individual objective function, using the following formula:

$$S_i = \sum_{i=1}^{N-1} D_{(i,i+1)} \tag{2}$$

After calculating the $\boldsymbol{S_i}$ distance, the smaller the objective function value of the individual in each generation, the easier it is to survive. We define the fitness function for the individual:

$$Z_i = \frac{1}{S_i} \tag{3}$$

Further define the probability $\boldsymbol{Pa_i}$ of the ith individual being selected:

$$Pa_i = \frac{Z_i}{\sum_{i=1}^{Num} Z_i} \tag{4}$$

Record the individual with the highest fitness, and then use roulette to select the Num individual. The selected individuals are mutated and cross-selected according to the probability of P_c and P_m, so as to generate the next generation population. Repeat the process, completing the algebra of evolution.

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The path planning results are as follows:

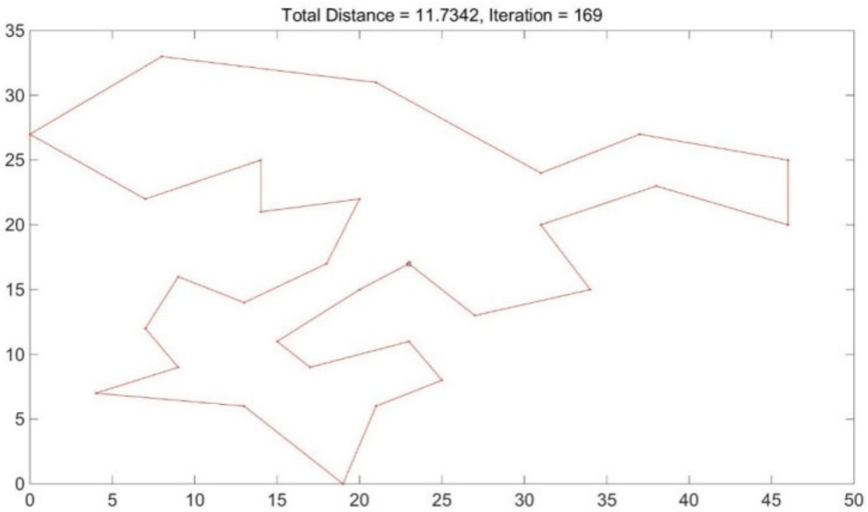

Figure 3. Path planning diagram of genetic algorithm

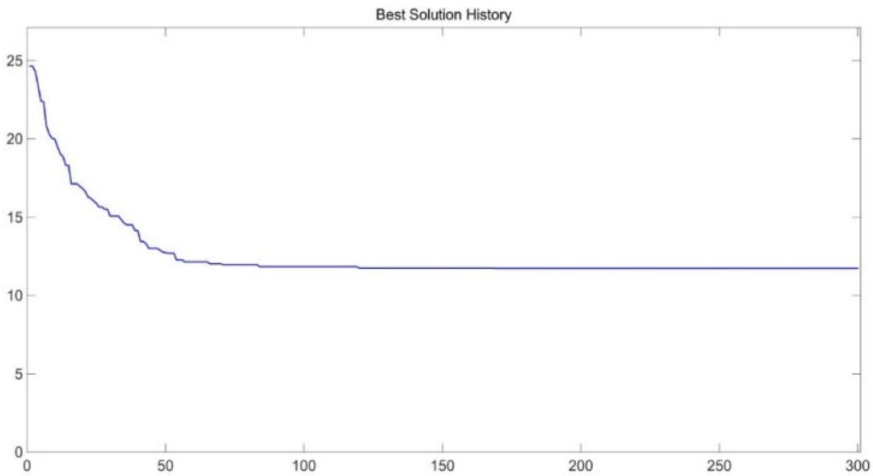

Figure 4. Iterative graph of genetic algorithm

2.3. Simulated Annealing Algorithm Solution

Since the genetic algorithm will be trapped in the local optimal solution, in order to ensure the accuracy of the solution, we adopted the simulated annealing algorithm for comparative research and analysis, and we carried out analysis and calculation according to the following algorithm [4].

Firstly, we set the initial value of temperature as $\boldsymbol{T_0}$, the lower limit of temperature as $\boldsymbol{T_{min}}$, and the annealing speed as $\boldsymbol{\lambda}$.

In general, the initial temperature is generally set to a larger value. Annealing mode using linear model $\boldsymbol{T = T_0 * \lambda}$, annealing speed $\boldsymbol{\lambda}$ value range is generally 0.8-0.99, through our many times running, the final determination of the annealing speed $\boldsymbol{\lambda = 0.99}$.

An initial solution is generated randomly by Randperm function of Matlab, and the objective function value of the initial solution is calculated.

We set the objective function $\boldsymbol{Z}$. In the case of a single mobile charger, we define the objective function $\boldsymbol{Z}$ to be equal to the total distance $\mathbf{S}$ of the moving path.

After randomly generating the initial solution by Randperm function, we get the total distance $\boldsymbol{S^1}$ of the moving path.

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We use random perturbation to generate a new solution. There are many ways to generate random perturbation, and the wider the range of new solutions generated by random perturbation is, the more conducive it is to search for the optimal solution. In general, there are three ways to carry out random perturbation:

Method 1: (Exchange method) To select two random positions, the numbers above the two random positions are exchanged.

Method 2: (Shift method) Three random positions are selected and the sequence of the first two random positions is moved immediately after the third random position.

Method 3: (Reverse order method) To select two random positions, and arrange the intercepted sequence in reverse order.

In this paper, three stochastic perturbation methods are used to generate new solutions. Because each method has different perturbation intensity to the original solution, the variation range of the new solution is different. After many tests, a 5:4:2 is adopted for the use of the three methods in the case of random disturbance, so as to improve the generation efficiency of new solutions.

Use the $\boldsymbol{Metropolis}$ principle to evaluate the new solution to see if it is accepted. In general, we adopt a certain acceptance or rejection of the new solution. However, this method is easy to make the solution fall into the local optimal solution.

Using the $\boldsymbol{Metropolis}$ principle

$$P_t = e^{-\frac{|Z(B)-Z(A)|}{T_t}} \tag{5}$$

$\boldsymbol{P_t}$ is the probability of accepting the new solution.

Then, the number 0-1 is randomly generated and compared with the probability of the new solution to determine whether to accept the new solution and complete the iterative process of the solution. Repeat the search for a new solution until the number of iterations is completed.

The path planning results are as follows:

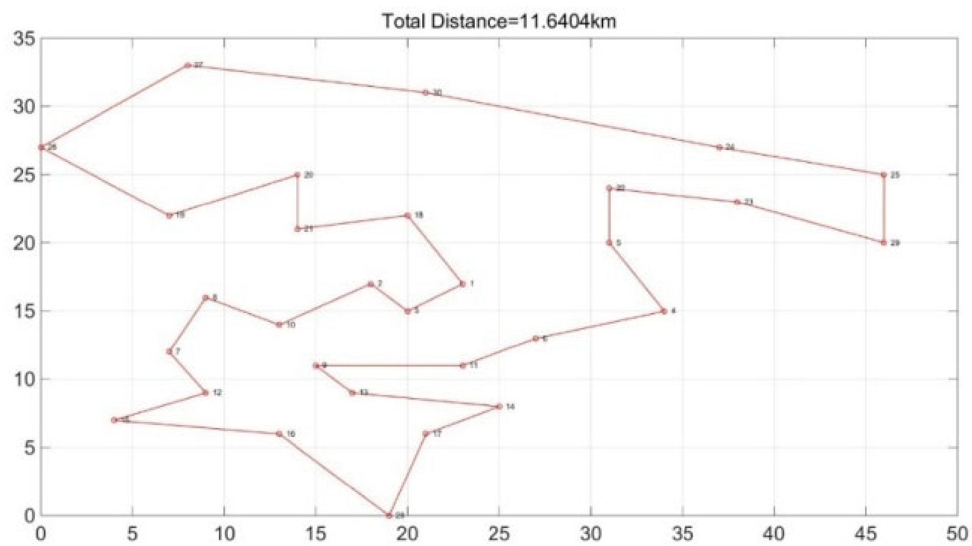

Figure 5. Path planning diagram of Simulated annealing algorithm

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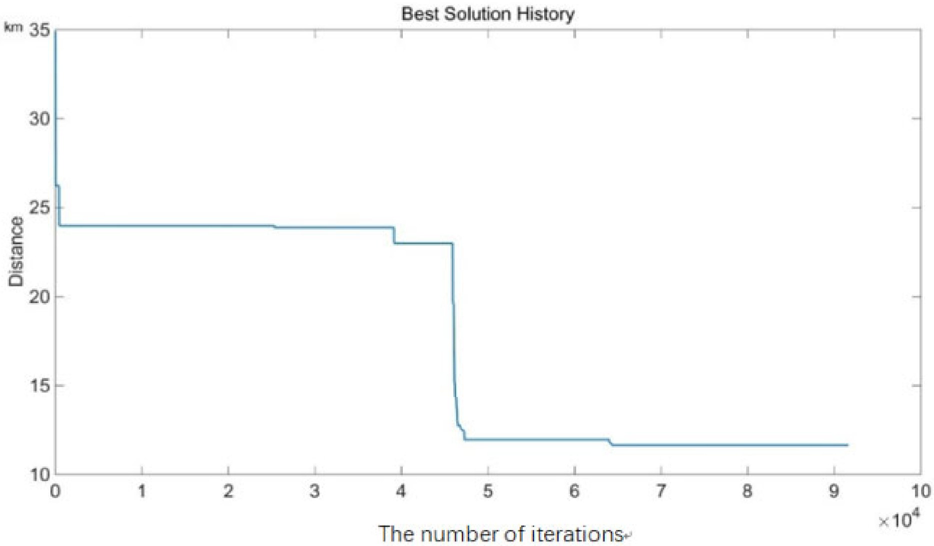

Figure 6. Iterative graph of Simulated annealing algorithm

2.4. Comparative Analysis Results

Compared with the results of the two algorithms in TSP, the precision of the simulated annealing algorithm is closer to the global optimal solution. The main reason is that the genetic algorithm is easy to get trapped in the local optimal solution, while the simulated annealing algorithm uses the Metropolis principle to make some new state solutions pass down with a certain probability, so it can jump out of the local optimal solution [5]. However, due to the application of the Metropolis principle, the convergence speed of the algorithm is significantly reduced. Although the annealing speed is adjusted within a certain range to improve the convergence speed, it still cannot make up for the fundamental reason of its own iteration number. Therefore, in terms of the running efficiency of the algorithm, genetic algorithm has more fast computing power.

The two algorithms can't find the optimal solution accurately in the problem solving. Generally, they generate suboptimal solution. The main reason is that the number of 30 sensor nodes is relatively large and the range of searching the optimal solution is large. It can be predicted that for NP-hard problems such as TSP, when the number of nodes is larger, if a solution is randomly generated and optimized, the computational efficiency will be greatly reduced.

The variation and crossover operations of genetic algorithm expand the range of solvable boundary, while the Metropolis principle of simulated annealing algorithm makes the algorithm jump out of the local optimal solution to find the global optimal solution. In view of their advantages and disadvantages, they can be combined theoretically to form a hybrid algorithm for related research.

3. ALGORITHM IMPROVEMENT

With multiple mobile chargers, the problem is often simplified to the multi-travel salesman problem MTSP[1]. In contrast, the search range of MTSP optimal solution is wider than that of TSP optimal solution, so it is necessary to propose a better algorithm to solve the efficiency problem. According to the assumption that we combine the two to form a hybrid algorithm, we will elaborate the research of hybrid algorithm below.

Firstly, $\boldsymbol{Num}$ individuals are randomly generated to form an initial population $\boldsymbol{Pop}$. The initial temperature $\boldsymbol{T_0}$, the lower limit temperature $\boldsymbol{T_{min}}$ and the annealing speed $\boldsymbol{\lambda}$ are set.

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Then, the objective function value Z of each individual in the $\boldsymbol{Pop}$ population is calculated, and the individual $\boldsymbol{x}$ with the smallest objective function value and the function value are recorded.

Each individual in the $\boldsymbol{Pop}$ population is perturbed randomly. The perturbing method is based on the three methods mentioned above to generate a new solution. Each individual is evaluated using the $Metropolis$ principle to determine whether the new solution is acceptable, thus obtaining a new $\boldsymbol{Pop}$ population. We use the improved roulette selection method to select the best solution from the new total group, and then use roulette to select $\mathbf{Num-1}$ individuals. Cross and mutate the selected $\mathbf{Num}$ individuals according to the probability of $\boldsymbol{P_c}$ and $\boldsymbol{P_m}$ respectively in the way of genetic algorithm. Repeat the above steps until the number of iterations is complete.

The path planning results are as follows:

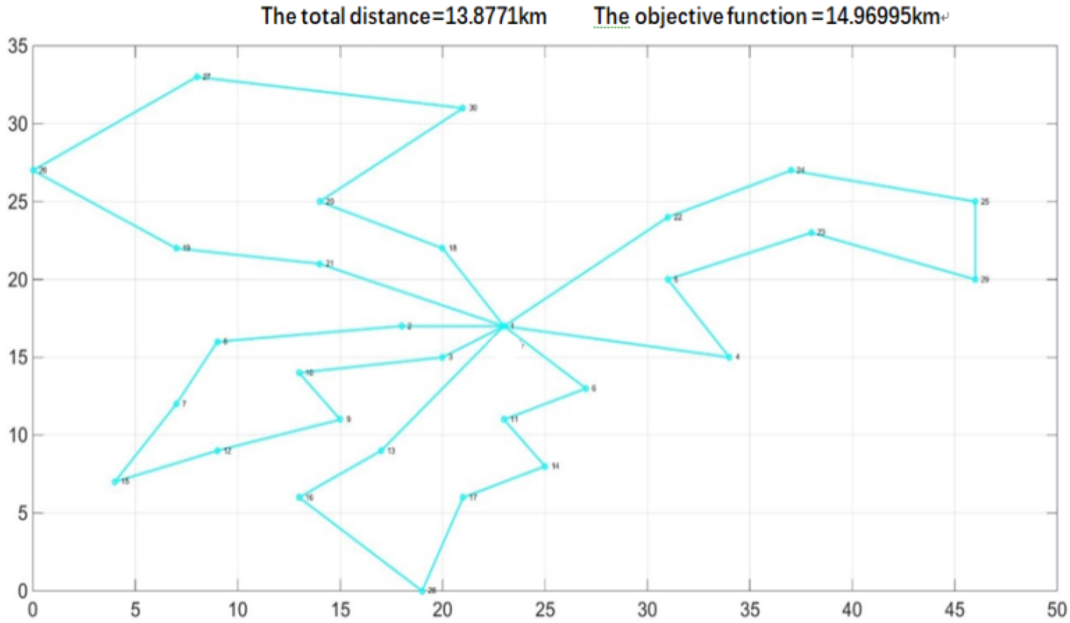

Figure 7. Path planning diagram of Hybrid algorithm

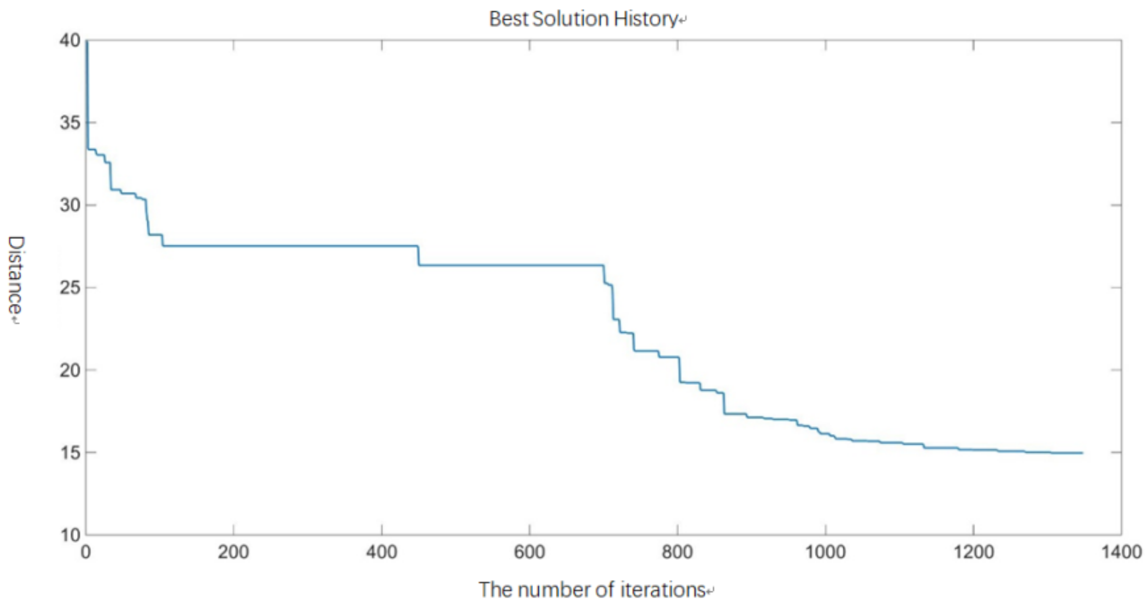

Figure 8. Iterative graph of Hybrid algorithm

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4. CONCLUSIONS

Through comparative analysis of genetic algorithm and simulated annealing algorithm, we can clearly see the advantages and disadvantages of single heuristic algorithm in the path planning problem. Although the genetic algorithm is more accurate, it is less efficient for the situation of more data. The simulated annealing algorithm is less accurate, but it is more efficient. Combining the two advantages, the hybrid algorithm is researched, which improves the ability of path planning and greatly improves the efficiency under the premise of ensuring accuracy.

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