Modeling and Optimizing Method for Charging Route Planning of Wireless Rechargeable Sensor Network

Jin Bai*, Hongyu Tan¹, Yang Yi¹, Jieyi Wang¹

¹South China University, Hengyang, Hunan, 421000, China

*Corresponding author’s e-mail: 20184570234@stu.usc.edu.cn

Abstract. Wireless rechargeable sensor network consists of a data center, several sensors and one or more mobile chargers. In order to make the wireless rechargeable sensor network (wrsn) work normally, the mobile charger needs to charge the sensor regularly to avoid its power below the threshold. The energy consumption of mobile charger will be caused when charging sensor nodes and on the way of charging sensor. In this paper, how to reasonably plan the charging route of the mobile charger and reduce the energy consumption of the mobile charger on the road are modeled. By comparing the Monte Carlo optimization simulated annealing algorithm with the improved genetic algorithm, the TSP traveling salesman problem with the minimum energy consumption of the mobile charger on the road is solved.

1. Model hypothesis
1. The data in the attachment of the hypothesis are true and reliable;
2. Suppose the mobile charger keeps moving at a uniform speed;
3. Assume that the power of each sensor is full at the beginning of the first cycle;
4. Suppose that the earth is a standard sphere with a radius of 6371km;
5. It is assumed that the charging time is consumed only at the mobile sensor;
6. Assume that the battery power of mobile charger is large enough and does not need to be charged in the data center;

2. Symbol description
Please follow these instructions as carefully as possible so all articles within a conference have the same style to the title page. This paragraph follows a section title so it should not be indented[2-3].

Table 1. Symbol description

| Symbol | Significance                        |
|--------|------------------------------------|
| f      | Minimum working power of sensor(mA) |
| v      | Moving speed of mobile charger(m/s) |
| r      | Charging rate of mobile charger(mA/s) |
| k      | Boltzmann constant                 |
| exp    | Natural index                       |
| R      | Radius of the earth                |
3. Establishment and solution of model

3.1. Conversion of longitude and latitude to actual distance

Since the data given in the annex is the longitude and latitude of each node, in order to calculate and directly describe the optimal charging route, it is necessary to convert the longitude and latitude into the actual distance.

The formula for the great circle distance (based on the cosine formula of the sphere) is as follows:

\[ AB = R \cdot \arccos(\cos(Aw)\cos(Bw)\cos(Bj - Aj) + \sin(Aw)\sin(Bw)) \]  

Where \( R \) is the radius of the earth, \( AJ \) and \( aw \) are the longitude and latitude of point a respectively; \( bj \) and \( BW \) are the longitude and latitude of point B respectively.

3.2. Problem 1: TSP traveling salesman problem of minimizing energy consumption of mobile charger on the road

If the longitude and latitude of each node are given, please consider how to plan the charging route of the mobile charger when only one mobile charger is dispatched, so as to minimize the energy consumption of the mobile charger on the road.

3.2.1. TSP problem. The first problem is to find the minimum path for a charger to start from the data center, pass through all the given sensors, and finally return to the data center, which belongs to the typical TSP traveling salesman problem.

Traveling salesman problem can also be called traveling salesman problem, traveling salesman problem, referred to as TSP problem. This problem is to start from the starting point of a single tourist, through all the required points provided, and then return to the origin to find the minimum route cost (distance or toll, etc.).

TSP problem is defined as follows: Input: the set of points (representing cities) such as \((x0, Y0), (x1, Y1),..., (xn - 1, yn - 1)\). Objective: to find the shortest length tour at the lowest cost. Calculation: stroke length = sum of distances between all points in the stroke.

3.2.2. Monte Carlo optimized simulated annealing algorithm for TSP problem. In 1953, metropolis proposed an importance sampling method. Let a new state \( j \) be generated from the current state \( I \). If the internal energy of the new state is less than the internal energy of state \( I \) (\( EJ < EI \)), then the new state \( j \) is accepted as the new current state; otherwise, the probability \( \exp \left[ - \frac{(EJ - EI)}{KT} \right] \) is used to accept the state \( j \), where \( k \) is Boltzmann constant. The above description is Metropolis criterion.

According to the metropolis (Monte Carlo) criterion, the probability of a particle approaching equilibrium at temperature \( T \) is \( \exp \left( \frac{-E}{KT} \right) \), where \( e \) is the internal energy at temperature \( T \), \( \Delta e \) is the change number, and \( K \) is the Boltzmann constant. The Metropolis criterion is often expressed as:

\[ P = \begin{cases} 1 & \text{if } E(x_{\text{new}}) < E(x_{\text{old}}) \\ \exp \left( \frac{-E(x_{\text{new}}) - E(x_{\text{old}})}{T} \right) & \text{if } E(x_{\text{new}}) < E(x_{\text{old}}) \end{cases} \]

(2)

According to the principle of thermodynamics, if the temperature is \( t \), the energy difference is expressed by \( De \), and the probability of cooling is \( P \text{(DE)} \):

\[ P(\text{d}E) = \exp \left( \frac{dE}{kT} \right) \]

(3)

The above formula shows that the higher the temperature, the greater the probability of cooling with a primary energy difference of \( P \text{(DE)} \); the lower the temperature, the less the probability of cooling.

In practical problems, the calculation of "certain probability" refers to the annealing process of metal smelting. In practical problems, the calculation of "certain probability" here refers to the annealing process of metal smelting. Assuming that the current feasible solution is \( x \) and the iterative updated solution is \( x_{\text{new}} \), then the corresponding "energy difference" is defined as:
\[ \Delta f = f(x_{\text{new}}) - f(x) \]  

(4)

The corresponding "certain probability" is:

\[
p(\Delta f) = \begin{cases} 
\exp\left(-\frac{\Delta f}{kT}\right), & \text{Minimal optimization problem} \\
\exp\left(-\frac{\Delta f}{kT}\right), & \text{Maximum optimization problem}
\end{cases}
\]  

(5)

Note: in practical problems, \( k = 1 \) can be set, that is, \( KT \) can be equivalent to a parameter \( t \). For example, setting \( k = 2 \) and \( T = 2000 \) is equivalent to setting \( T = 4000 \) directly.

The basic idea of industrial simulated annealing is to start from a given higher temperature and gradually reduce the temperature. By using the uncertainty and jumping of probability, we can randomly find the global optimal solution of the objective function in the given solution space. Even if we fall into the local optimal solution, we can also jump out of the probability and tend to the global optimal solution.

3.2.3. Improved genetic algorithm to solve TSP problem. Genetic algorithm (GA) is one of the most recent evolutionary algorithms in mathematics which is solved by the original heuristic natural selection process. Genetic algorithm usually uses mutation, crossover, selection and other biological initiators to produce high-quality optimization and search solutions. Referring to the theory of bioevolution, genetic algorithm simulates the problem as the process of biological evolution. The next generation of months and months will occur through genetic, crossover, mutation, natural selection and other operations. The year with low fitness function value will be eliminated gradually, and the year with high fitness function will increase. Like this, after \( n \) generation evolution, individuals with high adaptation are highly likely to evolve. It is generally suitable for the problem of finding the optimal solution under the condition of the objective function. This algorithm is widely used in optimization and search, and is used to find the best explanation (or best approximate solution).

Genetic algorithm to solve TSP problem, mutation operation based on binary coding is not applicable, and can not be realized by simple variable flipping. In TSP, the coding of an individual is a sequence of sensors and data centers. Two individuals are randomly extracted from this sequence, and then their positions are exchanged. In this way, the variation of item coding is realized. The algorithm steps are as follows:

Generate two random real numbers between 0 and 1; The two random real numbers are transformed into random integers from 0 to \( n \) (city number) - 1; The cities referred by these two random integers are exchanged;

3.2.4. Solution of model one. Annex I gives the longitude and latitude of 29 sensors and data center. Simulated annealing algorithm and genetic algorithm are used to find the optimal path from the data center to traverse all the sensors and finally return to the data center. Then longitude and latitude are converted into radians, and the actual distance between each sensor can be obtained by using the earth half diameter calculation.

3.2.4.1. Monte Carlo optimization of simulated annealing algorithm results. According to the data given in the attachment, based on Monte Carlo optimization simulated annealing algorithm, Matlab is used to solve the model (see the appendix for the specific code), and the optimal path is obtained as shown in the figure.
The optimal route scheme obtained by Monte Carlo optimization simulated annealing algorithm model is [0; 1; 2; 12; 8; 9; 7; 6; 11; 14; 15; 27; 16; 13; 10; 5; 3; 4; 22; 24; 23; 21; 29; 26; 25; 18; 19; 20; 17; 0] (0 is the data center, the rest are sensors), and the actual distance of this route scheme is 11179.7m.

3.2.4.2. Improved genetic algorithm results. According to the data given in the appendix, based on the improved genetic algorithm, Matlab is used to solve the model (see the appendix for the specific code), and the optimal route is obtained.
Figure 3. Improved genetic algorithm to find the optimal rout

The optimal path obtained by the improved genetic algorithm model is [0; 17; 20; 19; 18; 25; 26; 29; 21; 23; 24; 28; 22; 4; 3; 5; 10; 13; 16; 27; 15; 12; 8; 11; 14; 6; 7; 9; 1; 2; 0] (0 is the data center and the rest is the sensor). The actual distance of the scheme is 11438.0m.

Figure 4. Improved genetic algorithm to get the actual distance

4. Conclusion

By comparing the results of the two algorithms, we find that the result of Monte Carlo optimization simulated annealing algorithm is better than that of improved genetic algorithm. Therefore, the final optimal route scheme is [0; 1; 2; 12; 8; 9; 7; 6; 11; 14; 15; 27; 16; 13; 10; 5; 3; 4; 22; 24; 23; 21; 29; 26; 25; 18; 19; 20; 17; 0] (0 is the data center, the rest are sensors), and the actual distance of the optimal route scheme is 11179.7m, as shown in Figure 6 above.

References

[1] Yang Guiyuan, Zhu Jiaming, evaluation of excellent papers in mathematical modeling contest [M]
University Press of Chinese Academy of Sciences, 2013

[2] Cui Peng: a solution to multi-source traveling salesman problem [J]; forum of the Association for science and Technology (second half of the month); issue 09, 2010Mettam, G.R., Adams, L.B. (2009) How to prepare an electronic version of your article. In: Jones, B.S., Smith, R.Z. (Eds.), Introduction to the Electronic Age. E-Publishing Inc., New York. pp. 281-304.

[3] Wang Hailong; Zhou Huiren; Wei Yinghui; research on a kind of multi traveling salesman problem based on genetic algorithm [J]; computer application; issue 01, 2009.

[4] Li Fei; Bai Yanping; solving traveling salesman problem with genetic algorithm [J]; Journal of North China University (NATURAL SCIENCE EDITION); 2007-01.

[5] Finney, D. L. et al. A projected decrease in lightning under climate change. Nat. Clim. Chang. 8, 210–213 (2018).

[6] IPCC. Summary for Policymakers. in IPCC Special Report on the Ocean and Cryosphere in a Changing Climate (IPCC, 2019).