Research on Optimum Algorithm of Charging Pile Location for New Energy Electric Vehicle

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Abstract. Artificial intelligence algorithms such as ant colony algorithm and neural network do not need to rely on a large amount of gradient information when solving, especially for large-scale complex optimization problems which are difficult to solve by traditional methods, which provides a new perspective and thinking direction for solving such problems. Based on the analysis of the principles and advantages and disadvantages of RBF neural network and ant colony algorithm, this paper proposes a RBF neural network based on genetic mutation improved ant colony clustering algorithm to evaluate the location of charging station. The improved ant colony clustering algorithm based on genetic variation is used to determine the number of hidden layers of RBF neural network, so as to solve the problem that the initial parameters of RBF neural network can not be accurately selected without scientific methods. An example is used to prove the scientific and effectiveness of this method. Finally, the optimal scheme of charging station location is determined by comparing the comprehensive ranking values obtained by various methods used in this paper to judge the advantages and disadvantages of charging station location.

Key words: new energy; automobile; charging pile; algorithm optimization.

1. Introduction
Under the environment of global energy internet, electric vehicles, as integrated products of modern high-tech technologies such as new energy, new materials, new directions and new technologies, will bring about tremendous changes in energy, transportation, power, communications and other industries. This change may become an important driving force of the new energy revolution. At present, there are some problems in the construction of charging stations as basic supporting facilities, such as inconsistent understanding, imperfect policy support, difficult coordination and promotion, and imperfect standards, which seriously restrict the scale development of the electric vehicle industry.

In order to build charging stations more scientifically and regularly, this paper discusses the necessity and urgency of scientific location optimization of charging stations on the basis of fully considering the integration of electric vehicles and energy internet. Artificial intelligence algorithms such as ant colony
algorithm and neural network do not need to rely on a large number of gradient information to solve, so they are widely used in many disciplines and fields. Especially for large-scale complex optimization problems which are difficult to be solved by traditional methods, the application of artificial intelligence algorithm provides a new perspective and thinking direction for solving such problems[1].

2. RBF Neural Network
Radial Basis Function (RBF) neural network has simple structure, and its output is linear with input. Moreover, the function theory is compatible with the function approximation theory, which can approximate any non-linear system, especially for dealing with the problem of non-linear uncertain systems. RBF neural network has three layers: input layer, hidden layer and output layer. The activation function of neurons in the hidden layer is composed of radial basis function. Compared with multi-layer feedforward network, RBF network has good generalization ability and simple structure, which can reduce the complicated calculation process[2].

However, RBF neural network also has some defects and shortcomings. It is important to set the initial parameters for the traditional RBF learning algorithm. The traditional RBF learning algorithm relies too much on the number of clusters assumed by the initial sample data and the clustering center vector. And the selection of clustering centers mostly depends on the experience of past calculation, which is not accurate enough[3]. In addition, the traditional RBF algorithm is not a precise search process, but a rough search, so it is very easy to fall into local optimum, which will directly affect the final training results of RBF neural network. Therefore, this paper will use ant colony clustering algorithm to optimize and improve the traditional RBF algorithm, and then improve the accuracy of the algorithm to avoid local optimum[4].

3. Ant Colony Correlation Algorithms
Clustering methods based on ant colony algorithm can be divided into two kinds in principle: one is based on the formation principle of ant tombs and categorized larvae; the other is based on the number of pheromones secreted to achieve clustering analysis. In this paper, ant colony clustering algorithm based on foraging principle is used to cluster. Clustering analysis algorithm based on pheromone residue regards data object as ant population with several attributes, and regards the center of clustering as food source for ants to search for food. Unlike ant-based tomb construction and categorized larvae clustering, pheromone residue-based clustering analysis algorithm needs to specify the number of clusters K in advance. We assume that there are N data objects to be analyzed, and each data object has n attributes. Clustering analysis is to divide N objects into K classes according to certain partitioning rules, which makes the similarity and difference between classes the greatest[5].

The concrete steps of solving ant colony clustering algorithm are as follows:

1) Assuming that the number of ants is R, the maximum number of iterations is t_max, the dimension of the matrix of pheromone is N*K (sample number*cluster number), and the initial value is 0.01;

2) According to the size of pheromone value in pheromone matrix, we determine the path of ants. If the value of all pheromones in the sample is less than the pheromone threshold q, we choose the path with the largest pheromone value as the walking path in the process of finding food; if the value of pheromone is greater than the threshold q, we change the method to find the proportion of each path pheromone to the total pheromone of the sample, and determine the selection path according to the calculated probability size. After the path is determined, the identification character matrix is defined, and the dimension of the matrix is R*N+1. In order to calculate the initial value better and more conveniently, this paper defines 0 here.

3) According to the identified Path label, we find the clustering centers of each class and calculate the total deviation error F from the sample data to the corresponding clustering centers according to the formulas listed above[6]. According to the calculated value of F, we determine the best path at this time. The smaller the deviation error is, the better the clustering effect is.

4) We update the pheromone matrix by multiplying the original pheromone value by (1-rho) (where Rho denotes pheromone evaporation rate) plus the reciprocal of the minimum deviation value.
(5) After updating the pheromone matrix, we judge the selected path according to the new pheromone matrix.

(6) We calculate iteratively until the number of iterations reaches the maximum value or deviation error specified in this paper.

According to the specific calculation steps of the ant colony clustering algorithm, we can draw the flow chart of the traditional ant colony clustering algorithm as shown in Figure 1.

![Ant colony algorithm flow chart](image)

**Fig. 1** Ant colony algorithm flow chart

The purpose of using improved ant colony clustering algorithm based on genetic variation to determine the number of hidden layers of RBF neural network is to solve the problem that there is no scientific and systematic method to select the initial parameters of traditional RBF neural network. Because the ant colony clustering algorithm based on pheromone residue is used in this chapter, the number of clusters needs to be determined in advance\[7\].

In order to make clustering representative, the range of the number of clusters is $1 < K < N^2$. The best_solution variable is defined as the best path metric, and the initial value is defined as infinite and varies with the number of clusters. The criterion of judgment is that the smaller the best path metric is, the better the clustering effect is under the number of clusters\[8\].

| Clustering individual $K$ | 2   | 3   | 4   | 5   |
|--------------------------|-----|-----|-----|-----|
| Optimal path measure     | 9.7522 | 8.2767 | 7.0256 | 5.6970 |

**Table 1.** Optimal path measures corresponding to different clustering numbers
From Table 1, we can see that when the number of clusters is 5, the corresponding best path metric is the smallest. At this time, the cluster center values are shown in Table 2.

|   | c1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 | c10 | c11 | c12 | c13 | c14 | c15 | c16 |
|---|----|----|----|----|----|----|----|----|----|-----|-----|-----|-----|-----|-----|-----|
| 1 | 0.3| 0.3| 0.3| 0.9| 0.5| 0.29| 0.5| 0.3| 0.4| 0.4  | 0.3  | 0.6  | 0.3  | 0.5  | 0.5  |
| 2 | 0.1| 0.01| 0.5| 0.3| 0.5| 0.45| 0.8| 0.9| 0.7| 0.7  | 0.8  | 0.9  | 0.9  | 0.9  | 0.9  |
| 3 | 0.9| 0.8| 0.4| 0| 0.03| 0.45| 0.8| 1  | 0.6| 0.8  | 0.9  | 0.8  | 1    | 1    | 1    |
| 4 | 1  | 1  | 1  | 0.8| 0.9| 1    | 0.4| 0.2| 0.2| 0.2  | 0.1  | 0.2  | 0.3  | 0.2  | 0.2  |
| 5 | 0.1| 0.9| 0.3| 0.3| 0.1| 0.3  | 0.6| 0.8| 0.6| 0.7  | 0.65 | 0.8  | 0.75 | 1    | 0.8  |

When the number of clusters is 5, the spatial distribution clustering results of the alternative sites are shown in Fig. 2.

Ant colony clustering results (R=100, t=1000)

![Fig. 2 Clustering results with the number of clusters 5](image)

Therefore, in this chapter, we set the number of hidden layers of RBF neural network as the number of ant colony clustering is 5. The central value of the ant colony corresponding to the cluster number of 5 is taken as the central value of the hidden layer of RBF neural network.

4. Evaluation of Charging Station Location Based on RBF Neural Network

In order to get better prediction results, 100 training samples are selected to train the RBF neural network. After the training, we use the trained RBF neural network to predict the comprehensive evaluation value of the 10 candidate sites in Chapter 3 and determine the order of the 10 candidate sites according to the prediction results. In this study, we use newrb function to create a radial basis function (RBF) neural network, which defines the number of neurons added between two displays as 3. After training with 100 training samples, we can get the mean square error MSE of the neural network corresponding to the number of different training samples. Because of the large number, some data are selected here as shown in Table 3.

| Neurons | 0   | 9   | 18  | 27  | 36  | 45  | 54  | 63  | 72  | 81  | 90  | 99  |
|---------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| MSE     | 0.0071| 0.00243| 0.00092| 0.00059| 0.00030| 0.000198| 0.0001059| 5.653| 2.695| 1.233| 3.591| 2.81|

The change of error in sample training is shown in figure 3.
Fig. 3 The variation of error with the number of neurons

Fig. 4 Training results of each sample

The training results of each training sample are shown in Fig. 4. Through this graph, we can see that the training samples can be trained by the RBF neural network constructed above, which is very close to the actual value. The RBF neural network constructed can obtain the comprehensive evaluation value of the predicted alternative sites as shown in Table 4.

**Table 4.** Comprehensive evaluation and sequencing of each location.

| Address | 1    | 2    | 3    | 4    | 5    | 6    | 7    | 8    | 9    | 10   |
|---------|------|------|------|------|------|------|------|------|------|------|
| Value   | 0.6144 | 0.4805 | 0.4708 | 0.602 | 0.4386 | 0.5519 | 0.5637 | 0.5255 | 0.4924 | 0.4064 |
| order   | 1    | 7    | 8    | 2    | 9    | 4    | 3    | 5    | 6    | 10   |
5. Comparative analysis of methods
Because of the inconsistency of measurement data used in each method, this paper can not judge the advantages and disadvantages of each alternative station location by comparing the simulation values. However, the ranking of alternative station location under different methods is the result after eliminating the inconsistency of measurement data. Therefore, it is reasonable to synthetically judge the reasonable degree of each alternative station location by comparing the advantages and disadvantages of different methods.

The sequence of alternative station location corresponding to different judgment methods is shown in Table 5.

| address          | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|------------------|---|---|---|---|---|---|---|---|---|----|
| Weight method    | 2 | 7 | 6 | 1 | 10| 3 | 4 | 5 | 8  | 9  |
| BP method        | 1 | 7 | 5 | 2 | 9 | 3 | 4 | 6 | 8  | 10 |
| GA-BP development model | 2 | 8 | 6 | 1 | 10| 4 | 3 | 5 | 7  | 9  |
| Ant colony algorithm | 3 | 7 | 5 | 1 | 10| 4 | 2 | 6 | 8  | 9  |

Through the analysis of table 5, we can see that the alternative station location 4 and 1 are better, and the overall ranking is higher; the alternative station location 5 and 10 rank lower under each method. This paper considers that there are several indicators in the index system constructed by this paper that are not satisfied or have a great impact on the location of charging stations, which do not meet the needs of scientific and reasonable location of charging stations. In view of the above considerations, the alternative station location 4 and the alternative station location 1 are the primary options for the construction of charging stations under these conditions.

6. Conclusion
Based on the analysis of the principles and advantages and disadvantages of RBF neural network and ant colony algorithm, this paper proposes a RBF neural network based on genetic mutation improved ant colony clustering algorithm to evaluate the location of charging station. The improved ant colony clustering algorithm based on genetic variation is used to determine the number of hidden layers of RBF neural network, so as to solve the problem that the initial parameters of RBF neural network can not be accurately selected without scientific methods. An example is used to prove the scientific and effectiveness of this method.

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