Research on Material Allocation Path Based on Hopfield Neural Network and Simulated Annealing Hybrid Algorithm

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Abstract: When a natural disaster occurs, in order to ensure the basic material needs of the affected people, the delivery of emergency materials after the disaster occupies a very important position. Aiming at the defects that the Hopfield neural network algorithm is easy to fall into local optimum and the simulated annealing algorithm convergence speed is too slow, a hybrid neural network algorithm (SA-HNN) is proposed. Combining the advantages of Hopfield neural network and simulated annealing algorithm, the simulated annealing algorithm is the mechanism of receiving a poor solution with a certain probability is applied to the Hopfield neural network algorithm, which overcomes the defect that the neural network is easy to fall into the local optimal. Based on this hybrid algorithm, the vehicle distribution path optimization problem is solved. Compared with the traditional neural network algorithm, the algorithm is improved Calculation efficiency and accuracy.

1. Introduction

In recent years, the public emergencies emerge in endlessly inside cities with the frequent occurrence of natural disasters in the country, which have brought great difficulties to the post-disaster rescue, supplies distribution and personnel evacuation[1 ~ 3]. It is very necessary to formulate the scientific and reasonable emergency plan to minimize casualties and property losses caused by disasters and meet the basic needs of the people afflicted by the disasters [4 ~ 6], so it is of significance for the distribution of emergency supplies after disasters. At present, the research on the distribution of emergency supplies at home and abroad mainly focuses on the fairness and minimum distribution cost. The satisfaction of supplies demand and delivery time are considered in terms of fairness, the shortest transportation distance of vehicles or the minimum transportation time of vehicles are considered in terms of total distribution cost.

The mathematical model with maximizing the supplies satisfaction at the demand point as the optimization objective is set up by BEHESHTI and others based on this, and the evolutionary algorithm is adopted to solve the problems [7]; it is proposed by Tzeng and others that the multi-objective programming model with the consideration of the fairness of the supplies distribution is adopted in the distribution of emergency relief supplies, which can avoid the excessive deviation of satisfaction at some demand points in the distribution of emergency supplies [8]; Wang Ting and others considered the transit time of road vehicles and the road safety factor, designed a multi-objective path optimization algorithm, and then solved the model with a mountain climbing algorithm[9]; the research on the post-disaster relief and supplies distribution under the uncertain
information is conducted by Balcik and others, and the emergency supplies distribution model from supply point to resource demand point is set up with minimizing the total cost as the objective [10]. The combination of simulated annealing algorithm and genetic algorithm is adopted in terms of the path optimization of the supplies distribution by Ji Junjie, the efficiency and global optimization ability of the algorithm have been greatly improved with the combination of the trigonometric inequality theorem [11]; the emergency logistics network is set up by Gan Xizhi based on BP neural network algorithm, the theoretical modeling and simulation implementation have been completed by means of the research on the heuristic approach [12]. The shortest distribution distance is taken as the objective function in this article, the optimal path is to be obtained by means of Hopfield neural network and simulated annealing algorithm, and the advantages of hybrid algorithms are to be obtained compared with the traditional algorithms.

The continuous Hopfield neural network can be adopted well in terms of the path optimization, the network can reach the stable state according to the minimum energy function, at this point, the result is the optimal path after the optimization calculation. The high parallelism of neural network algorithm is adopted in the neural network-simulated annealing hybrid algorithm proposed in this article, which can greatly improve the speed and convergence of the algorithm. During the training of simulated annealing algorithm, the amount of adjustment to the connection weight is to be determined according to the temperature and energy of the network, the worse value can be accepted with the certain probability, and the results are to be fed back to the neural network, which can overcome the shortcoming that Hopfield network algorithm is easy to fall into local optimal solution, and the global optimal solution can be obtained effectively [13].

2. Continuous Hopfield Neural Network Model

The excitation function of the neurons in the continuous Hopfield neural network is a continuous function, and the working mode between the neurons is parallel. The network structure diagram is shown in Figure 1:

![Fig. 1 Structure diagram of Hopfield neural network](image)

It can be seen that there are two sets of inputs in each neuron in the structure: 1. constant external input; 2. feedback input from other neurons connected to it, which is the connection weight $w_{ij}$ between two neurons in the neural network.

In terms of the continuous Hopfield neural network model, the definition of energy function is listed as follows:

$$E = \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij} y_i y_j + \sum_{i=1}^{N} \int_{\mathbb{R}} f^{-1}(v_i) d\nu_i \sum_{i=1}^{N} I_i$$  \hspace{1cm} (1)
In general, the second term of the above equation is extremely small, and it can be omitted as a general rule, so the energy function is turned into:

\[ E = -\frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij} v_i v_j - \sum_{i=1}^{N} I_i v_i \]  

(2)

It is easy to prove that the energy function is monotonically decreasing according to Kirchhoff’s Current Law, and the energy function is bounded, the continuous Hopfield neural network is convergent and stable according to the sequence convergence theorem, that is the initial state of the network is provided, the iteration of energy function can be conducted until the local minimum is obtained.

3. Simulated Annealing Algorithm

The effective random searching technique for the physical annealing process of metal can be provided in the simulated annealing algorithm, any point in the search space is taken as the initial point, and a point in the field is to be selected based on the step size in each step, the probability of this step can be accepted according to the formula, and it is decided whether to accept this step change (status change) by means of Monte Carlo Method. The energy of the atoms in the metal (the neural network) can be improved by means of raising the temperature in this method, which can provide the ability for these atoms to get out of their original energy state and into a more stable state, that is global minimum energy state, the energy state distribution in the process is determined by the following relation:

\[ P(E) \propto \exp\left(-\frac{E}{kT}\right) \]  

(3)

Among this, \( P(E) \) indicates the probability that the energy of the system is E, \( k \) indicates Boltzmann constant, \( T \) indicates the absolute temperature of the system.

When the temperature is very high, the contribution of \( E \) in the above equation is very small, so for all the states \( E \), the value of \( P(E) \) is going to approach 1, the probability that the network is in high energy state and a low energy state are both very high; as the temperature declines, the weight of \( E \) is bigger and bigger in the above equation, the bigger \( E \) is, the smaller probability of \( P(E) \) is, that is, the probability that the system is in the high energy state is less than the probability that it is in the low energy state; when the temperature drops to near zero, only the energy function is close to zero, and the probability of \( P(E) \) is not zero, so the probability that the system is in the high energy state is almost zero, at this very moment, the probability that the system is in the low energy state is much higher than the probability in the high energy state.

4. Hopfield Neural Network - Simulated Annealing Hybrid Algorithm

By means of the above analysis, the process of neural network training can be seen as the process of the neural network to find the lowest energy state spontaneously, let the energy function of the network be the objective function of the problem to be solved. The initial temperature with higher value is defined at the beginning, and the initial state of the network is selected randomly, during the training of the network, the adjustment amount \( \Delta w_{ij}^{(p)} \) (step size) of the connection weight of the neural network unit is to be determined according to the energy state and temperature of the network, then the energy change of the network can be calculated at this moment:

\[ \Delta E = E\left[w_{ij}^{(p)} + \Delta w_{ij}^{(p)}\right] - E\left[w_{ij}^{(p)}\right] \]  

(4)

if \( \Delta E < 0 \), the disturbance is to be accepted; if \( \Delta E \geq 0 \), it need to judge whether the disturbance is acceptable according to the above probability distribution and Monte Carlo criterion.
disturbance is accepted, the system is to be changed from state \( \{ w_{ij}^{(p)} \} \) to state \( \{ w_{ij}^{(p)} + \Delta w_{ij}^{(p)} \} \); if the disturbance is not accepted, the state of the system remains unchanged.

Steps of the algorithm:
1. The connection weight matrix of each unit in the neural network is initialized, the initial temperature with higher value is set and the annealing method is specified;
2. The sample is selected randomly, \( w_{ij}^{(p)} \) is to be selected from his connection weight matrix \( \{ w_{ij}^{(p)} \} \), then the adjusted value \( \Delta w_{ij}^{(p)} \) of \( w_{ij}^{(p)} \) is generated according to the certain algorithm;
3. The energy function \( E(\{ w_{ij}^{(p)} \}) \) and the adjusted energy function \( E(\{ w_{ij}^{(p)} + \Delta w_{ij}^{(p)} \}) \) are to be calculated, and the difference value between the two is to be calculated, if the difference value is greater than zero: (1) a random number \( r \) is selected within the uniform distribution interval of \([0,1]\); (2) then the probability of accepting this adjustment is calculated according to Boltzmann distribution:

\[
P \left( E(\{ w_{ij}^{(p)} + \Delta w_{ij}^{(p)} \}) \right) = \exp \left( \frac{E(\{ w_{ij}^{(p)} + \Delta w_{ij}^{(p)} \})}{kT} \right)
\]

Comparing the probability \( P \) calculated in the above equation with the random number \( r \), if \( P \) greater than \( r \), the adjustment should be accepted, otherwise it should be changed to the step 2, until all the samples are adjusted once;
4. Determine whether the stable state can be reached at this temperature, if not, lower the temperature and repeat the above steps, if it can reach the stable state, jump out of the loop;
5. Check whether the temperature is small enough. If it is small enough, it is to be ended, otherwise turned to step 2.

A weight for all samples should be adjusted in the step 2 of the algorithm, and the order of adjustment for each sample is random, the value of adjustment amount can be calculated according to the following discussion: firstly, the step size \( \alpha \) should be defined for the probability distribution function according to the precision of the network, then the integral value within each step size interval is to be calculated by means of the numerical integration, the specific details are listed as follows:

| Table1 The corresponding relationship between adjustment amount and integral value |
|------------------|---------|---------|---------|------------------|
| \( \Delta w_{ij}^{(p)} \) | \( \alpha \) | \( \alpha \) | \( \alpha \) | \( N\alpha \) |
| \( \int_0^{\Delta w_{ij}^{(p)}} p(x)dx \) | \( C_1 \) | \( C_2 \) | \( \ldots \) | \( C_N \) |

According to the above table, a value \( C \) that's uniformly distributed in \([ C_1, C_N ]\) should be selected randomly, and then according to the formula:

\[
|C_k - C| = \min \left[ \left| C_1 - C \right|, \left| C_2 - C \right|, \ldots, \left| C_N - C \right| \right]
\]

The \( k\alpha \) corresponding to \( C_k \) is the adjustment amount \( \Delta w_{ij}^{(p)} \) of the required connection weight.

5. Mathematical Model for Emergency Supplies Distribution
5.1 Background of model construction

It can be named as the demand point for the area in need of supplies after the earthquake, its center is the geographic location in the demand area, it can be called the distribution center for the point of supplies. There are multiple demand points in the disaster area under normal conditions, and a distribution center is set up, it is assumed that the driving process of the vehicle should satisfy: In the process of supplies distribution, the construction of the distribution model that the car starts from the distribution center and returns to the distribution center eventually, the distribution is conducted in each demand point by one car at a time is listed as follows:

The dispatch center is responsible for transporting supplies for \( N \) demand points, it is ruled that the vehicle should start from the dispatch center and transport the supplies to the demand point in turn, and then back to the dispatch center finally, each demand point in the process can only be provided by one vehicle, which can only transport supplies to one point at a time. The number of dispatch center is 0, number of the demand points is 1, 2, 3... \( N \), the following variables are defined:

\[
x_{ij} = \begin{cases} 
1 & \text{The vehicle travels from point } i \text{ to point } j \\
0 & \text{else}
\end{cases}
\]

The mathematical model for vehicles optimal scheduling problem can be obtained:

\[
\begin{align*}
\min Z &= \sum_{k=1}^{O} \sum_{i=1}^{N} \sum_{j=1}^{N} d_{ij} x_{ij} \\ 
\sum_{k=1}^{O} \sum_{j=1}^{N} x_{ij} &= 1, \quad i = 1, \ldots, N \quad (7) \\
\sum_{j=1}^{N} x_{ij} &= 1, \quad j = 1, \ldots, N \quad (8) \\
\sum_{i=1}^{N} x_{ih} - \sum_{j=1}^{N} x_{ij} &= 0, \quad h = 1, \ldots, N \quad (9) \\
\sum_{i=1}^{N} x_{i,n+1} &= (11)
\end{align*}
\]

In the model, \( c_{ij} \) indicates the distance cost from point \( i \) to point \( j \), \( k \) indicates the number of the transport vehicle, equation (7) is the target function; it is restricted by equation (8) that each demand point can only be accessed once; it is restricted by equation (9), (10), (11) that the car starts from the distribution center and returns to the distribution center eventually after transporting the supplies to all the demand points.

5.2 Expression of model meaning

In terms of the distribution of emergency supplies, the starting point, passing point and ending point of the vehicle should be abstracted to the nodes in the network, the directed path between them should be abstracted to the edges of the network, so the directed graph \( G=(N, L, D) \) can be obtained, \( N \) indicates the number of nodes, \( L \) indicates the number of edges, and \( D \) indicates the distance adjacency matrix of nodes. The value of the corresponding matrix element is the length of the path if there is a path between two nodes; the value of the corresponding matrix element is \( \infty \) if there is no path between two nodes.

Representation method of vehicle path: as shown in the following table, rows indicate the order of vehicle delivery, and columns indicate the order number of the dispatch center (0) and the demand point (1, 2... \( N \)).

| Table2 Distribution sequence of supplies at deployment points |
|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
|                   | 1                | 2                | 3                | 4                | 5                | 6                | 7                | 8                |
|                   | 1                | 2                | 3                | 4                | 5                | 6                | 7                | 8                |

5
Suppose \( x \) and \( y \) to be node numbers, \( i \) and \( j \) indicate distribution sequence of the vehicles, the model can be set up as follows:

\[
\sum_{x \neq 0} \sum_{i \neq x} \sum_{j \neq i} V_{xi} V_{xj} = 0 \quad (12)
\]

\[
\sum_{i \neq x} \sum_{j \neq x} \sum_{y \neq x} V_{xi} V_{yi} = 0 \quad (13)
\]

\[
\left( \sum_{i \neq x} \sum_{j \neq i} V_{xi} - n \right)^2 \quad (14)
\]

\[
V_{01} = 1 \quad (15)
\]

It is indicated in the equation (12) that there is at most one non-zero element in every other row except the first row in the permutation matrix, and it is indicated in the equation (13) that there is at most one non-zero element in each column of the matrix, it is indicated in the equation (12), (13) and (14) that the vehicle is required to pass through the demand point only once, and must be only once, then return to the dispatch center; it is indicated in the equation(15)that the vehicles must leave from the dispatch center.

Objective function:

\[
f = \min \left[ \frac{1}{2} \sum_{x \neq y} \sum_{j \neq i} \left( V_{yj+1} + V_{yj+1} \right) \right] \quad (16)
\]

5.3 Model calculation

Each element in the distance adjacency matrix is corresponded to a neuron, the output of the neuron at \((x, i)\) is defined as \( V_{xi} \). The energy function of the network includes the output energy function of the network and the energy function transformed by each constraint, the specific details are listed in the following formula:

\[
E = \frac{A}{2} \sum_{x} \sum_{y \neq x} V_{xy} + \frac{B}{2} \sum_{x} \sum_{y \neq x} V_{xy} + \frac{D}{2} (V_{01} - 1)^2 + \frac{C}{2} \left( \sum_{x} V_{xi} - n \right)^2 + \frac{E}{2} \sum_{x} \sum_{y \neq x} d_{xy} (V_{yj+1} + V_{yj+1}) \quad (17)
\]

The first three items of the above energy function can be reduced to:

\[
E = \frac{A}{2} \sum_{x} \left( \sum_{y} V_{xy} - 1 \right)^2 + \frac{B}{2} \sum_{x} \left( \sum_{y} V_{xy} - 1 \right)^2 + \frac{C}{2} (V_{01} - 1)^2 + \frac{D}{2} \sum_{x} \sum_{y \neq x} d_{xy} V_{xi} V_{yj+1} \quad (18)
\]

The structure of the neural network can be inversely deduced after the energy function is obtained, that is the weight \( w_{ij} \) of the neuron and the external offset input \( I \), the corresponding dynamic equation of the neural network is set up from the network structure, the iteration can reach the stable state with the combination of the simulated annealing algorithm, which is the global optimal solution for the problem.
6. Case

6.1 Case background
It is supposed there is an earthquake in one place and 10 emergency supplies have been set up, the coordinates of the dispatching center (No.0) and the demand point are shown in the following table, it is required that the vehicles should serve all distribution points of the emergency supplies, and there must be only one vehicle for transporting relief supplies at each demand point, the optimal distribution path for the distribution of emergency supplies in trial planning should be conducted to minimize the sum of the transportation paths of the vehicles:

| Demand point number | X axis coordinate/km | Y axis coordinate/km | Demand point number | X axis coordinate/km | Y axis coordinate/km |
|---------------------|----------------------|----------------------|---------------------|----------------------|----------------------|
| 0                   | 0.1                  | 0.6                  | 6                   | 0.2                  | 0.8                  |
| 1                   | 0.2                  | 0.3                  | 7                   | 0.5                  | 0.9                  |
| 2                   | 0.4                  | 0.1                  | 8                   | 0.7                  | 0.6                  |
| 3                   | 0.5                  | 0.5                  | 9                   | 0.9                  | 0.8                  |
| 4                   | 0.7                  | 0.2                  | 10                  | 0.3                  | 0.6                  |
| 5                   | 0.8                  | 0.4                  |                     |                      |                      |

The dispatch center and deployment points are represented on the coordinate axis shown in the figure below:

Fig. 2 Location map of deployment center and demand points

6.2 Interpretation of results
The distribution paths of the supplies can be obtained after the Matlab simulation, The results are shown in Figure 3, The iteration process of the energy function of the hybrid algorithm and the traditional Hopfield neural network energy function is listed as follows:
Fig. 4 Iteration process of simulated annealing - Hopfield algorithm energy function

Fig. 5 Iteration process of traditional Hopfield neural network algorithm energy function

The hybrid algorithm is compared with the separate neural network algorithm, and the results are listed in the table below:

Table 4 Optimization scheme for paths

| algorithm                  | path                      | Operation time/s | Distance/km   |
|----------------------------|---------------------------|------------------|---------------|
| Hybrid algorithm           | 0→1→3→2→4→5→8→9→10→6→7→10→6 | 0.7916481        | 3.131850017974|
| Neural network algorithm   | 0→10→1→2→4→5→3→8→7→9→6   | 0.8274401        | 3.25898432786 |

By means of the comparison of the above results, it can be found that the optimization speed of the hybrid algorithm is faster than that of the traditional Hopfield neural network algorithm, in addition, the phenomenon of the energy mutation occurs in the middle of the energy function iteration process of the neural network algorithm, which indicates that the Hopfield neural network falls into a local minimum value in the iteration process with the influence on the accuracy and speed of the algorithm. By contrast, Hybrid algorithms can avoid this process, which speeds up the iteration speed and accuracy of the algorithm.

At the same time, the operation time of the two algorithms is respectively: the running time of simulated annealing - Hopfield hybrid algorithm is 0.7916481s, and the running time of the traditional Hopfield neural network algorithm is 0.8274401s, the same conclusion can be drawn by means of the comparison of the two.

7. Conclusion
At present, the idea of the global optimization has been unanimously accepted. The idea of global optimization is adopted to solve the problem of the supplies distribution of the vehicles in this article, firstly, the current situation of logistics at home and abroad is summarized and analyzed, and the methods of the global optimization are summarized, ensuring the global convergence of the algorithm, which is the most significant point that the proposed algorithm is superior to the traditional Hopfield neural network algorithm. The idea in this algorithm that the worse solution can be accepted with a certain probability by means of simulated annealing algorithm has avoided the Hopfield neural network falling into the locally optimal situation, which improves the accuracy and efficiency of the algorithm, and it is applied for the solution of the actual problem of the emergency supplies distribution with excellent effects.

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Reference

[1] Wang Fuyu, Ye Chunming, Wang Tao. Optimization of emergency material distribution routes under urban emergencies[J]. Journal of Anhui University of Technology (Natural Science Edition), 2016, 33(02): 177-184(in Chinese).

[2] Tang Zhihua. Research on LRP optimization of emergency logistics based on floyd and genetic algorithm [J]. Modern Business Industry, 2019, 40(19): 25-28(in Chinese).

[3] Yan Junai, Guo Yiyuan. Research on the optimization of the path of relief supplies transportation for unconventional emergencies[J]. Disaster Science, 2016, 31(01): 193-200(in Chinese).

[4] Wang Li; Zhou Xiancheng; Zhao Zhixue; Liu Limei; Yu Lingli. Integrated Decision of Emergency Vehicle Allocation and Emergency Material Delivery. Journal of Central South University (Natural Science Edition) 2018, 49 (11), 2766-2775(in Chinese).

[5] Chen Gang, Shuai Bin. Research on road emergency repair and optimal dispatch of emergency materials after the earthquake[J]. Chinese Journal of Safety Science, 2012, 22(09): 166-171(in Chinese).

[6] Xu Qin, Ma Zujun, Li Huajun. The location of urban public emergencies in emergency logistics-research on the path problem [J]. Journal of Huazhong University of Science and Technology (Social Science Edition), 2008(06): 36-40(in Chinese).

[7] Beheshti, A. K.; Hejazi, S. R.; Alinaghian, M., The vehicle routing problem with multiple prioritized time windows: A case study. Comput. Ind. Eng. 2015, 90, 402-413.

[8] Tzeng, GH; Cheng, HJ; Huang, TD, Mufti-objective optimal planning for designing relief delivery systems. Transp. Res. Pt. e-Logist. Transp. Rev. 2007, 43 (6), 673-686.

[9] Wang Ting; Guo Qiqian; Zhang Yumei, Research on post-earthquake rescue material resource distribution path planning. Computer simulation 2018, 35 (01), 321-326+344(in Chinese).

[10] Balci, B.; Beamson, B. M.; Smilowitz, K., Last mile distribution in humanitarian relief. Journal of Intelligent Transportation Systems 2008, 12 (2), 51-63.

[11] Ji Junjie. Research and implementation of path optimization algorithm in logistics distribution [D]. Southeast University, 2016(in Chinese).

[12] Gan Xizhi. Research on the construction of emergency logistics network based on BP algorithm[J]. Business Economics, 2018(08): 27-29+136(in Chinese).

[13] Wang Qiang. Research on supermarket logistics distribution route optimization based on simulated annealing algorithm [J]. Journal of Guangzhou Maritime University, 2019, 27(03): 39-41+48(in Chinese).

[14] Wang Qiang. Research on optimization of supermarket logistics distribution path based on simulated annealing algorithm [J]. Journal of Guangzhou Maritime University, 2019, 27(03): 39-41+48(in Chinese).

[15] Zhao Kun, Wang Shuai. Review of research on vehicle route planning [J]. Modern Trade Industry, 2019, 40(26): 204-205(in Chinese).