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Simulated Annealing Algorithm Based Path Selection for Propagation Information and Data Flow Efficiency Enhancement Strategy

Li Zhang[1,*]
[1] School of Liberal Arts Education and Art Media, Xiamen Institute of Technology, Xiamen, Fujian, 361021, China
Corresponding authors: (e-mail: lilyzhang0505@126.com).

Abstract In the Internet era, accurately establishing the propagation model of social network public opinion is of great help to the guidance and control of public opinion. Based on the social network information dissemination model and node identification algorithm, this paper organically combines the ant colony algorithm and simulated annealing algorithm, constructs the optimal path selection model for social network information dissemination, and designs a set of DAILY models for public crisis information dissemination adapted to the Internet information environment and technology, so as to realize the efficiency improvement of data flow. The accuracy of the model in this paper has obvious advantages compared with the traditional SIR model, and the model fitting curve is basically consistent with the real data curve, and its absolute error value and RMSE value are low. Meanwhile, the simulation results show that the proposed important node recognition algorithm has high accuracy and feasibility. Compared with the classical ant colony algorithm and Dijkstra's algorithm, the model in this paper can disseminate a larger amount of information per unit time and has a higher accuracy rate, with the highest accuracy rate of 90.32% in the three groups of experiments, which is able to find the optimal path of information dissemination, and has an important guiding role in analyzing and guiding the corresponding public opinion.

Index Terms social network information dissemination, optimal path, ant colony algorithm, simulated annealing algorithm, DAILY mode

I. Introduction

Communication information path is a crucial concept in information dissemination [1]. The communication information path refers to the process of information transmission from the source to the receiver [2], [3]. In this process, information passes through several links, such as communication channels and communication media [4]. The selection of communication information paths can help us to understand the change and loss of information in different links, so as to optimize the communication strategy, improve the communication effect, and have an impact on the efficiency of data flow [5]-[7]. In path selection, if the selected path is too complex, it will reduce the efficiency of data flow. And a good data flow efficiency improvement strategy can enhance the effect of information dissemination [8]-[10]. For this reason, this paper proposes a simulated annealing algorithm-based path selection and data flow efficiency improvement strategy for disseminating information.

The simulated annealing algorithm is an optimization algorithm proposed by simulating the behavior of matter in the annealing process [11], [12]. It simulates the crystal structure evolution process of a solid object when it is heated and cooled, and finds the global optimal solution by accepting the worse solution in the solution space according to a certain probability in order to avoid falling into the local optimal solution [13]-[15]. Annealing is the process of heating a material to a high temperature and then slowly cooling it down, during which the molecules of the material change with the temperature so as to reach the state of lowest energy [16], [17]. In the problem of propagating information path selection and data flow efficiency improvement strategies, the paths and strategies are regarded as materials, and the optimal paths and strategies are gradually found by randomly selecting and accepting the worse solution with a certain probability.

In this paper, the social network information dissemination model, node recognition algorithm, ant colony algorithm and simulated annealing algorithm are organically combined to realize the construction of the optimal path selection model for social network information dissemination, and on the basis of which the DAILY model for public crisis information dissemination is designed to improve the efficiency of data flow. The node identification algorithm therein, by adopting the weight disambiguation algorithm and constructing the zero model, realizes the effective identification of the nodes of the class kernel group. In order to verify the effectiveness of the constructed model, public opinion dissemination experiments, node identification experiments, and path selection model comparison experiments were conducted respectively.

II. Optimal information propagation path selection model based on simulated annealing algorithm

II. A. Modeling Information Dissemination on Social Networks

II. A. 1) Social networks and related metrics

(1) Social Networks

For the study of social networks, it is necessary to utilize the complex network method, which is an important method for the study of complex systems, and the main object of study is the complexity of macroscopic systems and network structure. The complexity of complex networks is mainly reflected in the structural complexity, network evolution, connection diversity, dynamical complexity, the diversity of nodes, and multiple complexity fusion.

(2) Measurement indicators

With the in-depth analysis of social networks, the application of complex network metrics has become richer. The basic concepts of graph theory and several basic metrics information are as follows:

a) Graph representation of networks

A real network G can be represented as $G(V,E)$, with V representing the set of nodes and E the set of connected edges. The network is represented by the adjacency matrix A: $a_{ij}=0$ means that there is no edge connection between nodes i, j, and $a_{ij}=1$ means that there is an edge connection between i, j. According to whether the connected edges have direction or not is categorized into directed and undirected networks, and according to whether the connected edges are given weights or not is categorized into weighted and unweighted networks.

b) Degree and Average Degree

Degree is the most basic indicator of a node's characteristics, which portrays the number of neighboring nodes of a node, and can also represent the number of connected edges of the node. In directed networks, degree is divided into in-degree and out-degree, in-degree indicates the number of edges pointing to the node, and out-degree indicates the number of edges pointing to the neighboring nodes of the node.

c) Co-matching coefficient

The degree of different nodes in the network is different, if the node with large degree tends to connect with the node with large degree; the node with small degree tends to connect with the node with small degree, then the network belongs to the same matching network. If nodes with large degrees tend to connect with nodes with small degrees, the network belongs to the heteropairing network. The covariance coefficient $\langle k_{nn}\rangle(k)$ is an index parameter that characterizes the network's homo- and hetero-matching properties, as in equation (1):

$$\langle k_{nn}\rangle(k)=\frac{1}{i_k}\sum_{i=1}^{i_k}\left(\frac{1}{k_i}\sum_{j=1}^{k_i}k_j\right) \tag{1}$$

where i_k denotes the i node with degree k, k_i denotes the degree of node i, and j denotes the jth neighbor node of node i.

d) Average path length

The distance between nodes i and j in the network is denoted as d_{ij} and is defined as the shortest path length connecting two nodes i and j. The diameter of the network refers to the maximum value (D) of the distance between any two nodes in the network.

II. A. 2) Models of communication on social networks

(1) SIR/SI/SIS infectious disease models

a) SIR model

SIR is one of the classical infectious disease models, which simulates the transmission process of infectious diseases, including three states: susceptible state S, already susceptible state I, and recovery state R [18]. Where the susceptible state changes to the susceptible state with a certain probability β, and the susceptible state changes to the recovered state with another probability γ, and the recovered state does not change again. In the formula, ΔT denotes the unit time, the number of susceptible state, the number of sensed state and the number of recovered state are denoted by $s(t)$, $i(t)$ and $r(t)$, respectively, and the differential equation expression of SIR is as follows:

$$\begin{cases} \frac{ds}{dt} = -\beta si \\ \frac{di}{dt} = \beta si - \gamma i \\ \frac{dr}{dt} = \gamma i \end{cases} \tag{2}$$

From the above equation:

$$\frac{1}{s}\frac{ds}{dt} = -\frac{\beta}{\gamma}\frac{dr}{dt} \tag{3}$$

Integrating both sides of the above equation gives:

$$s = s_0 e^{-\beta r/\gamma}, s_0 = s(0) \tag{4}$$

Bringing $i = 1 - s - r$ into Eq. (4) and utilizing Eq. (3), the following equation is obtained:

$$\frac{dr}{dt} = \gamma\left(1 - \gamma - s_0 e^{-\beta r/\gamma}\right) \tag{5}$$

The solution can be expressed in terms of the following integral:

$$t = \frac{1}{\gamma}\int_0^{\gamma} \frac{1}{1 - x - s_0 e^{-\beta r/\gamma}} dx \tag{6}$$

When the parameter values are given, the steady state value of the number of removed states can be obtained by ordering $d\gamma / dt = 0$ to be:

$$r = 1 - s_0 e^{-\beta r/\gamma} \tag{7}$$

For large-scale networks, it is generally assumed that there are only a few infected individuals at the initial moment, removing the infected population as 0, thus having $s_0 \approx 1$, $i_0 \approx 0$, and $r = 0$. Remembering that $\lambda = \beta / \gamma$, we have:

$$r = 1 - e^{-\lambda\gamma} \tag{8}$$

An intuitive interpretation of the parameter λ is that it represents the average number of other susceptible individuals that an infected individual can infect before entering the removal state, also known as the basic regeneration number.

b) SI model

The SI model is identical to the first half of the SIR model in that individuals in the susceptible state transition to the infected state with probability β, the difference being that the number of individuals in the infected state does not decrease.

c) SIS model

According to whether a node is in the infected state or not, the SIS model [19] divides the nodes of the network into two categories: susceptible nodes S and infected nodes I. The densities of the two categories of nodes at the moment of T are $s(t)$, and satisfy $s(t) + i(t) = 1$, $s(\infty)$ and $i(\infty)$, respectively, which denote the relative densities of susceptible nodes and infected nodes when the propagation reaches a steady state. If the two types of nodes are connected by edges, the susceptible node will be transformed into an infected node with probability β, and the infected node will be transformed into a recovered node with probability γ, but the recovered node does not have immunity, and it can be re-infected right away, where $\lambda = \beta / \gamma\left(\beta, \gamma > 0\right)$ is the effective rate of contagion.

(2) Propagation model based on the influence of neighboring nodes

a) Independent cascade model

The independent cascade model is a probability-based information propagation model. The assumption of this model is that the probabilities of the influence of all neighboring nodes on the node are independent of each other. In the network, the user accepts an idea or spreads the idea is called activation, the opposite state is inactivation, once a node is activated it will remain activated and will not change from activated state to inactivated state.

b) Linear Threshold Model

Unlike the independent cascade model, the linear threshold model calculates the cumulative influence of neighboring nodes on a node during the propagation process. Viral marketing can be defined as a discrete optimization problem where the linear threshold model is applied to calculate the network node influence.

II. B.Significant node identification algorithm for nucleus-like cluster nodes

In weighted networks, the zero model can be constructed by disrupting the weights, topology, etc., and the part and degree of disruption can be controlled by setting different disruption scales. In this paper, we apply the weight disruption algorithm to destroy the weight characteristics of the network and retain the topology, which is done by exchanging the weights of any two consecutive edges and repeating it many times.

Kernel-like clusters are mostly found in the homology network, in order to determine that the network is a homology network, the homology coefficient is utilized to make a judgment. If the coefficient of congruence is greater than zero, it is proved that this is a congruent network. If the coefficient of congruence is less than zero, it is proved to be a heterogeneous network. Assuming that the weights on each connected edge of the network represent the number of times the nodes communicate, the K-kernel decomposition treats the weights as heavy edges.

The purpose of constructing the zero model is to find out which nodes are connected to many nodes with slightly lower kernel values than their own $K-$. Using the weight disruption algorithm to change the number of node exchanges, if a node is connected to many neighboring nodes with slightly lower $K-$ kernel values than itself, after disrupting the weights, the weights of these neighboring nodes may become larger, and the $K-$ kernel value is elevated, and these nodes will not be disaggregated out of the same $K-$ kernel value when performing $K-$ kernel decomposition of the zero model network. Compared to the output of the $K-$ kernel decomposition of the original network, the $K-$ kernel values of these nodes change and do not reappear at the same $K-$ values. In the original network, it is sufficient to find the neighboring nodes of the vanishing node that disconnected the connecting edges when it was discretized, and among these neighboring nodes, the node with the smallest difference between the degree and the degree of the vanishing node is the class of kernel clusters node being sought. Of course, after disrupting the weights, it is possible that the node's $K-$ kernel value may become lower from low, but the probability of becoming lower is even smaller, because in the extreme case, if a node has a $K-$ kernel value of 3, the probability of its $K-$ kernel value becoming lower is:

$$P\left(K \to K_{\min}\right) = (3-1)/\infty \tag{9}$$

The probability of getting higher is:

$$P\left(K \to K_{\max}\right) = \left[\infty - (3-1)\right]/\infty \tag{10}$$

Moreover, the class kernel cluster node to be searched for is connected to a large number of $K-$ neighboring nodes with kernel values slightly lower than its own, and the class kernel cluster node can be identified as soon as one of these neighboring nodes' weights becomes larger.

II. C.Information propagation path selection based on simulated annealing ant colony algorithm

Based on the social network information dissemination model and node identification algorithm, this paper combines ant colony arithmetic and simulated annealing algorithm to propose an improved social network information dissemination path selection model.

II. C. 1) Ant Colony Algorithm

The Ant Colony Algorithm [20] was inspired by the behavior of ants in discovering paths during the search for food. In nature, ants mark paths by releasing a substance called pheromone, and other ants follow these paths to find food sources. Since pheromones evaporate over time, the concentration of pheromones on the shortest path gradually accumulates, guiding the ants towards the shortest path. The ant colony algorithm finds the optimal solution in an optimization problem by simulating this process and using the pheromone concentration as a guide for the search.

The basic steps of the ant colony algorithm are as follows:

Step1: Initialization of the algorithm

First, the relevant parameters are initialized, including the ant colony size, pheromone factor, heuristic function factor, pheromone volatility factor, pheromone constant, maximum number of iterations, and so on. In addition, the data need to be read into the program and preprocessed.

Step2: Selection of Ant Starting Points

Randomly select the starting node and initialize the pheromone matrix according to the pheromone initialization formula.

Step3: Movement of ants

After each ant randomly selects the starting point, it needs to calculate the probability of transferring to other nodes according to the state transfer formula, and then select the next node according to the roulette algorithm until the nodes are all gone.

Step4: Update pheromone increment

According to the adaptation of the path taken by the ants, use the pheromone increment update formula to update the pheromone increment in the path.

Step5: Update pheromone: Use the pheromone update formula to update the pheromone in the path and record the local optimal solution.

Step6: Iterate: Repeat Step2 and Step5 until the result satisfies a specific condition or a set number of iterations to get the global optimal solution.

The specific representation of the state transfer formula in Step3 above is as follows:

$$j_k = \begin{cases} \dfrac{\left[\tau_{ij}(t)\right]^{\alpha} \times \left[\vartheta_j\right]^{\beta}}{\sum \left[\tau_{ij}(t)\right]^{\alpha} \times \left[\vartheta_j\right]^{\beta}} & j_k \in unvisited_k \\ 0 & j_k \notin unvisited_k \end{cases} \tag{11}$$

where: j_k is the t th generation, where ant k walks through the node i th next node to be walked. $\tau_{ij}(t)$ is the pheromone concentration between the i th node and the j th node in the t th generation. α is the pheromone heuristic factor. β is the expectation heuristic factor. ñ$_j$ is the expectation information of node j.

The pheromone increment update formula in Step4 above is expressed as follows:

$$\Delta\tau_{ij}^{k}(t) = \frac{Q}{L_k} \tag{12}$$

where: $\Delta\tau_{ij}^{k}(t)$ is the pheromone left behind in the t th generation, when ant k passes through node i and node j. Q is the pheromone intensity. L_k is the fitness or quality of the path traveled by ant k.

The pheromone update formula in Step5 above is expressed as follows:

$$\tau_{ij}(t) = (1-\rho)\times\tau_{ij}(t-1) + \sum \Delta\tau_{ij}^{k}(t-1) \tag{13}$$

where: $\tau_{ij}(t)$ is the pheromone between node i and node j in the t th generation. ρ is the pheromone volatilization coefficient.

Ant colony algorithm has the advantages of parallelism and robustness, strong global search ability, self-organization, positive feedback mechanism, etc., but it also has the disadvantages that the algorithm is slow to converge and easy to fall into local optimum.

II. C. 2) Simulated annealing algorithm

The simulated annealing algorithm [21] is a stochastic optimization search algorithm based on Monte Carlo iterative solution method, and its starting point is based on the similarity between the annealing process of solid matter in physics and general combinatorial optimization problems. The simulated annealing algorithm starts from a certain higher initial temperature, accompanied by the decreasing temperature parameter, and combines the probabilistic jump property to randomly find the global optimal solution of the objective function in the solution space. The simulated annealing algorithm is essentially a two-layer loop, the outer loop controls the temperature change from high to low, and in the inner loop, the temperature is fixed, and a new solution is obtained by adding a random perturbation to the old one, and the new solution is accepted according to certain rules.

The basic steps of simulated annealing algorithm are as follows:

Step1: Initialization

Set the initial temperature and initial solution, and set the appropriate cooling strategy and termination conditions.

Step2: Generate new solution

Perturb the current solution using domain transformation to generate a new solution, if the new solution will be based on the Metropolis criterion, accept the new solution with a certain probability.

Step3: Reduce temperature

Reduce the temperature to prepare for subsequent iterations.

Step4: Termination condition

If the termination conditions are met, such as reaching the preset minimum temperature or maximum number of iterations, the algorithm ends. Otherwise, return to Step2 to continue execution.

The Metropolis criterion mentioned in Step2 above is done as follows: remember that the fitness of the current solution and the new solution are E_{cur} and E_{new}, if E_{new} is greater than E_{cur}, then the new solution will be retained, i.e., the new solution will be used to replace the current solution; if E_{new} is less than E_{cur}, then the new solution will be accepted with a certain probability to accept the new solution, where the probability is calculated as follows:

$$P = e^{\frac{E_{cur} - E_{new}}{T}} \tag{14}$$

where: T is the current temperature.

The simulated annealing algorithm has the advantages of strong local search capability, wide range of applicability, robustness and ease of implementation, but also suffers from the disadvantages of poor global search capability, result dependence on the initial solution and slow convergence.

II. C. 3) Optimal information dissemination path selection model

Ant colony algorithm is often used to solve the path selection problem, from the perspective of graph theory, its main purpose is to find out 1 Hemilton loop that can traverse out all nodes. In the actual information dissemination network, there is not only the path length information between any two coordinates, but also the information of the actual network condition and public opinion condition. Therefore, in this paper, we first use the ant colony algorithm to find the solution of the path optimization problem in the information dissemination network, and then use the simulated annealing algorithm to optimize the solution of the ant colony algorithm, and finally get the optimal information dissemination path.

(1) Improve the initial pheromone concentration allocation mechanism

In the ACO algorithm, the initial pheromone concentration on each path is set to 0, so that the initial selection of the ants is undifferentiated, but in the information dissemination network, the factor of network public opinion is a factor that affects the initial path selection. Changing the initial allocation mechanism of pheromone according to the actual network public opinion situation can improve the computational efficiency of the algorithm and accelerate the convergence speed of the algorithm. There are many factors affecting the path selection for information dissemination, and the core elements that can be identified according to the hierarchical analysis method are path length and information dissemination time. The initial pheromone concentration allocation of this algorithm is shown in equation (15):

$$\tau_{ij}(0) = \frac{M}{\left(w_1 * d_{ij} + w_2 * E_{ij}(t)\right)} \tag{15}$$

where $\tau_{ij}(0)$ is the pheromone concentration assigned on the path (i, j) at the initial moment, M is a constant, d_{ij} is the length of the path (i, j), and w_1, w_2 are the corresponding weights. $E_{ij}(t)$ is the expected value of information dissemination time on the path (i, j), $w_1 * d_{ij} + w_2 * E_{ij}(t)$ is the time and length information on the path considered comprehensively, which is also the most primitive network public opinion condition on the path. The shorter the path and the passage time, the larger the assigned initial concentration, and vice versa.

(2) Improvement of heuristic function

In the ant colony algorithm, the heuristic function is mainly determined according to the path length, but this selection mechanism often causes the algorithm to fall into the local optimum, so this paper considers the heuristic function of the algorithm comprehensively from the dual perspective of global and local.

The local factor mainly considers the length of the path to be selected, and the global factor needs to consider the influence of the path to be selected in the subsequent path selection. Let i denote the current coordinate position, j denote the next position to be selected for information dissemination, and s denote the final destination. In this paper, the shortest path D_{js} from coordinate j to destination s is obtained according to Dijkstra's algorithm. Therefore, the heuristic function $\eta(i, j)$ is calculated as shown in equation (16):

$$\eta(i,j)=\frac{Q}{\delta d_{ij}+\varepsilon D_{js}} \tag{16}$$

where d_{ij} is the length of the path (i,j), Q is the pheromone constant of the ants in this traversal, δ, ε are the corresponding weights. At this point, the heuristic function measures the local factors by considering the length of the current path d_{ij}, and the length of the distance from the end point of the next coordinate point is considered by D_{js}, so that the advantages and disadvantages of the current path are measured from the global point of view, and the algorithm is made to jump out of the situation of local optimization.

(3) Improve pheromone updating mechanism

In the traditional ACO algorithm, the ant colony mainly updates pheromone through the superposition mechanism of "positive feedback", i.e., if a path is chosen by more ants, then the pheromone on the path will be more and more, and the probability of ants choosing the path will be more and more, which is very easy to form a local optimum. In the actual information dissemination network, if the ant colony algorithm is applied directly, the more pheromones on the path, the more complicated the network public opinion will be, which will cause congestion. Therefore, this paper adds a "negative feedback" mechanism, i.e., updating pheromones according to the network public opinion. In addition, the global path information is borrowed to update the pheromone, so that the algorithm can go beyond the local optimization. The process of updating the local pheromone according to the actual network public opinion situation is illustrated in Fig. 1.

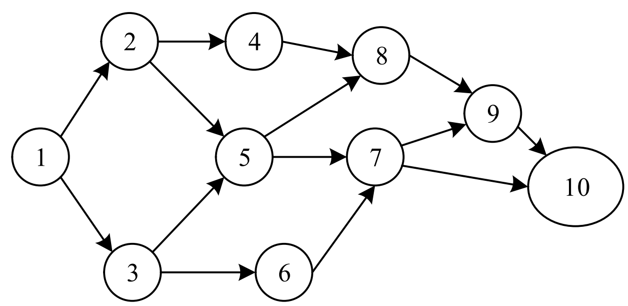

Figure 1: Path selection

In Fig. 1, information needs to be propagated from coordinate 1 to coordinate 10, and as the number of ants increases, if the path $1\to2\to5\to7\to10$ is determined to be optimal, then according to the superposition mechanism of "positive feedback", the pheromone on the path will become more and more, and the corresponding ants will become more and more, which will result in congestion. Phenomenon. At this time, the path $1\to3\to5\to7\to10$ is better, but according to the pheromone updating mechanism, this path will not be selected. Therefore, this paper adds a "negative feedback" mechanism to update the pheromone as in Eq. (17), taking into account the actual network public opinion situation:

$$\Delta\tau_{ij}^{k}(t)_1=\frac{Q}{\left(w_1*d_{ij}+w_2*E_{ij}(t)\right)} \tag{17}$$

where $\Delta\tau_{ij}^{k}(t)_1$ denotes the pheromone produced by the k th ant in the path (i,j), and Q denotes the pheromone constant produced by this ant. The pheromone updating mechanism takes into account the propagation distance and propagation time of the information as well as the network public opinion condition, which can avoid causing local congestion.

The pheromone update mechanism shown in Eq. (17) can only enable the algorithm to find the optimal path locally, and does not consider the pheromone allocation from a global perspective. For example, the initial optimal path is $1\to2\to5\to7\to10$, if the path $5\to7$ becomes congested, according to the local pheromone updating mechanism, the ants will turn to the path $5\to8$, and then with the increase of ants, the path $5\to8$ will become congested as well, and then it will take more time to determine the new optimal path, which reduces the convergence speed of the algorithm. Therefore, in this paper, we add the global information updating mechanism, let L_k denote the length of the path traversed by the k th ant this time, then this global pheromone update is shown in equation (18):

$$\Delta\tau_{ij}^{k}(t)_2 = \frac{Q}{L_k} \tag{18}$$

where $\Delta\tau_{ij}^{k}(t)_2$ denotes the global pheromone left by the k th ant after passing through the path (i,j).

Borrowing from the optimal worst ant colony algorithm, the pheromone update in this paper is shown in equation (19):

$$\Delta\tau_{ij}^{k}(t+1) = \begin{cases} \rho\left(\Delta\tau_{ij}^{k}(t)_1 + \Delta\tau_{ij}^{k}(t)_2\right) & (i,j) \in Optimal\ path\ p^* \\ \rho\left(\Delta\tau_{ij}^{k}(t)_1 - \Delta\tau_{ij}^{k}(t)_2\right) & (i,j) \notin Optimal\ path\ p^* \end{cases} \tag{19}$$

When the path (i,j) belongs to the optimal path p^*, it is rewarded by using $\Delta\tau_{ij}^{k}(t)_2$, and vice versa, it is penalized by using $\Delta\tau_{ij}^{k}(t)_2$. Therefore, this algorithm not only updates the pheromone from a global perspective, but also from a local perspective, which avoids the algorithm from falling into a local optimum, and at the same time increases the execution efficiency of the algorithm.

(4) Improved pheromone volatilization mechanism

In ACO algorithm, the pheromone on the path will be volatilized over time, this paper will measure the volatilization factor ρ according to the information flow T, i.e., the larger the information flow on the path, the smaller the volatilization factor will be, and vice versa the larger it will be, and the relationship between them is shown in Eq. (20):

$$\rho = \frac{1}{\lg T} \tag{20}$$

(5) Path optimization based on simulated annealing algorithm

According to the results produced by each iteration of the ant colony algorithm to get the initial solution of the simulated annealing algorithm, and then the initial solution is randomly perturbed to get 1 new solution, take Fig. 1 as an example, assuming that the optimal solution x_0 is obtained according to the improved ant colony algorithm: $1 \to 2 \to 5 \to 7 \to 10$, corresponding to the value of the objective function of $f(x_0)$, then a random micro-percussion can be carried out, and the x_0 becomes the optimal solution x_1: $1 \to 2 \to 5 \to 7 \to 9 \to 10$, corresponding to the objective function value of $f(x_1)$, and then according to the annealing probability to judge whether to accept the new solution, and so on. The calculation of the objective function value in this paper is shown in equation (21):

$$f(d,t) = w_1 * d_{ij} + w_2 * E_{ij}(t) \tag{21}$$

The objective function value measures the length of the path and the information propagation time. If the global optimal solution is found according to the simulated annealing algorithm, then the pheromone on the original path is cleared and the pheromone update is performed with equation (22):

$$\Delta\tau_{ij}^{k}(t+1) = \frac{Q}{L_{nc}} \tag{22}$$

(6) Flow of the algorithm

The flow of this algorithm is shown in Figure 2. Firstly, it simulates to find out the optimal information dissemination path by improving the ant colony algorithm and combining it with the actual network public opinion situation, and then achieves the global optimum by simulated annealing algorithm. The algorithm in this paper can avoid the shortcomings of ant colony algorithm such as slow convergence speed, easy to fall into local optimum, and weak optimization ability, and it can also determine the appropriate initial solution, which can speed up the convergence speed of simulated annealing algorithm.

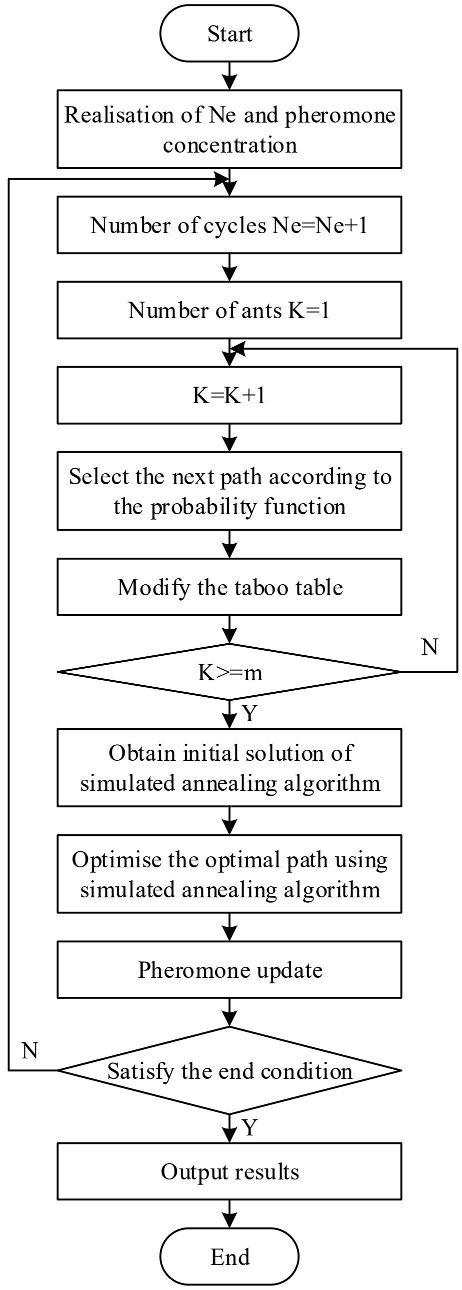

Figure 2: Algorithm flow

III. Model application experiment and result analysis

In order to verify the effectiveness of the proposed optimal information dissemination path selection model based on simulated annealing ant colony algorithm, this paper applies it to network public opinion dissemination experiments and important node identification experiments, and compares its performance with other models.

III. A. Comparative Experiments on the Fitting of Web Public Opinion Communication Models

III. A. 1) Opinion data acquisition

In this paper, we choose the popular opinion events in the current commonly used social software, select the popular opinion information in 2024, obtain the dissemination data such as forwarding of these information through the opinion big data platform, and select these data as the training data, so as to find out the optimal values of the parameters of the opinion dissemination model, and then build an accurate opinion dissemination model and compare and analyze it with the traditional SIR infectious disease model. The hardware platform of this paper chooses a computer with win11 system, CPU i7 6700k, and 32G RAM for data experiment.

III. A. 2) Comparative experiments on model fitting

Set the moment when the public opinion is released as the initial state, i.e., the moment of t. At that moment, the publisher of the public opinion information is the infected user, and the users who pay attention to him are the susceptible population, i.e., $I(t_0)=1$, $S(t_0)=K$, and K is the number of users who pay attention to him. In addition to the values of each parameter in the model, the simulated annealing ant colony algorithm is used to train the public opinion data so as to obtain the optimal parameters, from which the public opinion dissemination results of the model can be obtained. Here, the horizontal coordinate represents the time variable, which is selected at the early stage of the release of public opinion information, i.e., at the moment within 48 hours, and the unit is per hour, and the vertical coordinate is the amount of the dissemination of public opinion information, i.e., the total number of retweets. Meanwhile, this model is compared and analyzed with the traditional SIR contagion model, i.e., the model that does not consider the behavior of users' heart characteristics, and the results of the comparison of the model fitting effect are shown in Fig. 3.

It can be found that the trend of the dissemination of public opinion messages grows rapidly in the initial stage, and the number of retweets rises linearly. As time continues to grow, the trend of the dissemination of public opinion messages tends to flatten out, and the total number of retweets is in a slow-growth process, and the total number of dissemination of public opinion messages is basically unchanged after 20 hours, which indicates that the number of retweets is basically fixed and all of them are in the state of immunity. Meanwhile, from the figure, we can see that the fitting of the model in this paper is closer to the real data, although in the early stage, due to the selection problem of the initial value and the precocity phenomenon of the simulated annealing ant colony algorithm caused certain errors, with the passage of time, it is getting closer and closer to the real data, and it is good to simulate the propagation tendency of the public opinion information, on the contrary, traditional SIR contagion model does not take into account the influence of the user's psychological characteristics and behavioral parameters, resulting in a growing gap between the model and the real data at a later stage, with an increasing degree of distortion.

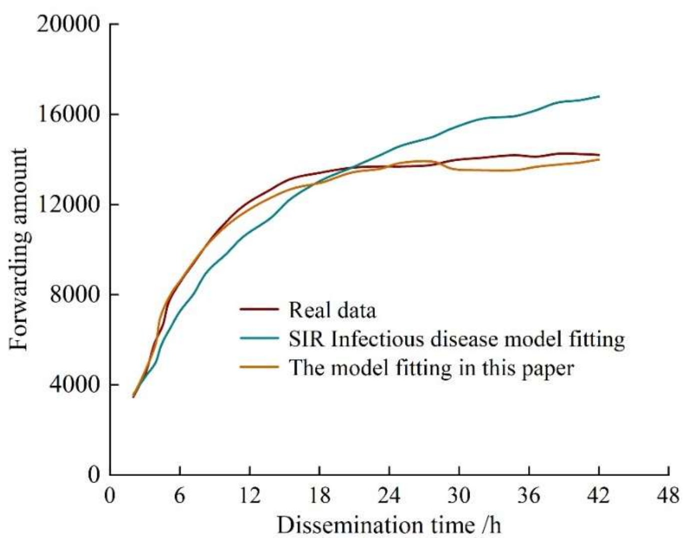

Figure 3: Comparison of model fitting effects

In order to be able to accurately compare the effectiveness of the two modeling algorithms, this paper chooses the absolute error and the root mean square error (RMSE) as two indicators to measure the error of the two modeling algorithms with the real data. Among them, the absolute error takes the absolute value for the convenience of expression. It is obvious to see that when the absolute error value is smaller, it means that the error with the real data is smaller, and the effectiveness of the algorithm is higher, and similarly the smaller the RMSE is, the higher the effectiveness of the algorithm is, too.

RMSE is calculated as follows:

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_t-Y_t)^2} \tag{23}$$

The simulation error analysis results of this paper's model and the traditional SIR infectious disease model are shown in Fig. 4 and Table 1, where Fig. 4 shows the absolute error values of the two models with the real data, while Table 1 shows the RMSE of the two models with the real data.

From the comparison results in Fig. 4, it can be seen that the absolute error value curves of the two models show opposite trends, the model of this paper has a larger error in the initial stage of public opinion dissemination, but the error with the real data is getting smaller and smaller with the dissemination time, while the SIR infectious disease model is just the opposite, and the error value of its error value increases with the growth of dissemination time, and it is getting further and further away from the error with the real data. In addition, it is also clear from the RMSE error comparison results in Table 1 that the RMSE value of this paper's model, 64.225, is much lower than the RMSE value of the traditional SIR infectious disease model, 491.386, which further shows the effectiveness of this model.

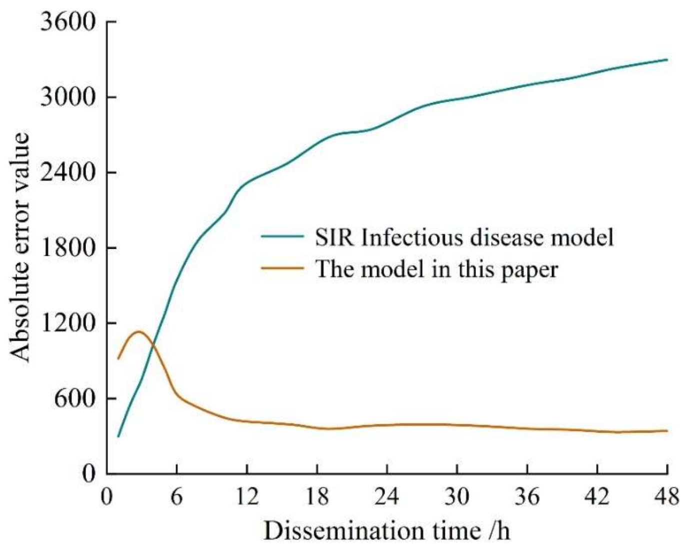

Figure 4: Comparison results of the absolute error values of the model

Table 1: The RMSE comparison results of the models

	The model of this article	The traditional SIR Infectious disease model
RMSE	64.225	491.386

In summary, it can be seen that the model given in this paper has an obvious advantage in accuracy compared with the traditional SIR model because it takes into account the user's psychological characteristics and behavioral factors, and the model in this paper is able to accurately predict the propagation trend of public opinion information, which has an important guiding role in analyzing and guiding public opinion.

III. B. Important node identification experiment

Firstly, the data of socfb-nips-ego information dissemination network is selected as the carrier, and then three commonly used centrality metrics such as degree centrality (DC), median centrality (BC), and Pagerank value are used as the representative features of each sample node, which replace the nodes as the input variables, while the indicators are used as the output variables, and the RBF predictor is used to mine the potential relationship between the variables. The step size is set to 10 and the number of iterations is set to 50,000.The RBF prediction results are shown in Fig. 5. It can be seen that the prediction accuracies of the models trained based on the information network data all reach more than 90%.

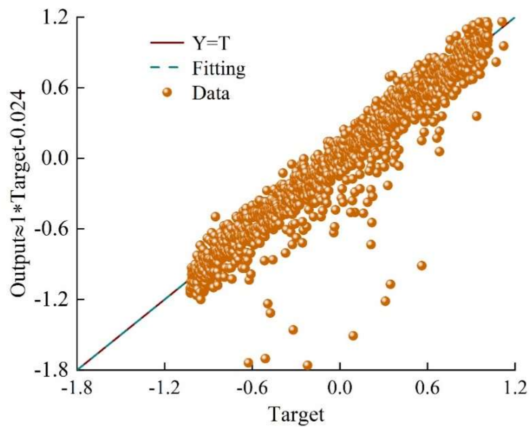

Figure 5: RBF Prediction

Next, the objective function and decision variables are identified and their specific expressions are shown in equation (24):

$$Minimize: f = -\frac{\arg\max \Phi_S\left(S^*\right)}{\lambda \cdot N} \tag{24}$$

where N is the size of the social network, λ is the equilibrium parameter, and $\Phi_S\left(S^*\right)$ is the number of nodes on the network that can be reached from the initial seed S^* in the model of this paper.

Finally, an artificial rabbit optimizer is used to obtain an approximation of the objective function.

The data predictor RBF is used as a black box for transforming the function in the objective, while the rabbit optimizer is used to obtain the important nodes. In this case, the population size of the rabbit optimizer is 120 and the maximum number of iterations is 240, and the obtained iterations of the optimization objective are shown in Fig. 6, which shows that the optimal value is reached in about 30 generations.

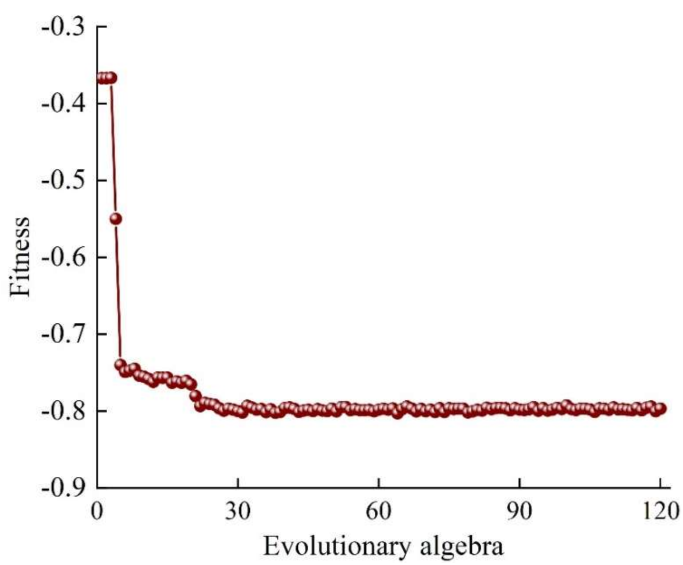

Figure 6: Optimization iteration

The index of 10 important information propagation nodes obtained after optimization is shown in Table 2, and the results obtained by degree centrality and meso centrality methods are also compared, which shows that the solution method in this paper has strong feasibility.

Table 2: Indexes of key nodes for information dissemination under different algorithms

This article	CC	DC
2765	297	614
614	258	297
1636	614	1636
721	728	258
18	730	2
228	1636	2782
725	721	1635
258	8	721
505	725	725
21	478	2765

III. C. Model comparison experiments

In this paper, the simulated annealing ant colony algorithm is simulated according to the simulated social network in Fig. 1 to conduct simulation experiments, and the experiments are based on the classical ant colony algorithm and Dijkstra's algorithm as a comparative model to verify the effectiveness of this algorithm.

According to the actual occurrence of online public opinion in the social network, the simulation is carried out with the social circle in Fig. 1, in which each node represents may be a netizen, or may represent a smaller social circle, and some of the users have a similar working background, and the period of the public opinion is set to be half a month, and the data is 10,000 items.

In this experiment, three sets of comparison experiments are set up according to the difference of data test sets, so as to conduct comparative analysis. In the three sets of experiments, the test set is set to 70%, 80%, and 90% of the total social network information data, respectively. The departure node is 1 and the receiving node is 10.

The first set of experiments: set the test data as 7000, the verification microblogging data as 3000, the optimal path according to the user behavior and the algorithm of this paper is 1→3→5→7→9→10, and the optimal path according to the classical ant colony algorithm and Dijkstra's algorithm is 1→3→6→7→10 and 1→3→5→7→10, respectively.

The second set of experiments: set the test microblog data as 8000, the validation microblog data as 2000, the optimal paths obtained according to the user behavior and this paper's algorithm, the classical ACO algorithm, and Dijkstra's algorithm are 1→2→5→7→9→10, 1→3→6→7→10, and 1→3→5→7→10, respectively, and the optimal path selection results of the latter two comparative algorithms are unchanged.

The third group of experiments: set the test microblog data as 9000 and the verification microblog data as 1000, the optimal path selection results obtained according to the user behavior as well as ACO and Diikstra algorithms remain unchanged and are still 1→2→5→7→9→10 and 1→3→5→7→10, respectively, while the optimal paths obtained according to the classical ACO algorithm are 1→3→6→7→9→10.

The optimal path lengths, $f(d,t)$ results, and accuracy rates obtained by the three algorithms in the three sets of experiments are shown in Table 3.

A side-by-side comparison of the results of the three groups of experiments, with the increase of the test set, the optimal path selection algorithm based on user behavior and the algorithm of this paper tends to stabilize, the amount of information propagated per unit time are increased, and the accuracy of the algorithm is also gradually increased. For the ant colony algorithm, the path with the increase of the test set, the path will produce corresponding changes, the amount of information propagated per unit of time in the test set increased to 9,000 on the contrary, the algorithm's accuracy also decreased. For Dikstra's algorithm, the amount of information propagated per unit of time and the accuracy of the algorithm decrease as the test set increases, although the paths do not produce changes.

A longitudinal comparison of the three sets of experiments shows that in each set of experiments, the optimal path selection algorithm based on user behavior and this paper's algorithm has a higher amount of information propagated per unit of time and higher accuracy of the algorithm than the other two algorithms, and this comparison is more pronounced with the increase of the test set. In the first set of experiments, the optimal path length selected based on user behavior and this paper's algorithm is more than the other two algorithms, which is mainly due to the fact that this algorithm will fully consider the behavioral relationship between the users, improve the pheromone updating mechanism as well as probabilistic selection function, and does not take the length of the path as the only pursuit of the goal. In addition, the convergence speed of this algorithm is significantly better than that of the classical

ACO algorithm, which is mainly due to the change of the initial pheromone allocation mechanism and the global update mechanism of the pheromone.

Table 3: Comparison of experimental results

The experimental group	Algorithm	Relationship distance	$f(d,t)$	Accuracy rate /%
Group 1	The algorithm of this article	61.35	2.2	82.47
	Classic ant colony algorithm	56.47	1.6	79.45
	Dikstra algorithm	39.72	0.6	46.72
Group 2	The algorithm of this article	67.35	2.6	84.15
	Classic ant colony algorithm	56.47	1.6	77.54
	Dikstra algorithm	39.72	0.5	39.32
Group 3	The algorithm of this article	67.35	2.9	90.32
	Classic ant colony algorithm	79.34	1.36	78.23
	Dikstra algorithm	39.72	0.36	32.14

IV. Design of DAILY model for public crisis information dissemination

Based on the proposed optimal information dissemination path selection model, this chapter designs the DAILY model for public crisis information dissemination.

The DAILY mode of public crisis event communication breaks the constant triangular link of the main body, and appears in a more diverse and accessible circular connection, and emphasizes the use of big data as the basic resource and innovation engine to carry out data portraits of public crisis meta-events, and constructs a real-time dynamic "digital twin information layer" to present all aspects of public crisis events in the form of big data. The closed-loop information path linking each subject implies that data and information are openly shared and integrated among the subjects, thus facilitating the in-depth collaboration among the various ports in a more scientific manner under the coordination of the government. The “audience” at the center of the double closed-loop is not only the final point of all information and services, but also can realize the diffuse output of demands and feedback of public opinion. "DAILY" refers to several key points in the model. "D" means that the government should take "data" as the core technological driving force for crisis management. "A" requires the media to take accurate and timely information "notification" as the top priority. "I" requires Internet technology platforms to be characterized by providing public information services to the public "promptly and timely". L refers to the requirement for online self-organizing, collaborative and in-depth cooperation to "lead" the positive development of public opinion. Y means that communication should be centered on the audience and an "agile" information and feedback network should be built.

V. Conclusion

In this paper, the optimal path selection model for social network information dissemination based on simulated annealing ant colony algorithm is constructed, and the DAILY model for public crisis information dissemination is designed on the basis of this model, which realizes the effective improvement of the data flow efficiency.

The error of this paper's model with the real data is large in the initial stage of public opinion dissemination, but it becomes smaller and smaller with the dissemination time, while the error value of the SIR infectious disease model increases with the growth of dissemination time. Meanwhile, the RMSE value of this paper's model is 64.225, which is much lower than the RMSE value of 491.386 of the traditional SIR contagion model, indicating the effectiveness of this paper's model in the dissemination of online public opinion. The prediction accuracies of this paper's models trained according to the information network data all reach more than 90%, and the feasibility of this paper's models in the identification of important nodes is verified by comparing the results obtained by the centrality of degree and centrality of median methods.

By comparing the classical ant colony algorithm and Dijkstra's algorithm, it can be found that the optimal path selection model in this paper can fully measure the characteristics of user behavior and user relationship, and can update the pheromone and the probability selection function from both global and local perspectives, which obviously improves the convergence speed of the algorithm. The optimal propagation path of the message is then obtained, which can provide technical support for accurately predicting the propagation path of the message in the network public opinion and judging the development trend of the public opinion.

In addition, the DAILY model of public crisis information dissemination designed in this paper takes big data as the basic resource and innovation engine, which can link the closed-loop information paths of each subject, openly share and converge the applications, output the demands and feedback public opinion in a diffuse way, and realize a more scientific and in-depth collaboration based on the coordination of political symbols.

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