

The Research on the Prediction of the Network Traffic Based on the Improved IAC-Gray Method

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With the development of the information technology, the network traffic problem has been more and more attention. The network forecasting problems are related to the control effect of the network traffic. In order to forecast the network traffic better, this paper combines the ant colony algorithm with the grey algorithm and proposes the IAC-GRAY algorithm. The algorithm applies on the optimal grey model parameters of the ant colony algorithm. And it improves the prediction accuracy. The experiment of this paper has achieved the good results. And it shows the effectiveness of the proposed algorithm.

1. Introduction

Due to the high burst and the randomness of the network service, control the network traffic becomes an effective method to solve the network congestion. Use the network and provide the better service quality becomes the increasingly concerned question (Yan Zhao et al. (2015)).

There were many scholars studying the network traffic. Due to the better adaptive learning of the neural network and the nonlinear approximation ability, Jing Ming and other people applied the neural network to predict the network traffic. The wavelet transform could be used to analyze the traffic data in the multi scales. Zhao Qigang, Li Dandan and Wang Peng combined the wavelet theory with the artificial neural network theory. And they applied the wavelet neural network to the network traffic forecasting and achieved the good results. In 2013, Dong-Chul Park applied the Bilinear recurrent neural network to predict the network traffic. The results showed that the method can reduce half of the training time and the forecasting accuracy was improved. Bao Rong Chang, Hsiu Fen Tsai (2009) proposed a novel hybrid method which combining adaptive neuro-fuzzy inference system (ANFIS) with nonlinear generalized autoregressive conditional heteroscedasticity (NGARCH). The model can improve the efficiency of the site management for 20%.

In this paper, we combine the ant colony with the grey model. We use the ant colony to optimize the parameters of the grey model. And we propose an improved algorithm of IAC-Gray method. Then, we apply the algorithm to predict the network traffic. The structure of this paper is as follows. The first part is the introduction. The second part is the ant colony algorithm. In this part, we introduce the ant colony algorithm. The third part is the improved IAC-Gray algorithm. In this part, we combine the ant colony algorithm with the grey model. Then we propose the improved IAC-Gray algorithm. The fourth part is the experiment and the last part is the conclusion.

2. The ant colony algorithm

The description of the ant colony algorithm is as follows (Udayraj et al. (2015), N.K. Sreeja, A. Sankar (2015)). We put n ants into a city randomly. In the initial time, the amount of the information on each path is equal. We set $\tau_{ij}(t) = Q$ (Q) as a constant. During the movement process, the ants determine their own transferred direction according to the amount of the information in each path. We use the taboo table TB to express the memory function of the ants. It records the cities that the ants walk through. The city set will change by the taboo table. During the continuous movement of the ant colony, the intensity of the pheromone will change. During the search of each ant, we calculate the state transfer probability P_{ij} of the ants by the heuristic

function and the amount of the information. At t time, the state transfer probability P_{ij} of the ant changes from the element city to the element city. We can calculate by the formula.

$$P_{ij}(t) = \frac{[\tau_{ij}]^\alpha \cdot [\eta_{ij}]^\beta}{\sum [\tau_{ij}]^\alpha \cdot [\eta_{ij}]^\beta} \quad (1)$$

α is the information elicitation factor. β is the expected heuristic factor. After one ant selects a city or completes a cycle of the city, the residual information in the path is needed to be updated (Ping Wang, Hui-Tang Lin, Tzy-Shiah Wang (2015), Mohamed M.S et al. (2015)). The amount of the information can be calculated by the following formula.

$$\tau_{ij}(t+n) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij} \quad (2)$$

$$\Delta\tau_{ij} = \sum_{m=1}^M \Delta\tau_{ij} \quad (3)$$

ρ expresses the residual coefficient of the pheromone. The reflected degree among the ants can be reflected. $(1-\rho)$ expresses the pheromone volatilization between t and $t+n$. $\Delta\tau_{ij}$ is the amount of the information in the path. That is the incremental sum of the pheromone for all of the ants from the path i to the path j (Vali Tawosi et al. (2015)).

3. IAC-Gray algorithm

The grey system model is a model which reveals the continuous development process of the system. Therefore, the model of the gray model is described by the differential equations. Among them, the most typical is $GM(1,1)$ model (Mingyue Zhao et al. (2015), Muhammad Saad Memon, Young Hae Lee, Sonia Irshad Mari (2015), Yu-Xia Jiang et al. (2015)). In this paper, we adopt the improved ant colony algorithm to estimate the parameters a, b and ε of $GM(1,1)$ model.

We call the algorithm as IAC-Gray algorithm (Improved Ant Colony Gray algorithm). The concrete steps of the algorithm are as follows.

The first step is to select the number of the ants.

The second step is to estimate the range of values of the parameters a, b and ε .

$$x_{a\min} \leq a \leq x_{a\max}, \quad x_{b\min} \leq b \leq x_{b\max}, \quad x_{\varepsilon\min} \leq \varepsilon \leq x_{\varepsilon\max}$$

Among them, x_{\min} and x_{\max} is the lower and upper limit of the variable values.

The third step is to divide the interval. We assume that the interval of each parameter is divided into M . The rectangular coordinate system which takes a, b and ε as the coordinate axis is divided into the matrix of $M \cdot M \cdot M$. The coordinate of each small box is the coordinate of the position for each ant.

$$(a_i, b_j, \varepsilon_p) = (x_{a\min} + \frac{x_{a\max} - x_{a\min}}{M} i, x_{b\min} + \frac{x_{b\max} - x_{b\min}}{M} j, x_{\varepsilon\min} + \frac{x_{\varepsilon\max} - x_{\varepsilon\min}}{M} p)$$

Where, $i, j, p = 1, 2, \dots, M$.

The fourth step is as follows. At the beginning, the pheromone concentration in the matrix is equal and is the constant. The pheromone concentration is zero and the initial position is assigned randomly.

The fifth step is to calculate the position $(a_i, b_j, \varepsilon_p)$ of the ant and the corresponding target value $objD$.

The target value is the average relative error function.

$$f(a, b, \varepsilon) = \min_{a, b, \varepsilon} \left[\frac{1}{n} \sum_{i=1}^n \frac{|\hat{x}^{(0)}(i) - x^{(0)}(i)|}{|x^{(0)}(i)|} \right]$$

In all ants, the ant that the target value is the smallest is the best ant. Then, the minimum value is. The sixth step is to update the pheromone concentration. The principle is as follows. The better the target value is, the stronger that the pheromone concentration is. The updated formula is as follows.

$$\tau_{ijp}(t+1) = (1-\rho)\tau_{ijp}(t) + \Delta(\tau_{ijp})$$

ρ is the information residual coefficient. $\Delta(\tau_{ij})$ is the information pheromone that the ants leave in the cycle path (i, j).

The definition is

$$\Delta(\tau_{ijp}) = \frac{1}{f_{best}}$$

Where, f_{best} is the objective value of the global optimal solution or the local optimal solution.

The seventh step is the ant foraging rules. Each ant finds the food in the sense of the perception. The ants select the walking direction according to the concentration of the pheromone. The stronger the concentration of the pheromone is, the bigger the probability that the ant selects is. The probability formula is as follows.

$$P_{ijp} = \frac{\theta_{ijp}^{\alpha} \eta_{ijp}^{\beta}}{\sum \theta_{ijp}^{\alpha} \eta_{ijp}^{\beta}}$$

Where, α and β are the information elicitation factor and the expected heuristic factor.

The eighth step is to judgment whether the optimal ant achieves the required accuracy or achieves the maximum number of the iterations. If it achieves the requirement, it will output the optimal objective function value and the optimal decision position. If it does not achieve, it returns to the fifth step.

The flow chart of the IAC-Gray algorithm is as follows.

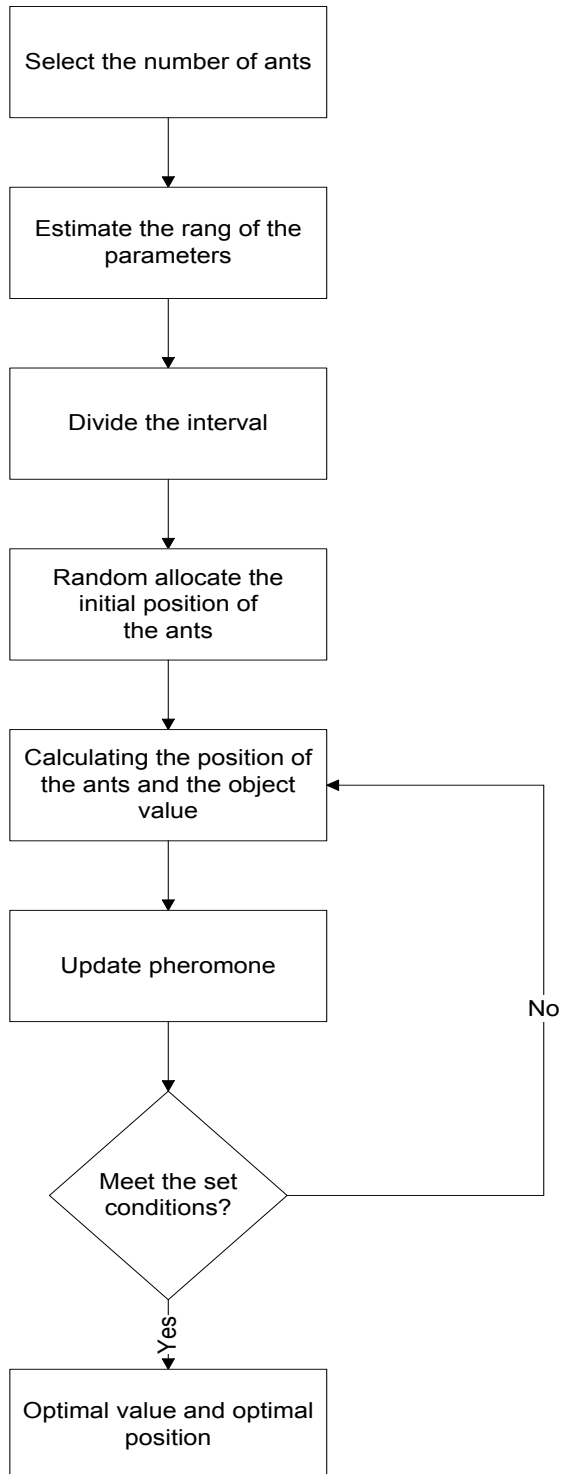


Figure 1: The flow chart of the IAC-Gray algorithm

4. The numerical Experiment

In this paper, we use IAC-Gray algorithm to predict the traffic of the campus network. We select the network traffic of 8 days. Among them, the network traffic of the first 6 days is as the training set, and he network traffic of the last 2 days is as the prediction set. The experimental data for the prediction set is shown as follows. The time interval is 3 hours.

Table 1: The training set data

Time sequence	Network traffic	Time sequence	Network traffic	Time sequence	Network traffic
1	2.13	17	2.11	33	2.21
2	5.65	18	5.45	34	5.97
3	13.12	19	12.98	34	14.23
4	15.17	20	14.34	36	15.70
5	11.21	21	11.08	37	12.04
6	17.34	22	15.43	38	18.31
7	14.13	23	13.58	39	15.31
8	4.13	24	4.05	40	4.88
9	2.08	25	2.15	41	2.10
10	5.71	26	5.77	42	5.66
11	12.11	27	13.56	43	13.14
12	14.25	28	15.64	44	15.27
13	11.34	29	11.62	45	11.23
14	17.21	30	17.89	46	17.51
15	13.99	31	14.50	47	14.20
16	4.21	32	4.76	48	4.11

We take the data of the training set into the IAC-Gray algorithm and we get the forecasting value. Then, we compare the forecasting value with the actual value.

Table 2: The comparison between the forecasting value and the actual value

Time sequence	Actual network traffic	Forecasting network traffic	Time sequence	Actual network traffic	Forecasting network traffic
49	2.14	2.25	57	2.23	2.31
50	5.21	5.31	58	5.34	5.33
51	15.43	14.78	59	14.75	14.89
52	16.25	16.03	60	17.76	17.43
53	13.98	14.56	61	14.98	16.01
54	10.77	10.40	62	12.87	11.32
55	13.65	13.71	63	12.49	12.97
56	4.89	4.54	64	4.77	4.56

From the forecasting results, we can see that the IAC-Gray algorithm achieves the good results and it shows that the method is effectiveness.

5. Conclusions

The occurrence of the internet has brought the great convenience to people's daily work and the study. However, if we do not interfere with the network traffic, it will produce the network congestion and the network paralysis. In order to change the chaotic situation, we need to control the network traffic. According to the traffic forecasting technology, we can get the relevant changes of the network traffic. Then, we can provide a

reference for the network traffic. This paper applies the ant colony algorithm to optimize the gray model. Then, this paper proposes an improved IAC-Gray algorithm.

The main work of this paper is as follows. Firstly, we introduce the development status of the network traffic forecasting. Secondly, we introduce the basic knowledge of the ant colony and the gray model. Thirdly, we propose the improved IAC-Gray method. The experiment shows that the method has the higher forecasting accuracy and it is an effective network traffic prediction model.

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