Network Traffic Prediction Using Radial Basis Function Neural Network Optimized by Ant Colony Algorithm

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Abstract: The disadvantages of the traditional radial basis function (RBF) neural network during the network traffic prediction process, such as a slow convergence rate and easy occurrence of local optima, result in low prediction precision. In this study, the ant colony optimization (ACO) algorithm is used to optimize the parameters of the RBF neural network for network traffic prediction. ACO is used to train the width and centre of the basis function of the RBF neural network, simplify the network structure, accelerate the convergence speed, prevent the occurrence of local optima, and improve the generalist ability of the RBF neural network. The experimental results show that compared with the genetic algorithm (GA)-RBF and particle swarm optimization (PSO)-RBF traffic prediction models, the proposed model exhibits higher prediction accuracy and can describe the varying trends in the network traffic well. The model used in this study exhibits strong generalization ability and good stability and therefore has practical value in network traffic prediction.

Keywords: Radial basis function (RBF) neural network, Ant colony algorithm, Basis function, Network traffic prediction.

1. Introduction

With the rapid development of the Internet, network traffic continues to grow. Therefore, network management is becoming more and more onerous, and the modeling and prediction of network traffic is becoming ever more important. Improving the precision of network traffic prediction has become a focus in network control [1].

In recent years, network traffic prediction algorithms have attracted more and more attention from scholars in China and other countries, who have so far proposed linear prediction methods based on the FARIMAL and ARMAL models and nonlinear prediction methods based on back propagation (BP) and radial basis function (RBF) neural networks [2]. For instance, H. Yin et al. [3] established network traffic prediction based on a new time series model. Based on the wavelet analysis and hopfield neural network, S. Guang et al. [4] proposed a network traffic prediction model that could provide relatively accurate network traffic prediction. C. Ren et al. [5], for the first time, used the niche genetic algorithm and BP neural network to predict the short-term traffic flow. The result showed that compared with the BP and RBF neural networks, this method provided a network traffic prediction with higher precision and better performance. Y. Chen et al. [6] used flexible neural tree for network traffic prediction. Compared with traditional network traffic...
prediction methods, this method improved the precision and efficiency of network traffic prediction. X. Tan et al. [7] used Wavelet Transform and ARMA for network traffic prediction. This network traffic prediction model exhibited better prediction capability. Among the aforementioned methods, the neural network prediction methods show better performance than the linear prediction methods because the neural network prediction methods can describe the non-linear characteristics of the network traffic. However, in practice, neural network prediction methods exhibit poor generalist ability. Therefore, it is necessary to develop a more efficient prediction algorithm and to further improve the efficiency and precision of network traffic prediction. Currently, during the network traffic prediction process, the RBF neural network exhibits such disadvantages as a slow convergence speed and the easy occurrence of local optima. Therefore, in this study, we propose a network traffic prediction method using ant colony optimization (ACO) algorithm-optimized RBF neural network parameters. We verify the effectiveness of this method through simulation experiments.

2. Key Concepts

2.1. RBF Neural Network

In 1989, C. Darken and J. Moody proposed a new neural network, the RBF neural network. The RBF neural network has a simple structure and a high learning speed [8]. Therefore, it has been widely used in such areas as the analysis and prediction of time series, pattern recognition, and function approximation [9]. The RBF neural network is a three-layered feed-forward neural network. The basic principle of the RBF neural network is the use of a radial basis function as the “basis” for the hidden unit to comprise the hidden layer space. The hidden layer transforms the input vectors by transforming low-dimensional model input data to the high-dimensional space, where linear inseparability problems become separable [10]. The RBF neural network has a simple structure, a fast convergence speed, and strong non-linear prediction ability. The structure of the RBF neural network is shown in Fig. 1.

One RBF neural network consists of n input nodes, m hidden nodes, and one output node. Hidden nodes are RBF functions and are expressed as follows:

\[ h = \exp \left( -\frac{\|x - c\|^2}{2\sigma^2} \right) \]

where \( c \) is the centre of the \( i \)th RBF hidden node; \( w \) is the output weight; and \( \sigma \) is the width of the RBF hidden nodes.

2.2. Ant Colony Optimization Algorithm

ACO was proposed by Italian scholar M. Dorigo et al. in the 1990s. ACO is a biomimetic random search algorithm that originated from the biological world. Since it was first proposed, ACO has drawn attention from many scholars both in China and in other countries. In recent years, there have been a number of published papers dedicated to the study of ACO, in which research results on ACO performance, models, and applications have been reported [11]. IEEE Transactions on Evolutionary Computation and Future Generation Computer Systems have both published their own special issues on the ACO algorithm. Nature has, on multiple occasions, published special reports on research achievements using the ACO algorithm [12]. The basic ACO algorithm model is shown below:

\[ P^k_{ij} = \frac{\tau^\alpha_{ij} \eta^\beta_{ij}}{\sum_{j \in A} \tau^\alpha_{ij} \eta^\beta_{ij}}, \]

\[ \tau_{ij}(n + 1) = \rho \tau_{ij}(n) + \sum_{k=1}^{m} \Delta \tau^k_{ij}, \]

\[ \Delta \tau^k_{ij} = \frac{Q}{\sum L_k} \frac{1}{\beta_{ij}}, \]

where \( r(k, i, j) \) represents whether or not ant \( k \) moves from position \( i \) to position \( j \); \( n \) represents the iteration number; \( m \) is the number of ants; \( i \) is the current position of the ant; \( j \) is the location that the ant can reach; \( \tau_{ij} \) is the pheromone strength of the path from \( i \) to \( j \); \( \Delta \tau^k_{ij} \) is the number of pheromones left by ant \( k \) when it moves along the path from \( i \) to \( j \); \( \beta \) is the weight of heuristic information; \( \alpha \) represents the weight of the path; \( \rho \) is the evaporation coefficient of the number of pheromones on the path; \( Q \) is the quality coefficient.

Fig. 1. RBF neural network structure.
of the pheromones; and \( P \) is the transition probability when ant \( k \) moves from position \( i \) to position \( j \).

3. ACO-EBF Network Traffic Prediction

Parameters \( w \), \( c \) and \( \sigma \) greatly affect the RBF neural network prediction. To obtain an RBF neural network with high prediction performance, it is necessary to first acquire optimum values of \( w \), \( c \), and \( \sigma \). The current optimization methods for the RBF neural network parameters \( w \), \( c \), and \( \sigma \) include the gradient descent, GA, and PSO algorithms. The gradient descent algorithm has a slow search speed and heavy computation. The traditional GA and PSO algorithms only individually optimize the RBF neural network parameters, without considering the relationship among the RBF neural network parameters. Therefore, it is difficult to acquire the optimum parameters for overall model prediction through these two algorithms. The optimization of \( w \), \( c \), and \( \sigma \) is a multi-parameter combinatorial optimization problem. We use the relationship among \( w \), \( c \), and \( \sigma \) as well as the global search and implicit parallelism of the ACO algorithm to simultaneously optimize \( r \), \( m \), \( w \), \( c \), and \( \sigma \).

3.1. Coding Scheme

In the ACO algorithm, considering the randomness of the coding during the population initialization, the following coding scheme is used:

\[
q_i = \left[ \cos(\theta_1) \cos(\theta_2) ... \cos(\theta_m) \right], \tag{5}
\]

where \( \theta_j = 2\pi \times \text{rand} \); \( i, j = 1, 2, ..., m \); \( \text{rand} \) is the random number in the range of \((0, 1)\); \( m \) is the population size; and \( n \) is the space dimension. Thus, every ant in the population occupies two positions in the argotic space. When the ant population size remains the same, the searchable space doubles, which accelerates the convergence speed.

3.2. Pheromone Update

The equation for pheromone generation is as follows:

\[
F_i(X) = [f_i(x) - f_i^{\text{min}}] \cdot a, \tag{6}
\]

where \( f_i(x) \) is the adaptability of the individual ant \( x \); \( f_i^{\text{min}} \) is the minimum adaptability of the individual ants of the \( i \)th generation; \( F_i(X) \) is the pheromone produced by the individual ant \( x \) at the central source point of the \( i \)th generation; and the value of \( a \) is determined by the adaptability function.

The equation for pheromone diffusion is as follows:

\[
\text{When } S < R: \quad F_i'(X) = f_i^{\text{min}} + f_i(x_0) \cdot ((R - S) / R), \tag{6}
\]

\[
\text{When } S \geq R: \quad F_i'(X) = f_i^{\text{min}}
\]

where \( R \) is the diffusion radius of the source; \( S \) is the distance between the central source point \( x \) and \( x_0 \); \( f_i(x) \) is the pheromone diffused from the central source point \( x_0 \) at chromosome \( x \); and \( f_i^{\text{min}} \) is the minimum pheromone in the chromosomes of the \( i \)th generation.

3.3. Optimization Steps

1) The initial population of the ACO algorithm is randomly generated.
2) The initial value of the evolutionary generation \( t = 1 \).
3) Encoding is performed. The model of the RBF neural network is established based on \( w \), \( c \), and \( \sigma \). The network traffic prediction precision for each set of parameters is obtained. The individual adaptability is calculated based on the MSE of the prediction results.
4) If the maximum evolutionary generation is achieved or the value of the optimum adaptability function of the population does not change significantly for multiple generations, then the parameters of the model reach their optimums. Skip to Step (7).
5) Add 1 to the evolutionary generation, i.e., \( t = t + 1 \).
6) Update the population according to the pheromone update and mutation operator, then jump to Step (3).
7) The optimum parameters for the network traffic prediction model, \( w \), \( c \), and \( \sigma \), are obtained.
8) The values of \( w \), \( c \), and \( \sigma \) are used as the parameters of the RBF neural network to establish the neural network training model. Prediction is performed on the test set, outputting the model network traffic prediction result.

The detailed process flow is shown in Fig. 2.

4. Experimental Results and Analysis

To verify the performance of the ACO-RBF model, the hourly network traffic data from the master node router of the network traffic library,
http://newsfeed.ntcu.net/~news/2014/, during the period from January 3, 2014 to February 23, 2014 was used for the simulation experiment. A total of 5,000 data files were collected. To prevent the prediction result from affecting the accuracy of the assessment result, the first 2,000 data files were used as the training set to establish the network traffic prediction model, while the last 300 data files were used as the test set to verify the performance of the established model.

The RBF neural network is most sensitive to $[0, 1]$ data. Fig. 3 shows the capriciousness, randomness, and large varying amplitude of the actual network traffic.

To improve the learning speed of the RBF neural network, the network traffic data are normalized prior to training:

$$x' = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}$$  \hspace{1cm} (8)

The normalization process is then reversed on the RBF neural network prediction result to recover the true network traffic prediction result:

$$x = x'(x_{\text{max}} - x_{\text{min}}) + x_{\text{min}}$$ \hspace{1cm} (9)

where $x'$ is the normalized network traffic value, and $x_{\text{min}}$, $x_{\text{max}}$ are the minimum and maximum network traffic values, respectively.

To evaluate its effectiveness, the MATLAB language is used to implement the ACO-RBF algorithm. Both the GA-RBF and the PSO-RBF neural network models are also tested to present contrasting examples and make the ACO-RBF prediction result more convincing. The evaluation indices for the performance of the models are the MSE and the mean absolute percentage error (MAPE), which are defined as follows:

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$ \hspace{1cm} (10)

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100$$ \hspace{1cm} (11)

where $y_i$ is the true network traffic value, and $\hat{y}_i$ is the prediction value obtained from the network traffic prediction model.

The normalized training sample is input into the PSO-RBF, GA-RBF and ACO-RBF models, respectively, for training. The parameters for each model are then optimized (listed in Table 1).

Table 1. Comparison among optimized parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>GA-RBF</th>
<th>PSO-RBF</th>
<th>ACO-RBF</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T$</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>$M$</td>
<td>4</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>$W$</td>
<td>2.2</td>
<td>2.2</td>
<td>2.2</td>
</tr>
<tr>
<td>$c$</td>
<td>9.4</td>
<td>8.8</td>
<td>6.4</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>1.3</td>
<td>1.9</td>
<td>2.4</td>
</tr>
</tbody>
</table>

Table 2 lists the performance evaluation indices for the three methods. From Table 2, we know the following:

1) The running time shows that the running speed of the ACO-RBF method is dramatically higher than the running speeds of the PSO-RBF and GA-RBF methods. This increased running speed can satisfy the real-time requirement for network traffic prediction.
2) For both the training and the test sets, both the fitting and the prediction errors of the ACO-RBF method decrease compared to the PSO-RBF and GA-RBF methods, indicating that using the ACO algorithm to optimize the RBF neural network parameters is effective. The ACO algorithm can improve the performance of the network traffic prediction model in all aspects and better describe the varying trends in modern network traffic. In addition, the ACO-RBF model is more suitable for long-term prediction.

### Table 2. Comparison among the overall performances of the three network traffic prediction methods.

<table>
<thead>
<tr>
<th>Method</th>
<th>Training set</th>
<th>One-step prediction</th>
<th>Multi-step prediction</th>
<th>Training set</th>
<th>One-step prediction</th>
<th>Multi-step prediction</th>
<th>Training set</th>
<th>One-step prediction</th>
<th>Multi-step prediction</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACO-RBF</td>
<td>0.55</td>
<td>62.34</td>
<td>16.7</td>
<td>14.9</td>
<td>3.67</td>
<td>166.2</td>
<td>15.8</td>
<td>3.99</td>
<td>169.3</td>
</tr>
<tr>
<td>PSO-RBF</td>
<td>0.69 %</td>
<td>1.71 %</td>
<td>11.30 %</td>
<td>2.29 %</td>
<td>5.19 %</td>
<td>2.60 %</td>
<td>3.69 %</td>
<td>6.50 %</td>
<td>3.61 %</td>
</tr>
<tr>
<td>GA-RBF</td>
<td>33 s</td>
<td>2.5 s</td>
<td>4.4 s</td>
<td>46 s</td>
<td>3.2 s</td>
<td>5.3 s</td>
<td>65 s</td>
<td>3.8 s</td>
<td>5.9 s</td>
</tr>
</tbody>
</table>

### 5. Conclusions

In this study, we propose a network traffic prediction method using ACO algorithm-optimized RBF neural network parameters. Compared with the GA-RBF and PSO-RBF traffic prediction models, the proposed prediction method has higher prediction accuracy and can better describe the varying trends in network traffic. Due to its strong generalization ability and stability, the proposed method has practical value in network traffic prediction.

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### References


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