Traffic Prediction Model Based on Improved Quantum Particle Swarm Algorithm in Wireless Network

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Abstract. With the rapid development of data transmission, how to achieve fast and accurate prediction of wireless network traffic is an important issue to data collection. In this paper, we propose a traffic prediction model, namely improved quantum particle swarm optimization based on BP neural network. We adopt BP neural network as the basic architecture. On this basis, wavelet multi-resolution analysis technology is introduced as the pre-processing method for prediction model input. Aiming at the shortcomings of slow convergence and easy falling into local optimum of BP neural network, the improved quantum particle swarm algorithm is used to optimize it. Simulation experiments show that compared with the traditional algorithms, the proposed model has higher prediction accuracy and faster convergence rate.

1. Introduction

The increasing frequency of wireless network usage has led to an explosion in network data traffic, Internet viruses, eavesdropping, and malicious attacks continue to increase [1]. Especially in the military field, discovering and utilizing the security flaws of enemy systems is seen to be the key to combat success. The predictability of network traffic plays an important role in the assessment of network system security. Accurate traffic prediction can be used not only as a military network attack aid, but also for the evaluation of network performance, large-scale network design, security services.

In the early research, researchers used linear time series models to build network traffic prediction models. Among them, moving average model, autoregressive model and autoregressive moving average model are common traditional models [2]. All of these models can capture the short-range dependence of linear time series, but due to the nonlinear process of network traffic time series, these models can't capture the uncertainty and sudden of network traffic [3].

With the expansion of the network and the rise of new services, network traffic presents more unstable characteristics. Many nonlinear models have been proposed to accommodate the new features of network traffic. Support vector machine (SVM) and artificial neural networks are widely used in pattern recognition, regression estimation and prediction [4, 5]. Bermolen Rossi explored the use of SVM for traffic forecasting [6]. Zhu Yi proposed a new artificial neural network model for IPV6 network traffic prediction [7]. Chang proposed a pipeline recurrent neural network (PRNN) model to generate MPEG video traffic through dynamic ATM networks for adaptive traffic prediction [8].

In this paper, from the characteristics of wireless network traffic, we combine wavelet multi-resolution analysis with neural network into a whole model, so that it can consider the time and...
frequency local characteristics of traffic at the same time. On this basis, we introduce the quantum particle swarm optimization algorithm with powerful global search ability into the prediction model, and improve the problem that the algorithm is easy to fall into the local optimal solution. The rest of this paper is organized as follows. In Section 2, the wireless network traffic prediction model is explained in details. Simulation results are given in section 3, and a conclusion is given in Section 4.

2. Model Design

2.1. Wavelet Neural Network

The combination of wavelet multiresolution analysis and neural networks is generally divided into two types: loose combination and compact combination [9, 10]. In this paper, a loose combination method is adopted, that is, wavelet multi-resolution analysis and BP neural network are sequentially connected to form a complete system. First, the input data is decomposed by wavelet multi-resolution analysis, and then the decomposition result is used as a traditional neural network input, and the output wave is obtained through the neural network. The specific form is shown in Fig. 1.

![Figure 1. Schematic diagram of loose combination of WD and NN](image)

2.2. Improved Quantum Particle Swarm Optimization

Quantum particle swarm optimization (QPSO) has strong optimization ability, can optimize the traffic prediction model. However, due to the lack of mutation operator, the diversity of particle swarm is weakening in the process of search and optimization, which makes the algorithm easy to fall into local optimal solution [11]. Therefore, in order to break through the shortcomings of the algorithm, this paper improves on the basis of its existing advantages in order to obtain better optimization algorithm.

2.2.1. Adaptive Contraction-Expansion Coefficient. In the quantum particle swarm algorithm, there is a search space in which there is a population of \( N \) particles, each particle continuously updates its speed and position according to the following formula, and searches in space [12].

\[
p(t) = \theta \cdot p_g(t) + (1 - \theta) p_i(t)
\]

(1)

\[
m(t) = \frac{1}{N} \sum_{i=1}^{N} p_i(t)
\]

(2)

\[
L(t+1) = 2\beta \cdot |m(t) - X(t)|
\]

(3)

\[
\beta = a - (a - b) \cdot \frac{t}{G_{\text{max}}}
\]

(4)

\[
X(t) = p(t) \pm \frac{L}{2} \ln \left( \frac{1}{u} \right)
\]

(5)

where \( p_i(t) \) and \( p_g(t) \) represent the optimal individual position and the global position at the \( t \)-th iteration, respectively; \( \theta \) and \( u \) are random values uniformly distributed in the interval \([0, 1]\); \( \beta \) is the contraction-expansion coefficient; and \( G_{\text{max}} \) is the maximum number of iterations. It can be seen that the contraction-expansion coefficient \( \beta \) in the QPSO decreases linearly with the iteration, but the optimization process of practical problems is often complex and nonlinear. Therefore, the degree of aggregation \( A(t) \) of the particle group is introduced and the definition is as follows:
\[ A(t) = \frac{\text{Sim}}{N} \]

\[ \text{Sim} = \frac{1}{1 + d(x,y)} \]

\[ d(x,y) = \sum (x_i - y_i)^2 \]

where Sim is the similarity coefficient; \( d(x,y) \) is the Euclidean distance between the particle and the global extremum. Then the particle swarm aggregation degree is introduced into the contraction-expansion coefficient \( \beta \), so that the value of \( \beta \) is more random, and the adaptive adjustment of the particle swarm is realized. The formula is as follows:

\[ \beta = 1 + \alpha \times A(t), \; \alpha \in (0,1) \]  

2.2.2. Renewal of Individual Extremum and Global Extremum. In the standard quantum particle swarm algorithm, the formula (1) - (5) can be used to derive the next search position of the particle as:

\[ X(t+1) = p(t) + \beta |m(t) - X(t)| \cdot \ln(1/u) \]  

It can be seen that the process of moving from the current position to the next position is a linear motion. However, polygonal motion travels through a wider area and has a larger search space than linear motion. Therefore, the particle position update formula is improved to the vector addition of \( pt \) and \( (1/\beta) \cdot m(t) - X(t) \cdot \ln(1/u) \). The location update process is shown in Fig. 2.

\[ \text{Figure 2. Demonstration of particle moving path} \]

If the fitness of the two path turning points of A and B is considered simultaneously on the basis of the original algorithm when updating the individual extremum, it will provide more choices for the individual extremum of the particles, making the algorithm converge to the optimal solution faster. The updating method of individual extremum is given:

\[ F(P_{\text{best},i}) = \min(F(A), F(B), F(P_{\text{best},i})) \]  

where \( P_{\text{best}} \) is the individual extremum; \( F \) is the fitness of the particle, the formula is as follows:

\[ F = k \sum_{i=1}^{n} \text{abs}(y_i - o_i) \]  

where subscript \( i \) represents the \( i-\text{th} \) sample data, \( n \) is the total number of sample data, \( y_i \) is the theoretical output, \( o_i \) is the actual output, and \( k \) is the coefficient used to adjust the fitness range.

When update the global extremum, the central particle \( P_{\text{center}} \) is introduced and defined as the center of all particle positions in the particle swarm. The global optimal solution will get closer to the center particle as the search progresses. Therefore, after all the particles update the position by each iteration, the global extremum \( G_{\text{best}} \) is updated, then the central particle \( P_{\text{center}} \) is updated, and the difference between \( G_{\text{best}} \) and \( P_{\text{center}} \) is used to guide \( G_{\text{best}} \) to perform local search. As shown in equation (13):

\[ G'_{\text{best}} = G_{\text{best}} + r \cdot dt \cdot (G_{\text{best}} - P_{\text{center}}) \]  

where \( r \) is a uniformly distributed random number between [-1, 1]. The role is to control the
direction of the local search. \( dt \) is the local scaling factor at the \( t-th \) iteration. In the initial stage of the algorithm, the distance between \( G_{best} \) and the optimal solution is generally far, the larger \( dt \) can have a larger search range which helps to improve the convergence speed. On the contrary, in the later stage of the iteration, the distance between \( G_{best} \) and the optimal solution is close, and the smaller \( dt \) can improve the accuracy of the optimization. So \( dt \) uses a linear decreasing strategy, specifically:

\[
dt + 1 = dt \cdot \left(1 - \frac{t}{T}\right)
\]

(14)

For the results of local search, the algorithm uses a greedy retention strategy, namely:

\[
G_{best} = \begin{cases} 
G'_{best}, & F(G'_{best}) > F(G_{best}) \\
G_{best}, & \text{others}
\end{cases}
\]

(15)

2.3. Overall Model

To achieve accurate prediction of network traffic, this paper combines wavelet multi-resolution analysis, BP neural network and improved quantum particle swarm algorithm to propose a wireless network traffic prediction model, namely improved quantum particle swarm algorithm based on BP neural network (ALQPSO-BPNN), as shown in Fig. 3.

![Figure 3. ALQPSO-BPNN model design frame](image)

Firstly, we use the multi-resolution analysis of wavelet transform to decompose the wireless network traffic into low-frequency and high-frequency components, which are separately divided into training and test set. And the initial weights and thresholds of BP neural network are determined by the powerful search ability of the improved algorithm. After the optimized neural network is obtained, the high-frequency and low-frequency component training data sets are used to train it, and the prediction model with better performance is obtained. Then the test data sets of high-frequency and low-frequency are input into the prediction model to realize the prediction of high-frequency and low-frequency components respectively. Finally, the real predicted output value will be restored by inverse wavelet transform of the predicted high and low frequency components.

3. Simulation Experiment

3.1. Simulation Data and Parameter

The data set used in the simulation experiment is the CRAWDAD traffic data set. In the simulation process, the common parameters of all models are set as shown in Table 1.

| Parameter                  | Value          | Parameter                  | Value          |
|----------------------------|----------------|----------------------------|----------------|
| Wavelet base               | db4            | Target error               | 1e-4           |
| Structure of BPNN          | 4-9-1          | Number of evolution        | 30             |
| Learning rate              | 0.01           | Individual scope           | [-1,1]         |
| Population size            | 40             | Maximum training times     | 200            |
| Wavelet decomposition scale| 1              | Other parameters           | Default value  |
3.2. Simulation Results and Analysis

The proposed model (ALQPSO-BPNN) is compared with the traffic prediction model based on quantum particle swarm optimization BP neural network (QPSO-BPNN) and the traffic prediction model based on genetic algorithm optimization BP neural network (GA-BPNN). The simulation experiments were all realized by MATLAB software.

To verify the effectiveness of the improved algorithm, Fig. 4 and Fig. 5 are graphs of the low and high frequency component fitness index of the three models, respectively. It can be seen from the figure that the fitness curve of the ALQPSO-BPNN model in the three models is at the bottom. Therefore, the optimization effect of the ALQPSO algorithm is better to some extent. Moreover, when the fitness curve reaches a steady state, the algorithm of ALQPSO-BPNN model performs the least number of iterations, which indicates that the improved algorithm optimization process takes less time and has faster convergence speed.

![Figure 4. Comparison of low frequency fitness](image1)

![Figure 5. Comparison of high frequency fitness](image2)

Fig. 6 and Fig. 7 respectively show the comparison of the prediction results and the normalized error rate of the three models with the actual values. It can be seen from the figure that the prediction results of the three models are generally consistent with the actual flow value, but the overall fluctuation of the ALQPSO-BPNN model error curve is smaller, and the prediction result is closer to the actual flow value than other models.

![Figure 6. Traffic prediction result](image3)

![Figure 7. Traffic prediction error](image4)

Table 2 is the average of the errors of the three models repeated training and predicted 30 times. It can be seen that the error value of the wireless network traffic prediction model designed in this paper is smaller than the error values of the other two models. It is indicated that the prediction results obtained by the prediction model proposed in this paper are the closest to the actual flow value, and the prediction precision is the highest.
Table 2. Comparison of Results of Three Prediction Models

| Prediction model     | MAPE   | MAE    | RMSE  | SMAPE  |
|----------------------|--------|--------|-------|--------|
| GA-BPNN              | 0.0984 | 0.0773 | 0.1085| 0.1847 |
| QPSO-BPNN            | 0.0769 | 0.0169 | 0.0261| 0.0972 |
| ALQPSO-BPNN         | 0.0412 | 0.0159 | 0.0232| 0.0604 |

4. Conclusion
Based on the full consideration of wireless network traffic characteristics, this paper combines wavelet analysis, neural network and improved quantum particle swarm optimization algorithm to design a wireless network traffic prediction model. In the simulation experiment, the design model is compared with two basic models, and the results show that the proposed algorithm not only improves the convergence speed of model training, but also reduces the error of prediction results.

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