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Prediction for Short-term Traffic Flow Based on Elman Neural Network Optimized by CPSO

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Abstract
Prediction of traffic flow is an important issue of intelligent traffic system, while accurate and real-time prediction of traffic flow becomes a crucial issue in traffic control. To further improve the traffic prediction precision

and control effect, combining the advantages of chaos particle swarm optimization and Elman neural network, a short-time traffic flow prediction model based on CPSO-Elman-NN is proposed. Furthermore, in order to make a contrastive analysis on predicted effect, Elman neural network and BP neural network are introduced to compare. Then, Beijing-Tianjin-Tanggu Expressway was selected to validate the model. According to the case result, this method can accurately predict traffic flow, and its effect is superior to the other two algorithms. Moreover, prediction precision of this method can properly meet practical needs of traffic control of expressway.

Keywords: INTELLIGENT TRAFFIC SYSTEM, SHORT-TERM TRAFFIC FLOW PREDICTION, TRAFFIC CONTROL, CHAOS PARTICLE SWARM OPTIMIZATION, ELMAN NEURAL NETWORKS

1. Introduction

Motor vehicle population has gradually increased with rapid economic and social development of cities. Sharp increase in traffic demand leads to increasingly serious traffic congestion in large and medium-sized cities of China. It is urgent to reduce traffic congestion and accidents. Intelligent traffic system provides effective ways to resolve problems of traffic congestion facing large and medium-sized cities, through real-time decision making and information dissemination. Accurate traffic flow prediction is the premise and key to its implementation. Therefore, accurate prediction of traffic flow and reasonable allocation of the existing road resources has become one of the important issues in current fields of urban traffic control and traffic guidance.

Currently, common models of traffic network prediction include ARIMA (Zhang G.P., 2003), Nonparametric Regression (Li Z.L., et al, 2008), Kalman Filter Model (Wang Y.B., et al, 2004), Nonparametric Regression Method (Sun Y., et al, 2002; Yang C., et al, 2013) and Neural Network Model (Dougherty M.S., et al, 1997). With application of neural network models, BP neural network (Wang C.B., et al, 2012), RBF neural network (Deng J., et al, 2014), and fuzzy neural network (Yin H., et al, 2002) have been adopted for urban traffic flow prediction. Among them, ARIMA is a method of linear time series prediction, while short-term traffic flow possesses high nonlinearity; Nonparametric Regression is simple and convenient for implementation, while lacking generalization ability and stability, with lots of restrictions in application. Kalman Filter Model is suitable for prediction of real-time dynamic traffic flow. However, the error term cannot be accurately determined; meanwhile, lots of matrix operations and parameter estimations are required in practical applications, without applicability in practical traffic. Gray Prediction Method mainly solves problems with less data quantity and large uncertainty; with fast operating rate and fast speed, but it's not applicable to urban traffic system with high volatility.

Elman neural network adopts updating methods of weights and thresholds consistent with BP neural network, namely gradient descent method, easily resulting in local minimum. Therefore, chaos particle swarm optimization method was used in the work to train the weights. Local optimization can be avoided through the improved chaos particle swarm optimization due to the feature of parallel search, ensuring fast and stable convergence of the algorithm. In the work, the improved CPSO-Elman neural network was used for short-term traffic flow prediction in order to test its adaptability, indicating well prediction effect. The empirical results show that the model is effective in application of urban short-term traffic flow prediction.

2. Chaos Particle Swarm Optimization

2.1. Particle Swarm Optimization

PSO (Particle swarm optimization) is an efficient search algorithm originating in foraging of birds. It can effectively optimize a variety of functions, with convenient implementation. PSO is an evolutionary computation technology proposed by Eberhart et al. in 1995, derived from simulation of a simplified community model. In PSO algorithm, each individual is regarded as a particle with a feasible solution in D-dimensional search space; the adaptive value of particle is calculated through fitness function. First of all, parameters of particle swarm scale and learning factors are determined; a group of particles are initialized, determining the initial position and velocity at random within prescribed limit. Then, each particle follows current optimal particle to find the optimal solution through iteration. In each iteration, the particles will obtain local minima pbest (optimal solution found by particles themselves) and global extreme gbest (current optimal solution found by the entire particle swarm).

Let position of the ith particle in D-dimension be . Current adaptive value of z_i can be calculated using fitness function. Let v_i be the velocity of particles, p_i the current optimal position of the particle, and p_g

the current optimal position of entire particle swarm. The velocity and position of particles can be updated according to the following equation:

$$v_{id}(t+1) = \omega v_{id}(t) + c_1\gamma_1(p_{id} - z_{id}(t)) + c_2\gamma_2(p_{gd} - z_{gd}(t)) \quad (1)$$

$$z_{id}(t+1) = z_{id}(t) + \Delta t \cdot v_{id}(t+1) \quad (2)$$

Where i=1,2...,m; d=1,2...,D; γ_1 and γ_2 are random numbers between 0 and 1, which can maintain diversity of the population; c_1 and c_2 are acceleration factors promoting particles to approach to historical optimal point or global optimal point; ω is the inertia weight, with the following function:

$$\omega = \omega_{\max} - k \cdot \frac{\omega_{\max} - \omega_{\min}}{k_{\max}} \quad (3)$$

γ_2 where $\omega_{\max}$ and ω_{min} are maximum and minimum values of inertia weight; k and $k_{\max}$ are current iterations and maximum allowable iterations, respectively. Particle swarm can adjust its global and local search capabilities by ω. Larger ω values are conducive to escaping from local minima, while smaller ω values conducive to convergence precision, thus ω values should be properly determined to achieve best search results.

2.2. Chaos Particle Swarm Optimization

PSO may result in local optimization despite simple algorithm, operating rate and strong search capability. However, CPSO algorithm (Tang X.l., et al , 2010;) can avoid the local optimal solution, with the following Logistic equation:

$$z_{n+1} = \mu z_n(1 - z_n) \quad (4)$$

In the formula, $n = 0,1,2\cdots,N; 0 \le \mu \le 4$, μ is the control parameter, and n is the number of iterations. When $0 \le z_n \le 1, \mu = 4$, the particles are in the state of complete chaos. Through Logistic equation of chaotic system, chaos sequence can be generated based on current optimal particle of particle swarm; fitness function is used to calculate chaos sequence, selecting the optimum particle; meanwhile, the optimum particle randomly replaces current position of a particle in particle swarm; thus, new particle swarm is formed for iteration, making PSO algorithm escape from local minima, finally achieving rapid search of optimal solution.

3. Elman Neural Network

Artificial neural network theory is a research frontier rapidly developed in the late 1980s around the world. It is the information system of expression, storage and conversion, composed of neurons in certain topological structure and connected relation. As an intelligent system imitating structure and activity of human brain, artificial neural network can simulate human imaginal thinking capability, with good ability in learning and acquiring knowledge.

As a neural network, Elman neural network is different from static neural networks, such as RBF neural network and BP neural network. Elman neural network is equipped with function of mapping dynamic characteristics by storing internal state. Thus, the system has capacity adapting to time-variant characteristics, which can more directly reflect dynamic characteristics. Elman neural network is generally divided into four layers. In addition to input layer, hidden layer and output layer similar to that of other neural networks, there is a copy layer in Elman neural network. Due to this structure, Elman neural network has strong sensitivity to historical state data, with delaying and storage capacity; meanwhile, internal feedback network can be constituted, thus increasing capacity of neural network in processing dynamic information. Input layer transmits the signal; output layer plays the role of linear weighting; hidden layer is generally the nonlinear transfer function; copy layer, which can be considered as the delay operator, is used to store the values outputted from hidden layer of the previous time, and return the values to input layer.

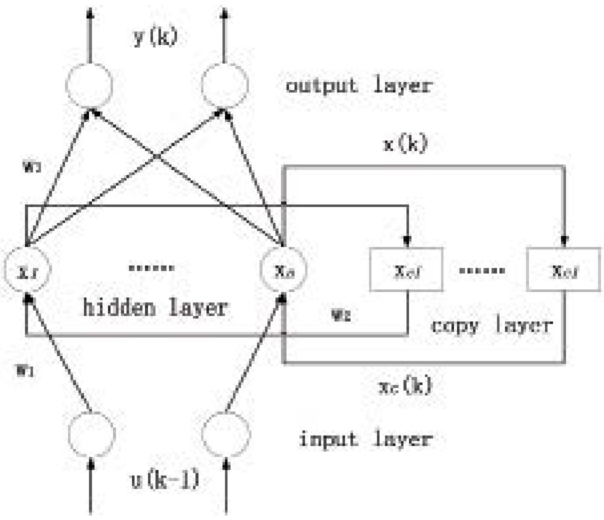

Figure 1. Infrastructure of Elman neural network

Nonlinear state space expression of Elman neural network is

$$y(k) = g(w_3 x(k)) \quad (5)$$

$$x(k) = w_1 u(k-1)) + f(w_2 x_c(k-1)) \quad (6)$$

$$x_c(k) = x(k-1) \quad (7)$$

Where u is r-dimensional input vector, x the node unit vector in n-dimensional middle layer, x_c the n-dimensional feedback state vector, and y the m-dimensional output node vector; w1, w2, w3 represent the connection weights from input layer to hidden layer, from copy layer to hidden layer, and from hidden layer to output layer, respectively; $g(\bullet)$ is transfer function of output neurons, is the linear combination of output from intermediate layer; $f(\bullet)$ is transfer function of intermediate layer neurons.

4. Prediction Model of Improved CPSO-Elman Neural Network

Chaos optimization mainly takes advantage of ergodicity of chaotic motion. However, logistic map is adopted in CPSO algorithm, with uneven trajectory points affecting the ergodicity. The adequacy and ergodicity of chaotic search can be improved by adopting Circle Map model (Alatas B., et al, 2009), avoiding defects of logistic map used in traditional algorithm. Equation of Circle Map model is described as follows:

$$z_{n+1} = z_n - \frac{1}{4\pi} sin(2\pi z_n) mod(1) + 0.2,\ 0 \leq z_n \leq 1 \quad (8)$$

In the standard PSO algorithm, parameters of γ_1 and γ_2 are usually random numbers in [0-1]. According to Equation (1), these parameters have significant impact on integrity and ergodicity of algorithm. In order to enhance chaotic modulation ability of the parameters and obtain better global search capability, Circle Map model was used to adjust parameters of γ_1 and γ_2, with adjustment equation as follows:

$$\gamma_{1,n+1} = \gamma_{1,n} - \frac{1}{4\pi} sin(2\pi\gamma_{1,n}) mod(1) + 0.2,\ 0 \leq \gamma_{1,n} \leq 1 \quad (9)$$

$$\gamma_{2,n+1} = \gamma_{2,n} - \frac{1}{4\pi} sin(2\pi\gamma_{2,n}) mod(1) + 0.2,\ 0 \leq \gamma_{2,n} \leq 1 \quad (10)$$

Traffic prediction of urban expressway without influences of sudden traffic incidents was researched in this work, constructing Elman neural network model based on improved CPSO. In Elman neural network, gradient descent method is used to update the weights and thresholds, with the defect of local minimum. Therefore, improved CPSO was adopted to train the weights of neural network in the work. Firstly, all connection weights of Elman network were integrated into a vector, as the position vector for optimization of CPSO algorithm. Secondly, fitness function of particles predicted error of Elman neural network; Circle Map was used to generate chaos particle swarm. Optimal global extreme could be obtained through iterations of the improved CPSO algorithm, thus completing the global search. Meanwhile, the global optimum particle was regarded as the initial value of Elman neural network. Local optimal search was performed using training algorithm of Elman neural network. If the deviation of optimization results exceeded the intended target, then algorithm returned to global search. This process was repeated until achievement of ultimate optimum. Figure 2 shows the workflow of the improved CPSO-Elman neural network model.

The detailed process of improved CPSO-Elman neural network model is described as follows:

Step 1: Elman neural network is established, determining dimensions of input layer, hidden layer, copy layer and output layer as R, N, N, M and R, respectively; R groups of input sample sets and M groups of output sample sets of neural network are given;

Step 2: Improved CPSO algorithm is used to train weights and thresholds of Elman network. First of all, connection weights between neurons in specific structures are decoded into individual vector. For example, if neural networks contain N optimizing weights, then each particle will be expressed as an N-dimension vector consisting of N weight parameters. Then, the size of particle swarm should be determined, initializing chaos particle swarm;

Step 3: Each individual particle vector is decoded, bringing into Elman neural network to obtain total error, namely pbest (individual extreme of the particle). The global extreme gbest of particle swarm is obtained by comparison, training weights and thresholds which are decoded from gbest. Then, optimal particle and optimal extreme gbest after local optimization can be obtained;

Step 4: The gbest is determined whether it satisfies the exit condition of CPSO—whether the gbest reaches the set value and maximum number of iterations. If it satisfy the condition, then the process exit CPSO optimization, turning to Step 6 of Elman neural network for optimization;

Step 5: The optimal particle after optimization of Elman neural network is performed with chaotic optimization. Then, the optimal particle after chaotic optimization replaces a particle in particle swarm. Substituting Circle Map model Formula (8), (9), and (10) into Formula (1) and Formula (2), the global optimal

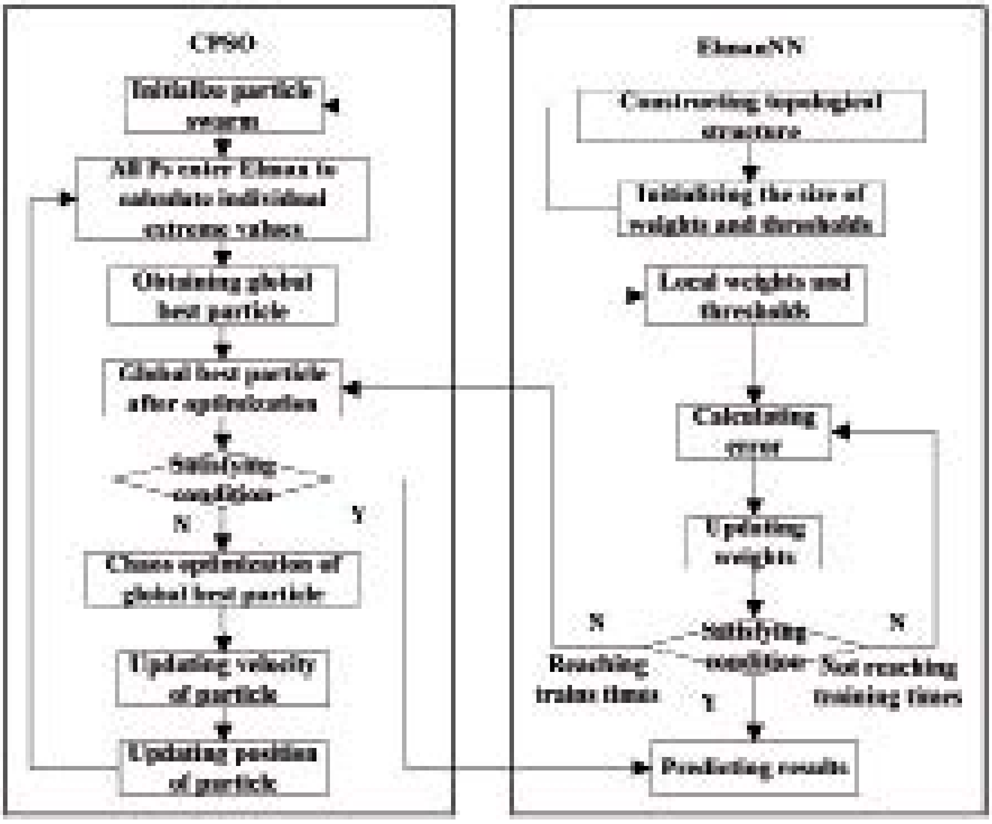

Figure 2. Prediction of improved CPSO-Elman neural network

particle is performed with chaotic optimization. The optimal particle after chaotic optimization replaces a particle in particle swarm, then updating velocity and position of each particle. Then, returning to Step (3) for global search based on CPSO algorithm, the optimum can be ultimately achieved.

Step 6: The optimal trained Elman network can be applied into actual traffic flow prediction.

4. Case Analysis

Experimental data used in the work was selected from section traffic flow detected by RTMS (excluding the data influenced by sudden incidences) near Shibali Bridge in southeast Fourth Ring Road of Beijing in China. Based on the section traffic flow data detected by RTMS with cycle of 2min, traffic flow in April 14, 2014 was collected as the data source for example verification. The measured data was compared with predicted results; meanwhile, prediction methods of Elman neural network (Yang Q.F., et al , 2012) and BP neural network (Wu X.B., et al , 2014) were used for experimental comparison, verifying validity and accuracy of CPSO-Elman neural network algorithm.

According to experimental analysis of traffic flow prediction, prediction for the data within 30 min (30 detection periods) was more accurate. Thus, data of 20 cycles were selected to predict current traffic flow. Accordingly, the number of nodes in input layer of Elman neural network was 20; there were 1 node in output layer, namely traffic flow. After preliminary testing, when the number of neurons in hidden layer was 28, the algorithm had better convergence, with best pre-training effect of network and relatively small test error. This is because the copy layer performed storage and delay for hidden layer, while the number of neurons in copy layer was 28 as well. Transfer function of hidden layer was tansig, while it was purelin for output layer and trainln for network training. Learning rate was set as 0.1, the largest number of training as 100, and the training

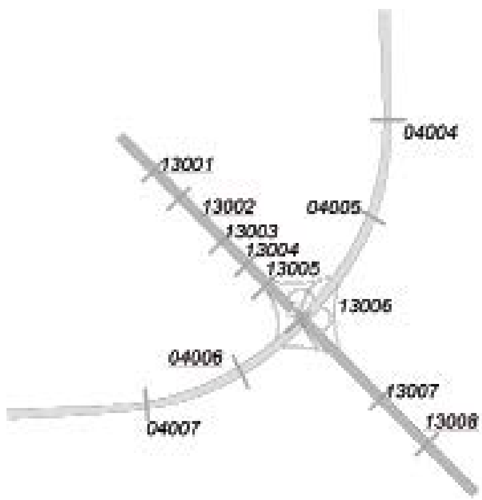

Figure 3. Shibalidian interchange structure in Beijing

target as 0.001. Particle number of particle swarm was 50; learning factor c1 and c2 were both 2; maximum number of iterations was 200 and the largest number of chaos optimization was 20. In order to evaluate and compare the results, common performance indexes used in BP neural network and Elman neural network were adopted in the research. The structures of both BP neural network and Elman neural network were 20-28-1, with 20 nodes in input layer, 28 nodes in hidden layer and 1 node in output layer. Figure 4 and Figure 5 showed the results of prediction (the 04004 traffic data in inner ring of the forth ring road was adopted for analysis). Figure 4 showed the comparison between predicted value of traffic flow using improved CPSO-Elman neural network algorithm and the measured data; Figure 5 showed prediction error curve of three traffic flow prediction models.

According to experimental results of Figure 4 and Figure 5, the accuracy of prediction for three models was all greater than 0.94, indicating that the models could well reflect the changes of actual traffic flow, with small error between prediction results and measured values. In particular, the improved CPSO-Elman neural network model had the highest accuracy of prediction, reaching 0.97%; meanwhile, it had higher convergence rate, with stronger adaptability in rapidly changing traffic. This indicates that CPSO-Elman neural network model is more suitable for traffic prediction of urban expressway. In short, according to analysis of case study and prediction error, the improved CPSO-Elman model can conduct accurate prediction on short-term traffic flow of urban expressway; meanwhile, the prediction effect of improved CPSO-Elman model is better than that of Elman neural network and BP neural network.

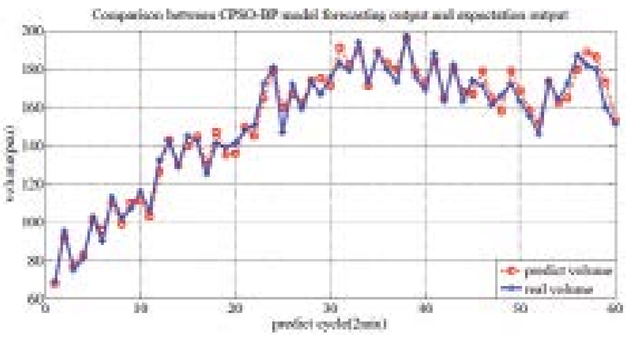

Figure 4. Comparison between CPSO-BP prediction output and expectation output (04004)

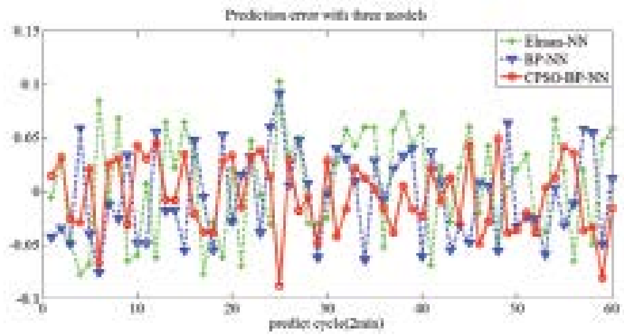

Figure 5. Prediction error with three models (04004)

5. Conclusions

In the work, improved CPSO-Elman neural network model is used to predict traffic flow in urban expressway based on RTMS traffic flow data. The results show that the model can be applied to short-term traffic flow prediction for urban expressway, with good convergence rate and prediction accuracy. Updating method of network weights used in Elman neural network and BP neural network easily results in local minimum. Thus, CPSO algorithm is used to train initial network weights and thresholds to overcome its shortcoming, improving convergence speed and prediction accuracy of Elman model. The proposed model is focused on prediction of single-section traffic flow for urban expressway, while intelligent traffic control requires short-term traffic flow prediction for complex road network. Therefore, further research should focus on achieving traffic flow prediction for complex road network.

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Research on the Optimization of Distributed Logistics Routing Based on Particle Swarm Optimization Algorithm and Ant Colony Algorithm

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Abstract

Aiming at the traditional logistics distribution path that paid much emphasis on cost factors but ignoring the factor of the delivery time, leading the problem of the long working time of driver affecting the quality of service, optimization of logistics distribution routing problem is a kind of NP complete problem with very high practical value. In