

## Utilize Improved Particle Swarm to Predict Traffic Flow

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**Abstract**—Presented an improved particle swarm optimization algorithm, introduced a crossover operation for the particle location, interfered the particles' speed, made inert particles escape the local optimum points, enhanced PSO algorithm's ability to break away from local extreme point. Utilized improved algorithms to train the RBF neural network models, predict short-time traffic flow of a region intelligent traffic control. Simulation and test results showed that, the improved algorithm can effectively forecast short-time traffic flow of the regional intelligent transportation control, forecasting effects is better can be effectively applied to actual traffic control.

**Keywords**- Improved particle swarm; RBF neural network; Traffic flow prediction

### I. INTRODUCTION

Section traffic intelligent control system can reasonably control the traffic flow in the urban road network, use the intersection in a time-period to avoid traffic accidents, reduce or prevent traffic congestion, reduce flue gas emissions and energy consumption, provide traffic information for associated personnel on the vehicles in good time to improve traffic and pedestrian safety [1-2]. To achieve the above control, the system needs real time communications instant understanding of the situation, must install a large number of advanced detectors on the roads to collect traffic information, analyze the gathered information, generate the future traffic flow data that is traffic flow [3-4]. Forecasting can divide into short-term forecasting, medium-term forecasting, long-term forecasting; respectively services in different study fields. Short-time traffic flow forecast can better forecast the future state of urban road network traffic flow information within a short time, can meet a city traffic control system the real-time performance and the accuracy requirements of traffic flow information in a short time, get the correct control strategy, achieve to network smooth, and efficient run; research forecasting method of short-time traffic flow on a city traffic control system has important significance [5-7].

Short-time traffic flow prediction is mainly used for urban traffic signal control system, which is at the bottom and the most fundamental part--the intersection control (control). Intersection control is more sensitive than the main road (linear control), urban area control (control) in implementation of control, short-time traffic flow forecasting of real-time, has high-accuracy requirements. Short-time traffic flow prediction accuracy directly influences the

quality of intersection traffic control; so short-time traffic flow forecasting research on the study of the urban traffic signal control intersection control system has important significance [8-10].

For current traffic flow forecast in the exists of problem, in this paper, presented a traffic flow forecast method, utilize improved PSO algorithm to optimize RBF Neural network model, use improved particle group to optimize RBF Neural.

### II. MODEL AND ALGORITHM DESIGN

#### A. Improved Particle Swarm

PSO is an evolutionary computing developed by Kennedy and Eberhart in 1995 [11-12], is a class of a stochastic optimization algorithm based on swarm intelligence [13-14]. In PSO algorithm, each individual look as a particle in a d-dimensional search space, fly at a certain speed in the search space, dynamically adjust the speed according to themselves and companion flying experience [15]. Each of the particles has an objective function to determine the adaptation value, particles search the optimal solution followed the current optimal particle in the solution spaces, find the optimal solution by iteration. In each iteration, particle by tracking individual extreme values and global extreme values to update myself, in the process of looking for the two extremes, the particle updates own speed and location according to the following location:

$$V_{id}(i+1) = \omega \times V_{id}(i) + \lambda_1 \times rand() \times (P_{best} - L_{id}(i)) + \lambda_2 \times rand() \times (G_{best} - L_{id}(i)) \quad (1)$$

$$L_{id}(i+1) = L_{id}(i) + V_{id}(i+1) \quad (2)$$

$$\delta = \frac{\mathcal{E}_{max} - (\mathcal{E}_{max} - \mathcal{E}_{min}) \times N}{N_{max}} \quad (3)$$

In formula (3),  $N$  and  $N_{max}$  separately represents the current evolution algebra and the maximum number evolution;  $V_{id}(i)$  and  $V_{id}(i+1)$  separately represents the current particle speed and the updated particle speed;  $L_{id}(i)$  and  $L_{id}(i+1)$  separately represents the current particle location and the updated particle location;  $\mathcal{E}$  is inertia weight, used to balance global search and local search;  $\lambda_1$  and  $\lambda_2$  represents learning factors, here set  $\lambda_1 = \lambda_2 = 2$ .

PSO algorithm as a new stochastic search algorithm, it has shortcomings that is slow convergence and easy to fall into the local optimum. To overcome these disadvantages, scholars' research on improved PSO algorithms from different angles, which main include: improve parameters,

improvement evolution equation, fuse other intelligence optimization algorithms, etc....

In this paper, IPSO is used to improve the mutation operation of particle velocity, introduced a crossover operation for the particle location together. The crossover operation enhanced PSO algorithm's ability to get rid of local extreme point, further improving the algorithm convergence rate and the global convergence. Its main thought can be described as follows: after updating the population each time, pick out  $m$  particles randomly, choose the current location  $L_i$  of  $m$  particles to cross with corresponding individual extreme value  $P_i$ , the crossing rule is sorted by fitness values, which are top n better individual extreme values  $SP_i$  of the particle  $m$ . Then get  $m$  new particle position  $L'_i$ , if the adaptation value of new location  $f(L'_i)$  is better than corresponds to individual extreme of history optimal adaptation value  $f(SP_i)$ , then  $f(L'_i)$  replaced  $f(L_i)$ , as same as  $L'_i$  replaced  $L_i$ . Obviously, this cross operation makes particles in an evolutionary, takes advantage of its own historical experience information, also using good individual experience information; increases the diversity of particles, also increasing the population evolution quality of, further increase particles find global optimal possibilities.

In addition, can see from the evolution of standard Particle Swarm, later in the iteration, when certain particle's location and its individual optimal extreme global extreme is closing to the population. Its update speed decided by  $\omega$ , as  $\omega < 1$ , at this point, the particles' speed will rapidly toward zero, inert particles run to appear. As the iteration progresses, other particles would soon gather around these inert particles, make a particle premature convergence in  $G_{best}$  and stopping moving, the particles' velocity becomes 0. Actually,  $G_{best}$  just is the current best finding-point, can't guarantee it is the global optimal solutions of the optimization problem.

Particle close to  $G_{best}$  is relative to the size of the particle velocity. Therefore, can interfere with the particles' speed, make inert particles escape the local optimum points, let the algorithm converge to the global advantage as much as possible. Obviously, to get algorithm out of local optimization, should determine the algorithm is likely to fall into local optimum under what circumstances. Based on the above analysis, the assessment criterion is shown as follows in this article: when the fitness of population global extreme  $f(G_{best})$  is greater than optimal problem's accuracy error  $Err$ , and appearing "lazy" particles in population; can consider algorithm is likely to fall into the local optimum. While judging algorithm is likely fall into local optimum, utilize speed mutation on the inert particles whose speed is less than a given threshold, get rid of the "inert", effectively reduce the possibility of algorithms into a local optimum.

### B. Test function

Utilized the typical test function Griewank to simulate, the convergence effect is shown in Figure 1, from Figure

1 can see, the improved IPSO has good convergence properties.

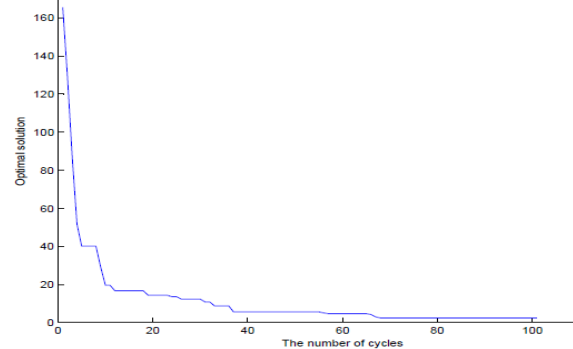


Figure 1. Convergence performance

### C. RBF model

RBF neural network is a three-layer feed-forward neural networks, use radial-basis functions as a hidden unit "matrix", constitute a hidden-layer space, hidden-layer transform the input vector, transform low-dimensional model-input data to higher-dimensional space, linear integral problems in low-dimensional space can be divided in a higher-dimensional space. RBF network structure is simple, fast convergence, has the ability to approximate arbitrary non-linear function, has broad application prospects for time-series forecasting.

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RBF neural network consists of  $n$  input node,  $m$  hidden layer node and one output node, the hidden layer node is RBF function, can be expressed as follows:

$$h_i = \exp\left[-\frac{\|\omega_i - \lambda_i\|}{2\phi_i^2}\right] \quad i = 1, 2, \dots, m \quad (4)$$

In formula (4),  $\omega_i$  represent the output weights,  $\lambda_i$  represent the  $i$  RBF hidden node centre,  $\phi_i$  is RBF width of hidden node. the output weights  $\omega_i$ , hidden node centre  $\lambda_i$  and width  $\phi_i$  in RBFNN, have a significant impact for predicting forecast performance of the RBF neural network model, so must select appropriate parameters to improve the RBF Neural network forecast performance.

Set neuron represent all input weights sum and a certain threshold of nonlinear function  $\alpha(\cdot)$ , meet  $\alpha(-\infty) = 0$  and  $\alpha(\infty) = 1$ , which can be described as follows:

$$\alpha(x) = \frac{1}{1 + e^{-cx}} \quad (5)$$

In formula (5),  $c$  is a CONST, determine the shape of the function.

As RBF neural network has a certain infinite approximation capacity, for multiple-input and single-output, the output is the hidden layer neurons weights sum for output, it can be expressed as follows:

$$y = \sum_{j=1}^p t_j \alpha \left( \sum_{i=1}^n \omega_{ij} x_i + \omega_{n+1,j} \right) \quad (6)$$

In formula (6),  $\omega_{ij}$  and  $t_j$  represent adjustable weights,  $n$  and  $p$  separately represent the number of neurons in input layer and hidden layer.

Use RBF neural networks to identify the nonlinear function  $\alpha(\cdot)$ , make the estimation value  $q_N(k+1)$  which produce by neural networks possibly approximate the actual traffic flow measurement values  $q(k+1)$ . Set  $N_{\alpha}(\cdot, \theta_{\alpha})$  represent neural networks of the nonlinear function  $\alpha(\cdot)$ ,  $\theta_{\alpha}$  is the weight vector of neural networks, in the times  $kT$ , traffic estimates value, estimation error which produce by the model  $N_{\alpha}(\cdot, \theta_{\alpha})$  of the weight  $\theta_{\alpha}$ , can be separately shown as follows:

$$q_N(k+1) = \beta q(k) + N_{\alpha}(H(k); \theta_{\alpha}(k)) \quad (7)$$

$$e(k) = q_N(k+1) - q(k+1) \quad (8)$$

In formula (7),  $\beta$  is a CONST, its absolute value is less than or equal to 1.

Combined genetic algorithm with PSO algorithm to produce parameters, to optimize RBF Neural network model, produce a new generation of individuals, eliminate individual parent, up to the maximum number of evolution or to generate optimal solutions, finally get optimal neural network, output weight  $\omega_i$ , hidden units center  $\lambda_i$  and width  $\phi_i$ . For short-time forecasting of traffic flow, first, can collect historical traffic data; then, process and analysis the raw data; finally, determine the optimum parameters of the model, predict future traffic flow.

#### D. IPSO Steps

In RBF Neural network, output weight  $\omega_i$ , hidden units in the centre  $\lambda_i$  and the width  $\phi_i$ , which Have a great influence for the predictive performance of the RBF neural network forecasting model, however, it is difficult to determine the appropriate value of the  $\omega_i, \lambda_i, \phi_i$  in advance.

As PSO has a strong global search capability, in this article, use genetic algorithm combined PSO algorithm to optimal the parameters  $\omega_i, \lambda_i, \phi_i$  of RBF Neural network, the steps are shown as follows:

Step 1: Determine the scope of speed variable  $V_1$  and location variable  $L_1$ , initialize the individual extreme  $P_{best}$  and global extreme  $G_{best}$ ;

Step 2: Transform each individual component in the Particle Swarm into neural network parameters, compose a

neural network, input the training samples for neural network to train, calculate the mean square error in the training set;

Step 3: According to individual fitness to evaluate the search position of each particle, calculate individual extreme value and population global extreme value of the current particle;

Step 4: Update individual search location based on the above formula (4), (5) and (6), speed, and connection weights of each particle;

Step 5: If reaching the maximum iteration's number, or matching mean square error of the initial set value, end particle search, output the optimal particle position. Otherwise, return to step three, repeat the iterative optimization. The obtained optimal parameter values of a set of particles as optimal results input the measured data and forecasting traffic flow.

### III. SIMULATION AND APPLICATION

A large number of studies have shown that, traffic flow at some point of traffic section in an urban traffic network, which is intrinsically linked with the traffic flow of some previous time-period, can use section sequences of traffic flow data to predict future traffic flow. In this article, collected 2 days of traffic flow data, recorded the traffic flow at one time every 15 minutes; then, collected a total of 288 data points, used the data of 2 days before to train neural networks; at last, used 96 data points of 4<sup>th</sup>-day traffic data to verify the accurate forecasting of traffic flow, traffic data is shown in Figure 2.

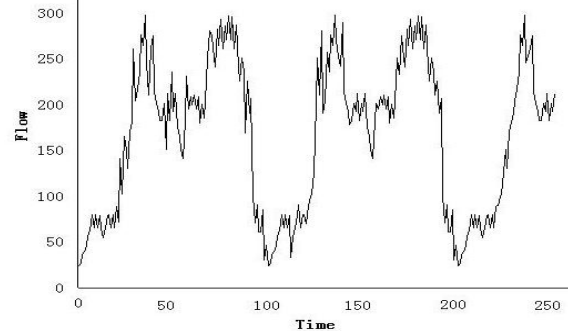


Fig. 2 Traffic flow

To eliminate the quantity magnitude differences between the dimensional data, avoid causing larger network prediction error for the quantity magnitude differences of the input/output data is larger, while speeding up the training speed, normalize data processing, set all naturalization data between 0 and 1. In this article, utilize max-min to normalized data, which is shown in the following:

$$x_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \quad (9)$$

In formula (9),  $x_{\min}$  and  $x_{\max}$  separately represent Extreme value data.

Get the optimal parameters of RBF Neural network through using IPSO, determine BP neural network's structures according to input and output data of the system, according to short-time traffic flow patterns, set RBF Neural network structure is 4-6-1, that is, input layer has 4 nodes,

hidden layer with 6 nodes, 1 nodes at the output level. Train BRF neural network with the training data, train 100 times over and over again, Use already trained BRF neural network to forecast short-time traffic flow, analyze the forecast results, which is shown in Figure 3.

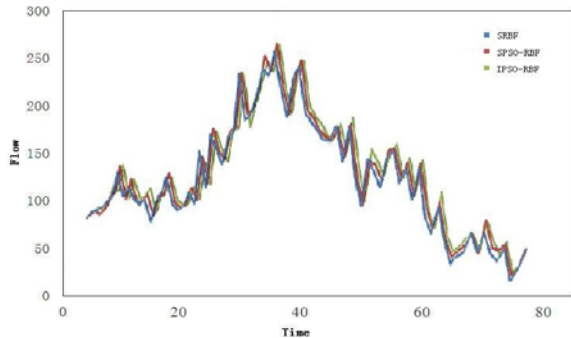


Fig. 3 Forecast results

To further validate the designed algorithm's effectiveness, carried out comparative experiments at the same time through using the following algorithms: standard RBF Neural Network (SRBF), RBF Neural Network based-on standard PSO algorithm (SPSO-RBF), RBF Neural Network based-on improved PSO algorithm (IPSO-RBF), the results are shown in Table 1.

TABLE I. PREDICTION DATA

Algorithms	maximum evolution algebra	average relative error percentage	maximum relative error percentage	generalization ability
SRBF	300	8.81	11.04	poor
SPSO-RBF	200	6.79	9.03	general
IPSO-RBF	100	5.67	7.65	better

Through comparatively analyzing data in the table can see, the designed algorithms have higher prediction accuracy than other methods, which is suitable for practical application; fast convergence speed, reduce the training time of samples; has better generalization ability, error values are relatively stable.

In General, through above simulation and error analysis can know, the designed algorithms can accurately forecast short-time traffic flow of the regional intelligent transportation control, forecasting effect is better, can be effectively applied to actual traffic engineering.

#### IV. CONCLUSIONS

Combined genetic algorithm with improved PSO algorithm to optimize RBF Neural network model, predict short-time traffic flow of a region intelligent traffic control, its forecasting result compared to other methods, has higher

prediction accuracy, the forecast results provide a strong protection for the region intelligent traffic control.

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