Short-time Traffic Flow Prediction Method Based on Universal Organic Computing Architecture

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***Abstract*—Designed a DNA-based genetic algorithm under the universal architecture of organic computing, combined particle swarm optimization algorithm, introduced a crossover operation for the particle location, can interfere with the particles' speed, make inert particles escape the local optimum points, enhanced PSO algorithm's ability to get rid of 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 error analysis of experimental results showed that, the designed algorithms can accurately forecast short-time traffic flow of the regional intelligent transportation control, forecasting effects is better, can be effectively applied to actual traffic engineering.**

Keywords- Short-time traffic flow; Organic computing; Particle Swarm Optimization algorithm; RBF Neural network

I. INTRODUCTION

With the accelerated development of economic construction and urban scale, foreign exchanges become more frequent and the improvement of people's material and cultural living standards, increasing traffic demand. According to statistics, all road vehicles are growing at a rate of 2-3 times in the world [1-2]. To solve this problem, countries all over the world are developing intelligent transportation systems (ITS) research, intelligent transportation system has been an important development direction of 21st century modern transportation system [3].

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 [4].

In this article, proposed a new short-time traffic flow forecast method(IPSO-RBFNN), combined genetic algorithm based on DNA computing with PSO algorithm to optimize RBF Neural network model under organic computing environment [5-6], use improved particle group to optimize RBF Neural, simulation experimental results indicate that, compare to BP neural network, RBF Neural network based on PSO optimization has higher forecast precision, convergence speed also corresponding accelerates, provide the theoretical basis and the reference value to resolve or alleviate the growing congestion of city.

II. STRUCTURE AND MODEL DESIGN

A. Organic Computing universal Architecture

Organic computing is emerging in recent years on a challenging area for future information processing. Proposed organic computing because of more and more autonomous systems combination in the future, these autonomous systems are equipped with sensors, actuators etc., can sense its environment, can cross freely between them. To accomplish a task or action, which also can automatically self-organization [7]. Intelligence system network has opened a fascinating application field in life, at the same time it has its own control. Therefore, must construct the following characteristics of the system: robust, secure, flexible and reliable, especially, fully centralized, single-technology applications may better meet the humans' needs. To accomplish this objective, system need to be more independent, flexible and autonomous, as organic computing systems can dynamically adapt current environment [8-9].

It is a key part of OC systems for responding emergency incident as a whole, can adopt a way to move from a centralized system to a decentralized system, which includes a number of related subsystems. To evaluate the behavior of the system, use cyclical feedback control to allow the system to respond to the dynamics external environment, the observer/controller architecture is shown in Figure 1.

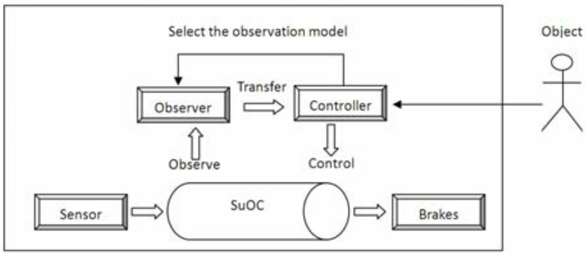

Figure 1. OC observation/control architecture

This universal architecture allows for self-organization, at the same time, have an adequate response to control and coordinate the whole acts of self-organization technology systems, which may be unpredictable sometimes. Distributed system is called the observation / control system, the observer and the controller is responsible for the proper supervision and feedback itself. Through suiting the different observation model, different choices for different properties and tools, the observer can be made into different modes. Data analyzer and Predictor can be regarded as a method of observing toolbox, the universal architecture doesn't point the machine learning mechanisms in detail. Currently use methods are shown as follow: artificial neural network, learning classification system, compulsory learning, and evolutionary algorithms etc... Such as evolutionary algorithms can create new rules, the crossover and mutation of genetic operation can modify the existing rules, in addition, simulation is also necessary for prediction and control whether the action is successful.

In this article, follow the universal OC architecture, combine genetic algorithm based on DNA computing with PSO algorithm, to optimize three-layered feed-forward RBF Neural network model.

B. RBF neural network 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 [10].

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:

$$h_i = \exp[-\frac{\| \omega_i - \lambda_i \|}{2\phi_i^2}] \qquad i = 1,2,...,m \tag{1}$$

In formula (1), ω_i represent the output weights, λ_i represent the i RBF hidden node centre, ϕ_i is RBF width of hidden node. the output weights ω_i, hidden node centre λ_i and width ϕ_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 $\alpha(.)$, meet $\alpha(-\infty)$ =0 and $\alpha(-\infty)$ =1, which can be described as follows:

$$\alpha(x) = \frac{1}{1+e^{-cx}} \tag{2}$$

In formula (2), 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:

$$y = \sum_{j=1}^{p} t_j \alpha(\sum_{i=1}^{n} \omega_{ij} x_i + \omega_{n+1,j}) \tag{3}$$

In formula (3), ω_{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 $\alpha(.)$, 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 $N_\alpha(.,\theta_\alpha)$ represent neural networks of the nonlinear function $\alpha(.)$, θ_α is the weight vector of neural networks, in the times kT, traffic estimates value, estimation error which produce by the model $N_\alpha(.,\theta_\alpha)$ of the weight θ_α, can be separately shown as follows:

$$q_N(k+1) = \beta q(k) + N_\alpha(H(k);\theta_\alpha(k)) \tag{4}$$

$$e(k) = q_N(k+1) - q\ (k+1) \tag{5}$$

In formula (4), β is a CONST, its absolute value is less than or equal to 1.

Combined genetic algorithm based on DNA computing 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 ω_i, hidden units center λ_i and width ϕ_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.

III. ALGORITHM DESIGN

A. Improved Particle Swarm Optimization

In PSO algorithm, 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:

$$V_{id}(i+1) = \omega \times V_{id}(i) + \lambda_1 \times rand() \times (P_{best} - L_{id}(i)) + \lambda_2 \times rand() \times (G_{best} - L_{id}(i)) \tag{6}$$

$$L_{id}(i+1) = L_{id}(i) + V_{id}(i+1) \tag{7}$$

$$\delta = \frac{\varepsilon_{\max} - (\varepsilon_{\max} - \varepsilon_{\min}) \times N}{N_{\max}} \tag{8}$$

In formula (8), 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; ε is inertia weight, used to balance global search and local search; λ_1 and λ_2 represents learning factors, here set $\lambda_1 = \lambda_2$ =2.

In this article, DNAGA-PSO algorithm 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 ω, 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. Algorithm process

In RBF Neural network, output weight ω_i, hidden units in the centre λ_i and the width ϕ_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 ω_i, λ_i, ϕ_i in advance. As PSO has a strong global search capability, in this article, use DNA-based genetic algorithm combined PSO algorithm to optimal the parameters ω_i, λ_i, ϕ_i of RBF Neural network, the steps are shown as follows:

(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};

(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;

(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;

(4) Update individual search location based on the above formula (2), (3) and (4), speed, and connection weights of each particle;

(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 an optimal result, input the measured data and forecasting traffic flow.

IV. APPLICATION AND ANALYSIS

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 four days of traffic flow data, recorded the traffic flow at one time every 15 minutes; then, collected a total of 384 data points, used the data of three days before to train neural networks; at last, used 96 data points of 4th-day traffic data to verify the accurate forecasting of traffic flow, traffic data is shown in Figure 2.

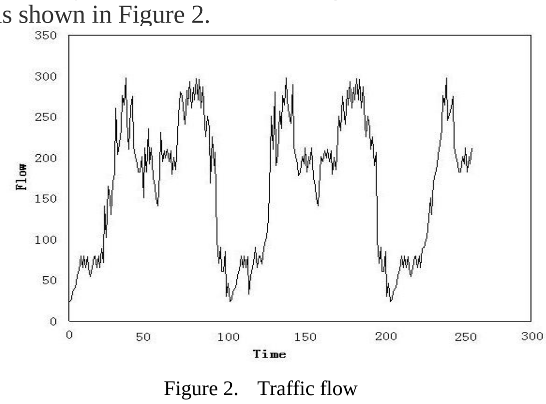

Figure 2. Traffic flow

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 to 1. In this article, utilize max-min to normalized data, which is shown in the following:

$$x_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{9}$$

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

Get the optimal parameters of RBF Neural network through using DNAGA-PSO, 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, 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. 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, standard RBF Neural Network based-on PSO algorithm, standard RBF Neural Network based-on PSO algorithm and genetic algorithm, RBF Neural Network based-on PSO algorithm and DNA computing genetic algorithm, which is shown in Figure 3 and Table 1.

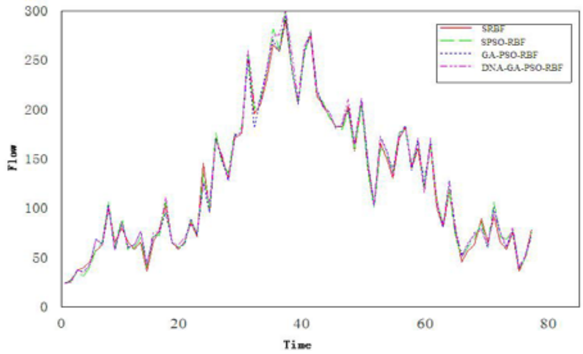

Figure 3. Various forecast results

TABLE I. PREDICTION PERFORMANCE OF VARIOUS ALGORITHMS

Algorithms	**maximum evolution algebra**	**average relative error percentage**	**maximum relative error percentage**	**generalization ability**
SRBF	300	8.94	12.12	poor
SPSO-RBF	200	6.76	9.08	general
GA-SPSO-RBF	100	4.58	6.63	better
DNA-GA-SPSO-RBF	100	3.69	5.77	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.

V. CONCLUSIONS

Combined genetic algorithm based on DNA computing with 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.

In addition, the designed algorithm performance highly depends on the data collection precision of the prediction region, When the accuracy of data acquisition is lower, the effectiveness of the algorithm is lower; this needs further research and improvement.

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