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Research of Prediction Scheme Based on Adaptive Particle Swarm Wavelet Neural Network Model

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***Abstract*—Traffic flow prediction have the characteristics of complexity, non-linearity and randomness. Researchers are resorting to hybrid neural networks fusing more effective algorithms into forecast process. This paper advances a fresh algorithm with both the thought of variation and adaptive to conquer the poor global optimization capability and slow convergent rate of traditional back propagation neural network (BPNN). Mathematically, this algorithm constructs an adjustable formula to generate acceleration factors based on a logistic curve equation. Variable random initialization strategy has been introduced simultaneously. Simulations reveal that in contrast to auto-regressive integrated moving average model (ARIMA), back propagation neural network and wavelet neural network (WNN), the mean relative error reduced from about 10% to nearly 5%, the running time dropped from 5 seconds above to 2.5 seconds below, and the quality of the traffic flow prediction has a great improvement, which verifies the superiority of the brand new method proposed in this paper.**

Keywords-intelligent transportation system; traffic flow prediction; adaptive; variation; neural network; particle swarm optimization

I. INTRODUCTION

Prediction accurately of traffic flow in real-time is one of the key steps in realizing Intelligent Transportation System. It can either provide scientific basis for traffic management and control or offer scheme timely for road-induced. Thus bring the utilization of current traffic facilities into full play while guarantee commuters' travel quality.

Various methods and models of forecast traffic flow are presented by experts and scholars. Among them, algorithms based on linear system theory such as Kalman filtering in [1] and time series model are simple to use but have a relative low fitting towards complicated nonlinear dynamic problems. Though have better suitability, wavelet analysis and chaos theory in [2] for example which depend on nonlinear system theory need some background knowledge and the parameter computing is rather complex. In contrast, take both neural network model and support vector machine as in [3,4] for example, these intelligent models of knowledge discovery can easily reflect the correlation of inputs and outputs only by less preparation, but have poor global search ability which influences forecast accuracy. Traffic simulation in [5] like cellular automaton and dynamic traffic assignment have limited applied scope which influenced by the simulated environment.

Back propagation neural network (BPNN) can get an optimal approximation mapping towards any nonlinear relationship and have rather good generalization ability. Reference [6] built a short-term prediction model by multilayered back propagation neural network. And came to a conclusion that the measured data and predicted data have rather high correlation. Thus verifies the favorable estimated performance of neural network. Reference [7] utilized binary neural network to predict traffic flow and reached the effect of "training once, repeatedly use". But the BPNN remains to be improved on account of mainly three weaknesses. That is easily trapped into local optimal solution, slow convergent rate and diverse parameter structure. In view of the first two problems, a new adaptive particle swarm wavelet neural network (APSWNN) algorithm is proposed. APSWNN unites wavelet analysis, adaptive particle swarm optimization (PSO), variation concept and BPNN together. In this paper, we adopt the traffic flow in current period of time with three periods before as the network input variables and the traffic flow in next period as output. Experiments demonstrate that APSWNN has obvious advantages in predictive quality comparing to auto-regressive integrated moving average model (ARIMA), BPNN and wavelet neural network (WNN).

II. THEORY OF WAVELET NEURAL NETWORK AND PARTICLE SWARM OPTIMIZATION

A. Back Propagation Neural Network Algorithm Overview

BPNN is an abstract mathematical model derived from modern neuroscience. Similar to the process synapses dealing with information, BPNN realizes peculiar functions by means of employing counter-propagation error to regulate weights and threshold between connections. It's a kind of multi-layer feedback forward neural network with hidden layer [8].

Figure I depicts the basic component unit of neural network namely neuronal model. There are four basic elements: a set of connection w_{ij}, a summation unit u_j, an excitation function $f(x)$ and a threshold b_j (or bias $\theta_j = -b_j$). Formulas can be demonstrated as follows:

$$u_j = \sum_{i=1}^{n} w_{ij} x_i, v_j = net_j = u_j - b_j, y_j = f(v_j). \tag{1}$$

Wavelet-based function Morlet is adopted as the excitation function in the hidden layer. The expression is described in (2).

$$y = \cos(1.75x)e^{-x^2/2} \tag{2}$$

B. Particle Swarm Optimization Algorithm Profile

PSO, which stems from the simulation of birds flock's foraging behavior, treats each bird namely potential solution as particle in the searching space for optimization problem. Every particle takes position, velocity and fitness value as feature for itself. Therefore, particles can continue to seek in solution domain following the current best ones which included individual's and group's [8].

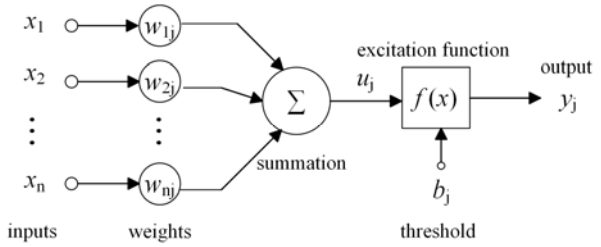


FIGURE I. NEURONAL MODEL

Assume that dimension of search space is d, population size i = 1, 2, ... N, for the ith particle: the position $\boldsymbol{X}_i^t=[x_{i1},x_{i2},...x_{id}]^t$, the velocity $\boldsymbol{V}_i^t=[V_{i1},V_{i2},...V_{id}]^t$, individual's extremum is $\boldsymbol{P}_i^t=[P_{i1}, P_{i2},...P_{id}]^t$, $\boldsymbol{P}_g^t=[P_{g1}, P_{g2},...P_{gd}]^t$ is group's extremum. The fitness value of particle i can be computed in line with the objective function.

Particles need to be updated by P_i and P_g among the iterative process. Renewal for velocity and position can be indicated as below:

$$V_{ij}^{(t+1)} = \omega V_{ij}^{\ t} + c_1 r_1 (P_{ij}^{\ t} - X_{ij}^{\ t}) + c_2 r_2 (P_{gj}^{\ t} - X_{ij}^{\ t}), \tag{3}$$

$$X_{ij}^{(t+1)} = X_{ij}^{\ t} + V_{ij}^{(t+1)}, 1 \le i \le N, 1 \le j \le d. \tag{4}$$

where t is the current iteration, ω is inertia factor, c_1 and c_2 are accelerated factors that should be non-negative constant, r_1 and r_2 are random number range from 0 to 1. To avoid blind search, velocity and position of particles restricted to interval of [—$\boldsymbol{V}max$, $\boldsymbol{V}max$] and [—$\boldsymbol{X}max$, $\boldsymbol{X}max$].

III. THE NEW ADAPTIVE PARTICLE SWARM WAVELET NEURAL NETWORK PREDICTION ALGORITHM

A. Definition of Self-adaptive Accelerated Factors

Accelerated factors c_1 and c_2 represent individual and group cognition respectively. Self-adaptive accelerated factors designed on the basis of the principles detailed below which conform to the real situation. When in the initial phase of hunt, a larger individual cognition c_1 and a smaller group cognition c_2 should be given. Conversely, with the accumulation of experience, a smaller c_1 and a larger c_2 would be set.

Definition 1: Individual cognition accelerated factor c_1 is an adaptive coefficient that adjusts cognition for particle itself according to iterations.

Definition 2: Group cognition accelerated factor c_2 is an adaptive coefficient that modulates cognition for the whole group according to the accumulation of experience.

The adaptive factors c_1 and c_2 can be fitted through logistic function, formulas are shown below:

$$c_2 = ak/[1+\exp(-r \cdot t / t_{\max})] - a, \tag{5}$$

$$c_1 = a - c_2. \tag{6}$$

where k is constant and assumed to be 2, r is constant and supposed to be 6, a is range from 0 to 2, t is the current iteration and t_{max} is the largest iteration.

The relation of c_1 and c_2 can be expressed by Figure II.

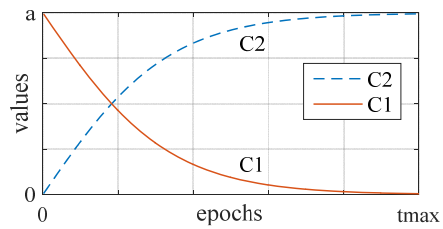


FIGURE II. EPOCH CURVES OF ACCELERATED FACTORS

B. Variable Random Initialization Strategy

Mutation operation, which initializes certain amount of variables with specified probability, makes the diminishing searching space broader as iteration times increasing. Therefore, the probability for finding better solution is improved.

Variable random initialization strategy designed based on the following policies. When the average distance between particles and the present best falls below a certain number, particles under a fixed ratio can be randomly initialized.

Definition 3: Position of the ith particle in t generation is a string of d real numbers in length presents the weights and thresholds connected the BPNN. Suppose that dimension of searching space is d, population size i = 1, 2, ... N, the position $\boldsymbol{X}_i^t=[x_{i1},x_{i2},...x_{id}]^t$, and $\boldsymbol{P}_g^t=[P_{g1}, P_{g2},...P_{gd}]^t$ is the best among group in t generation.

Definition 4: E^t is the average distance between particles and the present best P_g in t generation, of which the calculation formula can be expressed as below:

$$E^t = \left[\sum_{i=1}^{N}(X_i^{\,t} - P_g^{\,t})\right] / N = \left[\sum_{i=1}^{N}\sum_{k=1}^{d}(x_{ik}^{\,t} - P_{gk}^{\,t})\right] / N. \tag{7}$$

C. Implementation of the APSWNN Algorithm

The realization of APSWNN divides into three parts that is initialization of the network topology, optimization of the original weights and thresholds, training and forecasting. Figure 3 displays the overall flow chart of the algorithm.

At first, network topology and relevant parameters should be initialized according to the problems yet to be worked out. For the three-layer structure of which number of neurons in the input layer, hidden layer and output layer respectively be n, l and m, the dimension of search space would be $d=n\times l+l+l\times m+m$. Weights and thresholds should be random initialized through real coding rules.

In the following course, the original weights and thresholds would be optimized by the thought of variation and adaptive. Search P_i and P_g according to the computation of fitness function. Calculating adaptive accelerated factors c_1 and c_2 by (5) and (6) separately. Then using the adjustable c_1 and c_2 to update velocity and position by (3) and (4) . Computing average distance by (7) and applying variable random initialization strategy accordingly. While the stop condition like reaching the set iterations or the error's goal is fulfilled, we may get the better weights and thresholds which would be the initial parameters for the wavelet neural network.

In the end, training and forecasting by wavelet neural network. As the optimized parameters are passed to this step, renewing weights and thresholds of the network by batch learning mode and L-M training method. Thus the fitted model is generated, then the network can predict output.

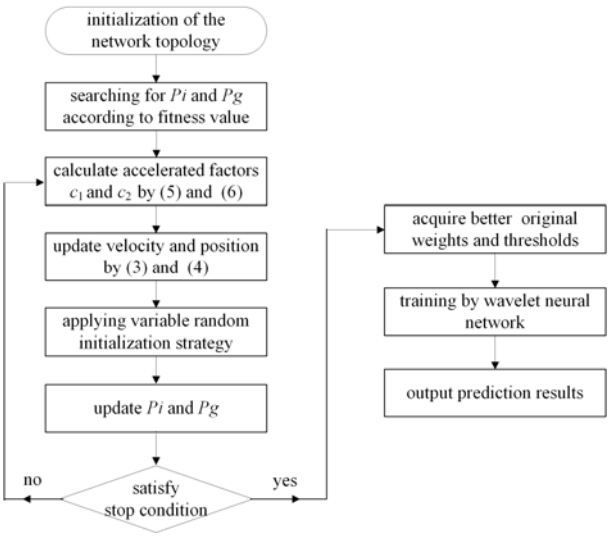


FIGURE III. FLOW CHART OF APSWNN ALGORITHM

IV. Modeling for the Traffic Flow Forecast

The current traffic flow for a certain section of the road is closely related to the previous periods of time. In this paper, we employ traffic flow in current period of time with three periods before as the network input variables and the traffic flow in next period as output. Assumed that the number of neurons in hidden layer be 6. Interval of time period is 15 minutes. Adopting data in chapter 32 of [8] as the training and predicting source.

This paper builds the prediction model of ARIMA, BPNN, WNN and APSWNN in Matlab2015b. Presumed that number of epochs is set to be 100, learning rate is 0.01. The transfer function in hidden layer of BPNN is tansig. Purelin is the designated excitation function in output layer for BPNN, WNN and APSWNN.

In order to measure the veracity of the models, definitions of three types of error are raised as follow:

Mean Absolute Error(MAE):

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|\boldsymbol{Y}_t - \hat{\boldsymbol{Y}}_t| \tag{8}$$

Mean Relative Error(MRE):

$$MRE = \left[\frac{1}{n}\sum_{t=1}^{n}(|\boldsymbol{Y}_t - \hat{\boldsymbol{Y}}_t| / \hat{\boldsymbol{Y}}_t)\right] * 100\% \tag{9}$$

Root Mean Square Error(RMSE):

$$RMSE = sqrt(\frac{1}{n}\sum_{t=1}^{n}(\boldsymbol{Y}_t - \hat{\boldsymbol{Y}}_t)^2) \tag{10}$$

where $\boldsymbol{Y}_t$ is the predicted value of the network, $\hat{\boldsymbol{Y}}_t$ is the actual measured value of the traffic flow.

V. Analysis and Verification of Simulation Test

Figure IV (A) - (E) depict comparison of predictive traffic flow value by different algorithm strategies. The three kinds of error mentioned above are computed and shown in Table 1. Table 2 reveals the running time.

TABLE I. ERROR CORRESPONDS TO DIFFERENT STRATEGIES

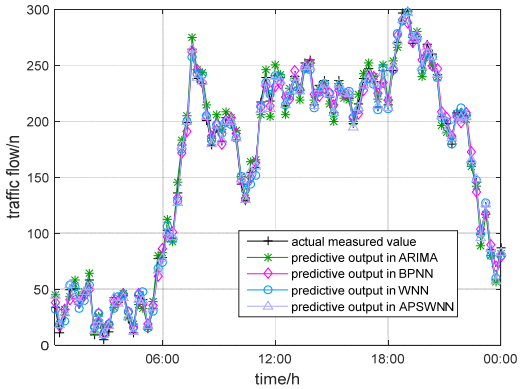
	ARIMA	***BPNN***	***WNN***	***APSWN***
MAE	6.21	5.56	4.15	2.83
MRE	10.00%	8.76%	7.51%	5.19%
RMSE	6.85	6.31	4.95	3.60

TABLE II. RUNNING TIME TO DIFFERENT ALGORITHM STRATEGIES

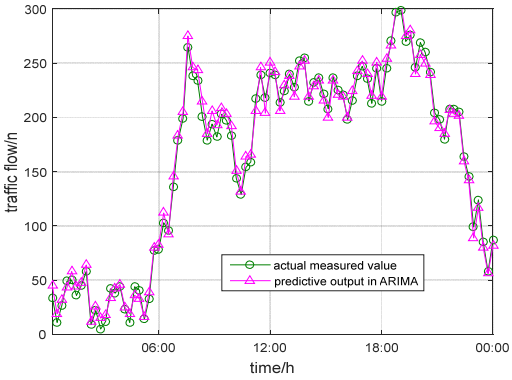
	ARIMA	***BPNN***	***WNN***	***APSWN***
Time[sec]	5.9286	4.6349	3.8945	2.3117

As seen in Figure IV and Table I, corresponding algorithms to forecast error in the order of smallest to largest may be APSWNN, WNN, BPNN, ARIMA. BPNN can predict the future trends and reflect rather complex non-linear relationship intelligently. It has certain advantages relative to traditional ARIMA. WNN introduces the wavelet analysis theory on the foundation of standard BPNN. To some extent, it can improve the defect which is easily plunge into local minimum. APSWNN not only simplifies the iterative process of the

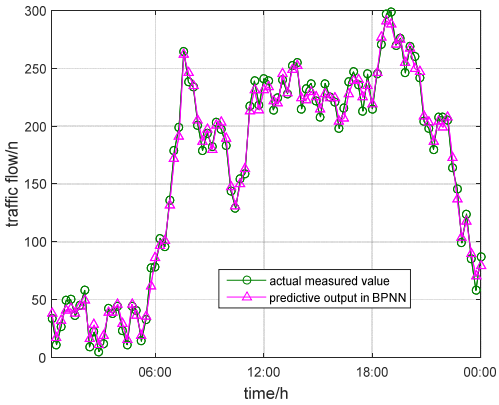
network, but also increases the global optimization performance with the application of adaptive accelerated factors. The variable random initialization strategy gives the algorithm possibility of jumping out of local optimum. Table II details that the prediction time of APSWNN is less than others. To sum up, we conclude that APSWNN is a rather effective algorithm forecasting traffic flow. It only has 5.19% of MRE and 2.31 seconds of running time.



(A) RESULTS OF ALL FOUR ALGORITHMS

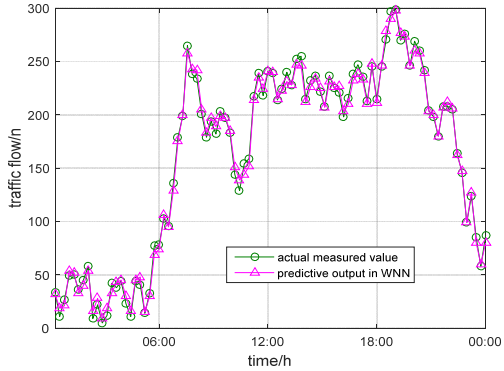


(B) ARIMA AND MEASURED VALUE

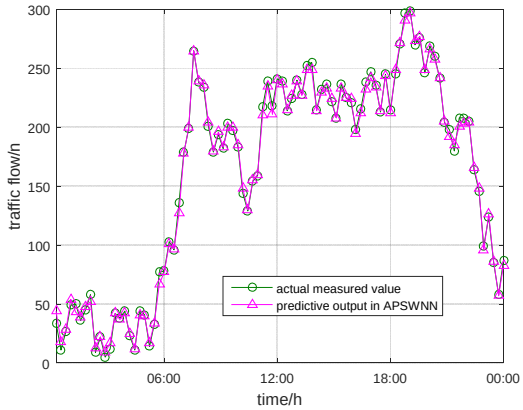


(C) BPNN AND MEASURED VALUE

FIGURE IV. THE COMPARISON CHART OF PREDICTIVE VALUE IN DIFFERENT ALGORITHMS AND ACTUAL MEASURED VALUE (A-C)



(D) WNN AND MEASURED VALUE



(E) APSWNN AND MEASURED VALUE

FIGURE IV. THE COMPARISON CHART OF PREDICTIVE VALUE IN DIFFERENT ALGORITHMS AND ACTUAL MEASURED VALUE (D-E)

VI. SUMMARY

For traffic flow prediction, this paper proposes a new adaptive particle swarm wavelet neural network algorithm (APSWNN) which links wavelet analysis, adaptive PSO, variation concept of genetics and BPNN together. We adopt the traffic flow in current period of time with three periods before as the network input variables and the traffic flow in next period as output. The new method reduces the iterative time and improves the global optimization performance in the meanwhile. Comparing to ARIMA, BPNN and WNN, APSWNN has obvious advantages in predictive quality and running time in traffic flow prediction.

ACKNOWLEDGMENT

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