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Short-Term Road Speed Forecasting Based on Hybrid RBF Neural Network With the Aid of Fuzzy System-Based Techniques in Urban Traffic Flow

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ABSTRACT With the rapid economic development, urban areas are seeing more and more vehicles, leading to frequent urban traffic congestion. To solve this problem, the forecasting of traffic parameters is essential, in which, road operating speed (hereinafter referred to as ''road speed'') is a key parameter for forecasting road congestion. This paper proposes a hybrid radial basis function (RBF) neural network algorithm for forecasting road speed. First, it proposes a fuzzy RBF neural network structure by combining the fuzzy logic system with the RBF neural network. Then, it incorporates factors such as weather, holidays and road grades into the input layer. Considering the uncertainty and sensitivity of the initial centre of the traditional membership function layer, it uses fuzzy C-means clustering to determine the centre and other parameters of the membership function layer. Then using the gradient descent method, it trains the weights between the fuzzy inference layer and the output layer. Finally, this paper trains the proposed hybrid RBF neural network with the traffic road network data and weather data of a city, and uses the trained hybrid neural network to predict the road speed and the congestion status. The prediction results show that, compared with simplex prediction methods, such as BP neural network, time series method, and RBF neural network, the hybrid RBF neural network has a higher forecasting accuracy, with the mean absolute percentage error (MAPE) being reduced to 6.4%. Experimental results verify the accurate forecasting, enhanced learning feature and mapping capability of this method in short-term road speed forecasting, indicating that it can provide reliable predicted values to help solve urban congestion problems.

INDEX TERMS Urban traffic flow, speed prediction, fuzzy C-means, fuzzy-RBF, neural network.

I. INTRODUCTION

Regional traffic congestion is commonly seen in most cities, especially during rush hours. The intelligent transportation system is an effective method to solve this problem, but the key to guaranteeing the effective operation of such a system is the real-time accurate forecasting of traffic parameters [1], [2]. Traffic parameters include road speed, flow, density and travel time, among which, road speed is the key parameter for predicting road congestion. Forecasting the road speed in short-term traffic flow is also important to road managers in road network management and to travellers in travel planning. Road speed is greatly affected by environmental factors, such as weather, holidays and road grades; however, currently most road traffic flow prediction algorithms do not take environmental factors into account. As a result, these methods will become inaccurate or even ineffective when the above factors experience significant changes.

In recent decades, the prediction of short-term traffic flow has been one of the research hotspots in the field of intelligent transportation. Commonly used traffic variables for

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short-term traffic prediction include traffic flow, travel time and road speed. Ghosh *et al.* [3] proposed a novel time series model called structured time series model (STM) (multivariate form), and developed a concise and computationally simple multivariate short-term traffic condition prediction algorithm. Çetiner *et al.* [4] used the artificial neural network (ANN) to build a model using historical data and predicted traffic flow based on historical data at each major intersection in the city. Abdi *et al.* [5] proposed a traffic prediction model that focuses on correcting learning peaks, improving prediction accuracy, reducing computation time and meeting multi-objective prediction requirements. Sun and Zhang [6] proposed a model consisting of prediction components based on two signal states (red or green) to predict the corresponding vehicle running time from the upstream intersection to the downstream one. Since the computational efficiency is dependent on the time complexity of the prediction algorithm, Daraghmi *et al.* [7] proposed a spatiotemporal multivariate prediction model based on the negative binomial additive model. Prediction not only provides information on future traffic conditions, but also helps evaluate the control decisions before they are implemented. In addition, considering the accuracy and timeliness of the prediction model, the time series model [8]–[10], Kalman filter model [11], support vector machine [12], non-parametric regression method [13]–[15] and long-term and short-term memory neural network [16], etc. have also been proposed for the prediction of short-term traffic flow in urban road networks.

The previous methods have promoted huge progress in traffic flow forecasting; however, as traffic flow is highly non-linear and susceptible to external factors, many linear prediction or shallow structure prediction methods cannot obtain accurate results. Considering the wide application of the fuzzy logic system and the radial basis function neural network in the identification of nonlinear systems, this paper applies them in the forecasting of road speed in short-term traffic flow. It is well known that a feed-forward layered neural network can approximate a non-linear function to any precision by adjusting variable weight connections. The multilayer perception (MLP) [17] and the radial basis function (RBF) [18] are two typical types of feed-forward neural network. As RBF uses high-dimensional mapping for local approximation, the RBF model learns faster than the MLP model [19]. Zhang *et al.* [20] integrated the functions of the RBF neural network with the fuzzy control theory. The research results show that the RBF neural network provides a simple and effective method for fuzzy control, and makes great use of the fuzzy theory. Jia and Tian [21] proposed a short-term power load prediction model based on the fuzzy RBF neural network, which overcomes the shortcomings of the BP algorithm such as slow convergence speed and easiness of falling into local minimum. Cai *et al.* [22] introduced a tunable, transferable radial basis function (TT-RBF) model for online prediction based on the RBF neural network. The RBF model is a global-oriented interpolation algorithm, which is particularly applicable for small sample prediction problems. Since the daily traffic conditions in urban areas do not change much, the model can be well trained with historical traffic flow data. However, in the traditional RBF neural network, the determination of the basis function centre of the hidden layer has a great impact on the forecasting result. Inappropriate selection of the initial centre can easily lead to local optimal solution and other problems, and the K-Means algorithm, which is used to determine the centre point, is sensitive to noisy data, and cannot automatically identify the centre. If external environmental factors affecting traffic flow are added to the dataset, the traditional model will no longer be applicable.

Regarding the above problems, this paper will construct a fuzzy RBF neural network structure by utilizing the fast inference speed of the radial basis function neural network (RBFNN) and the heuristic search of the fuzzy logic system (FLS) for short-term road speed forecasting in urban traffic flow. Considering that road speed is affected by environmental factors, such as weather, holidays and road grades, the design incorporates environmental factors into the road condition prediction data set. As for the uncertainty of the initial centre of the traditional membership function layer, fuzzy C-means clustering is used to determine the centre and other parameters of the membership function layer. With the help of fuzzy system-based techniques, this paper proposes a hybrid RBF neural network, which is trained with historical data. The trained hybrid RBF neural network is compared with simplex prediction methods such as the BP neural network, the time series method and the RBF neural network, and the test results show that the proposed prediction method is effective and accurate. The main contributions of this research are summarized as follows:

1. The proposed hybrid prediction algorithm incorporates weather, holidays and road grades for forecasting road speed.
2. The fuzzy C-means clustering is utilized to determine the centre and other parameters of the membership function layer to avoid local minimum.
3. The presented method can provide more accurate prediction results than traditional prediction methods.

The rest of this paper is organized as follows: Section 2 analyses road speed in urban traffic flow; Section 3 proposes the hybrid RBF neural network with a fuzzy logic system; Section 4 designs a short-term road speed forecasting method based on the hybrid RBF neural network; Section 5 gives the experimental results; and Section 6 presents conclusions and prospects.

II. ANALYSIS OF ROAD SPEED IN URBAN TRAFFIC FLOW

A. INFLUENCING FACTORS TO ROAD SPEED

Most urban road congestion situations are evaluated by the road speed in traffic flow [11]. The road speed forecasting method uses traffic flow data collected at an interval of several minutes as samples for training, and then uses new data for forecasting. But for road congestion, time is not the only influencing factor. Many external factors, such as weather, road grades and holidays, are also factors that cannot be ignored [13]. Current research has hardly included external influences in urban traffic flow forecasting. Although some studies have qualitatively considered these environmental factors, their influences on urban traffic flow have not been quantified. For example, different rainfalls have different impacts on road speed, and on roads of different grades, the speed of the vehicles are also different. For example, the maximum speed allowed on expressways is significantly greater than that on trunk roads or branch roads.

Regarding weather conditions, the impact of bad weather on traffic flow is obvious - the speed of vehicles on roads will decrease significantly as the weather worsens, which can easily cause road congestion [7], [13]. As for road grade, there are four grades, namely expressways, trunk roads, secondary trunk roads and branch roads. As different roads have different traffic volumes and speeds, road classification is more conducive to data statistics and prediction of traffic flow. The speed of vehicles on the upstream road will indirectly affect that on the current road, so it is also one of the important factors affecting traffic flow. On holidays, with more people travelling, traffic will increase, and road congestion is more likely to occur.

In summary, all these factors have significant impacts on road speed. Therefore, this paper will consider weather, road grades, upstream road speed and holidays as the influencing factors to road speed.

B. AVERAGE ROAD SPEED MODELLING

Without regard to the type of vehicle, the traditional method calculates the average road speed using the speeds of vehicles traveling on the road, whose model is:

$$V_f = \frac{1}{N}\sum_{i=1}^{N} V_i \tag{1}$$

where, V_f is the average road speed; N is the number of vehicles traveling on the road over a period of time; V_i is the speed of the i-th vehicle. This algorithm does not take into account the differences between different types of vehicles, so this speed cannot represent the speed of various vehicles on the road. If the differences between different vehicle types are taken into full account, the average road speed $\overline{V}$ can be expressed as follows:

$$\overline{V} = \frac{1}{n+m+h+k}\left(\sum_{i=1}^{n} V_{car,i} + \sum_{j=1}^{m} V_{taxi,j} + \sum_{a=1}^{h} V_{bus,a} + \sum_{b=1}^{k} V_{truck,b}\right) \tag{2}$$

where, $\overline{V}$ is the average road speed, $V_{car,i}$ is the speed of the i-th passenger car; $V_{taxi,j}$ is the speed of the j-th taxi, and $V_{bus,a}$ is the speed of the a-th bus; $V_{truck,b}$ is the speed of the b-th truck; and n, m, h, k indicate the total number of passenger cars, taxis, buses, and trucks on the road, respectively.

III. III HYBRID RBF NEURAL NETWORK WITH A FUZZY LOGIC SYSTEM

A. RBF NEURAL NETWORK

As shown in Figure 1, the RBF neural network is a local approximation network consisting of three layers: an input layer, a hidden layer and an output layer [23], [24]. In the RBF neural network, Gaussian function is usually used, which defines a random input vector $X \in R$ (X is an input sample set) as:

$$R_j(x) = \exp[-\left\|X - C_j\right\|^2/(2\sigma_j^2)], \quad j = 1, 2, \ldots, N. \tag{3}$$

where, $R_j(x)$ is the output of the j-th node of the hidden layer; $X = [x_1, x_2, \ldots, x_n]^T$ is the input vector of the network, and $i = 1, 2, \ldots, n$; C_j is the central vector of the j-th neuron centre in the hidden layer; σ_j is the normalized parameter of the first hidden node, i.e. the width of the hidden node; N is the number of nodes in the hidden layer.

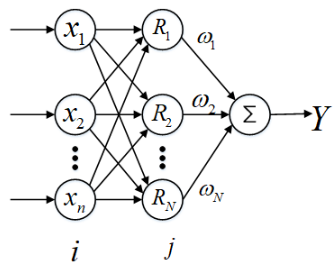

FIGURE 1. RBF neural network.

When the network inputs the training sample X_n, the actual output is:

$$Y(X_n) = \sum_{i=1}^{N} \omega_i R_i(X) \tag{4}$$

where, ω_i is the connection weight matrix between the hidden layer and the output layer.

B. FUZZY THEORY

The basic definition of a fuzzy inference system is that the output fuzzy variables are inferred from the input fuzzy variables according to a set of logical inference rules, which are extracted from the fuzzy system's knowledge base [25], [26]. The fuzzy rule base contains a set of fuzzy if-then rules. The core of the fuzzy inference system is the if-then rules and other parts (such as the membership function). These rules have been implemented in a reasonable, real and effective way. The mapping from the fuzzy set of the input domain $U \in R^n$ to that of the output domain $V \in R$ is defined as follows:

$R^{(1)}$: if $x_1 = F_1^i, x_2 = F_2^i, \ldots, x_n = F_n^i$; then y is W^i

where: F_1^i and W^i are fuzzy sets; $x = (x_1, x_2, \ldots, x_n)^T \in U$ is the input domain, and $y \in V$ is the output domain.

C. FUZZY RBF NEURAL NETWORK

Based on the fuzzy rules, the fuzzy RBF neural network can be expressed as follows:

if $x_1 = F_1^i, x_2 = F_2^i, \ldots, x_n = F_n^i$; then $y_1^i = w_{i1}, y_2^i = w_{i2}, \ldots, y_o^i = w_{io}$
where: x_n is the input value of traffic flow; y_o is the output value of the neural network.

The fuzzy system uses the mean value method, and the output value is:.

$$y_k = \sum_{i=1}^{m} \omega_{ki}\alpha_i / \sum_{i=1}^{m} \alpha_i \tag{5}$$

where, α_i is the incentive strength of the i-th rule.

The structure of the fuzzy RBF neural network adopted in this paper is shown in Figure 2.

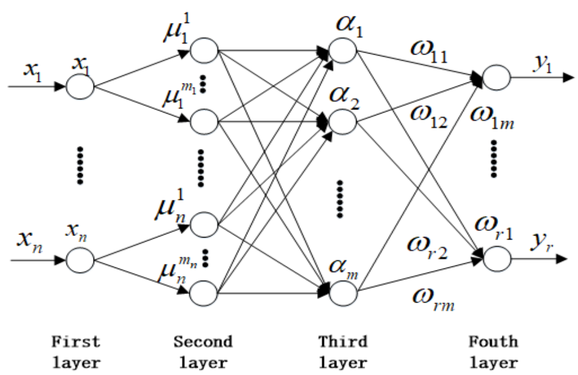

FIGURE 2. Structure of the fuzzy RBF neural network.

The functions of the structure and its nodes are described below:

The first layer is the input layer: nodes and the input directly form the connection u_i to pass the input vector $U = [u_1, u_2, \ldots, u_n]$ to the next level. The total number of nodes in level 1 is $N_1 = n$.

The second layer is the membership function layer: each node represents a fuzzy set. If the normal distribution of the membership function is defined, then the output function corresponding to each node constitutes the membership function of the fuzzy set.

$$\mu_i^j = \exp[-\frac{(u_i - c_{ij})^2}{\sigma_{ij}^2}] \tag{6}$$

where, $i = 1, 2, \ldots, n, j = 1, 2, \ldots, m_i$, c_{ij} and σ_{ij} represent the centre and width of the j-th membership function through the fuzzy partition of the i-th variable, respectively. The total number of nodes in this layer is $N_2 = \sum_{i=1}^{n} m_i$.

The third layer is the fuzzy inference layer: each node represents an inference rule for fuzzy operations, that is,

$$\alpha_l = \min(\mu_1^{i_1}, \mu_2^{i_2}, \ldots, \mu_n^{i_n}) \tag{7}$$

where, $i_1 \in \{1, 2, \ldots, m_1\}$, $i_2 \in \{1, 2, \ldots, m_2\}, \ldots, i_n \in \{1, 2, \ldots, m_n\}$, $l = 1, 2, \ldots, \prod_{i=1}^{n} m_i$. For a particular input vector, the closer its centre is to the variable at the input point, the larger its membership function will be. If the centre is far away from the linguistic variable at the input point, the membership function will be small, or even zero. The total number of nodes in this layer is $N_3 = m = \prod_{i=1}^{n} m_i$.

The fourth layer is the output layer:

$$y_k = \sum_{l=1}^{m} \omega_{kl}\alpha_l, \quad k = 1, 2, \ldots, r \tag{8}$$

where, ω_{kl} is the connection weight matrix between the output node and each node in the fourth layer.

The selection of the membership function centre c_{ij} of the membership function layer in the fuzzy RBF neural network has a great influence on the forecasting accuracy and generalization ability of the network model. The proposed fuzzy RBF neural network uses fuzzy C-means clustering to determine the membership function centre of the membership function layer in the fuzzy RBF neural network and then determine other parameters related to the membership function centre. In addition, the BP algorithm is used to adjust and optimize the membership function [27]. The structure of the learning algorithm with the aid of fuzzy techniques is shown in Figure 3.

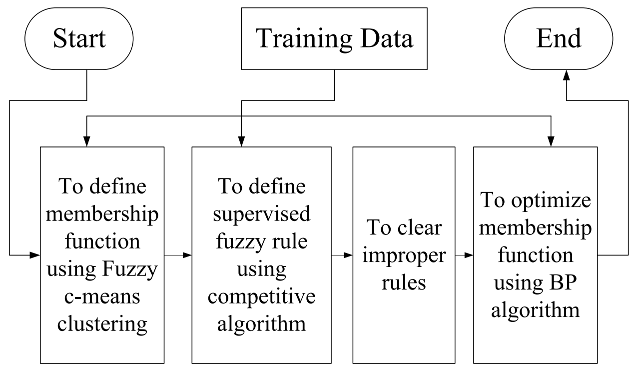

FIGURE 3. Structure of the learning algorithm.

IV. SHORT-TERM ROAD SPEED FORECASTING BASED ON HYBRID RBF NEURAL NETWORK

A. DESIGN OF THE INPUT LAYER

Firstly, considering the impacts of external factors on road speed, weather, road grades and holidays are taken as parameters. Secondly, as road speed is related to time and space, the road speeds at three time points of the current road (before 5min, 10min and 15min) and three time points of the upstream road (before 5min, 10min and 15min) are included into the input layer. Considering all these factors, the input layer is designed to consist of 9 nodes. The 9 inputs are namely weather, road grade and holiday and road speeds before 5min, 10min, and 15min, and upstream road speeds before 5min, 10min, and 15min. The overall road speed data set based on the fuzzy C-means clustering RBF neural network is then designed. The qualitative environmental factors are quantified to reduce the qualitative definition of data.

B. DESIGN OF THE MEMBERSHIP FUNCTION LAYER

Commonly used clustering algorithms such as k-means are quite sensitive to the initial cluster centre, so the clustering results are susceptible to the initial input. The fuzzy

C-means (FCM) algorithm can effectively solve this problem [28]–[30]. The main idea is to fuzzify the previous definitions and use membership function to determine a certain clustering degree.

The fuzzy C-means algorithm divides n vectors $x_p \subset R^s$ into N_2 groups ($k = 1, 2, \cdots, n$), where s is the dimensionality of the vector x_p. Then it needs to solve the cluster centre. The membership matrix $U = \{\mu_i^p\}_{c\times n}$ is used to classify the data, where μ_i^p represents the membership of the p-th sample in the i-th clustering centre, whose value is within the interval [0,1] due to normalization, and the sum of the memberships of all samples is 1. The detailed expression is as follows,

$$V = [v_1, v_2, \cdots, v_{N_2}]^T \tag{9}$$

where, $v_i = [v_{i1}, v_{i2}, \cdots, v_{is}]$ is the s-dimensional vector ($i = 1, 2, \cdots, N_2$). After being processed, the objective function κ can be expressed by the following equation:

$$\kappa(U, v_1, v_2, \cdots, v_{N_2}) = \sum_{i=1}^{N_2} \kappa_i = \sum_{i=1}^{N_2} \sum_{k=1}^{n} (\mu_i^p)^m d_{ip}^2 \tag{10}$$

where, $d_{ip} = \sqrt{\sum_{q=1}^{s} (x_{pq} - v_{iq})^2}$ is the Euclidean distance between the i-th cluster centre and the p-th fuzzy group; m is the fuzzy weighting exponent, and $m \in (1, +\infty)$, $N_2 \geq 2$, $\sum_{i=1}^{N_2} u_{ip} = 1$, $u_{ip} \in (0, 1)$.

With the following cluster centre and membership matrix equations, the value of (10) can be minimized as shown below:

$$c_i = \frac{\sum_{j=1}^{n} (\mu_i^j)^m x_j}{\sum_{j=1}^{n} u_{ij}^m} \tag{11}$$

$$\mu_i^j = \frac{1}{\sum_{k=1}^{N_2} \left(\frac{d_{ij}}{d_{pj}}\right)^{2/(m-1)}} \tag{12}$$

The FCM algorithm is optimized through continuous iterations. The detailed steps of the algorithm are as follows:

(1) Set the values of c and m. Set the number of iterations $t = 0$, select the iteration stop threshold $\varepsilon > 0$, and initialize the membership matrix U.

(2) Determine the cluster centre, and update the calculation according to (11).

(3) Determine the membership matrix, and update the calculation according to (12).

(4) Determine whether the iteration is over. If $\left|V^{(p+1)} - V^{(p)}\right| > \varepsilon$, repeat steps (2) and (3), and $p = p+1$; if $\left|V^{(p+1)} - V^{(p)}\right| < \varepsilon$, stop the iteration to obtain the optimal $\kappa(U, V)$.

During training, the weight w_j between the fuzzy inference layer and the output layer is trained by the gradient descent method (error back propagation). Let the predicted output be $y(t)$ and the actual value be $y_m(t)$. The weight is adjusted as follows:

$$\Delta w_j(t) = -\eta \frac{\partial E}{\partial w_j} = \eta(y(t) - y_m(t))\alpha_j \tag{13}$$

$$w_j(t) = w_j(t-1) + \Delta w_j(t) + \xi(w_j(t-1) - w_j(t-2)) \tag{14}$$

where, $\eta \in (0, 1)$ is the learning rate and $\xi \in (0, 1)$ is the factor of momentum.

C. OVERALL STRUCTURE AND STEPS

The steps of the fuzzy RBF neural network algorithm based on fuzzy C-means are as follows.

(1) Select training sample data $X = (x_1, x_2, x_3, \cdots, x_n | y_1, y_2, y_3, \cdots, y_n)^T$, where $x_i \in R^s$, $y_i \in R_k$, $i = 1, 2, \cdots, n$; s is the input dimension of the training sample data, and k the output dimension of the training sample data.

The sample data

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1s} \\ \vdots & \ddots & \vdots \\ x_{t1} & \cdots & x_{ts} \end{bmatrix},$$

where t is the length of the time series.

Because the dimensions of the time series data are different, the data have to be normalized for comparison. Generally they are converted through scaling, for which the conversion equation is:

$$x_{ij} = \frac{x_{ij} - x_j^{\min}}{x_j^{\max} - x_j^{\min}} \tag{15}$$

If $x_j^{max_j^{min}}$, $x_{ij} = -1$.

In (15), $x_j^{max\ max\{x_{1j}, x_{2j}, \cdots, x_{tj}\}}$, and $x_j^{min\ min\{x_{1j}, x_{2j}, \cdots, x_{tj}\}}$, $i = 1, 2, \cdots, t; j = 1, 2, \cdots, k$.

Apply the fuzzy C-means algorithm to the normalized time-series multivariate data X to obtain the cluster centres of n classes, and then there is:

$$C = \begin{bmatrix} c_{11} & \cdots & c_{1s} \\ \vdots & \ddots & \vdots \\ c_{n1} & \cdots & c_{ns} \end{bmatrix} \tag{16}$$

(2) Select the upper limit of error ε and the upper limit of the number of iterations T_{max}. The initial value of the number of iterations is $t = 0$, and let the initial weight be W_0 and the cluster centres be C.

(3) Obtain the output of each node in the membership function layer according to (6).

(4) Obtain the output of the predicted value according to (8).

(5) If $(t > T_{\max}) \cup (E \leq \varepsilon)$, the calculation ends, and inverse normalize the output according to (17); otherwise, $t = t + 1$, $E = 0$.

$$x_{ij} = y_i(x_j^{\max} - x_j^{\min}) + x_j^{\min} \tag{17}$$

where, $x_j^{\max} = \max\{x_{1j}, x_{2j}, \cdots, x_{tj}\}$, $x_j^{\min} = \min\{x_{1j}, x_{2j}, \cdots, x_{tj}\}$, $i = 1, 2, \cdots, t; j = 1, 2, \cdots, k$.

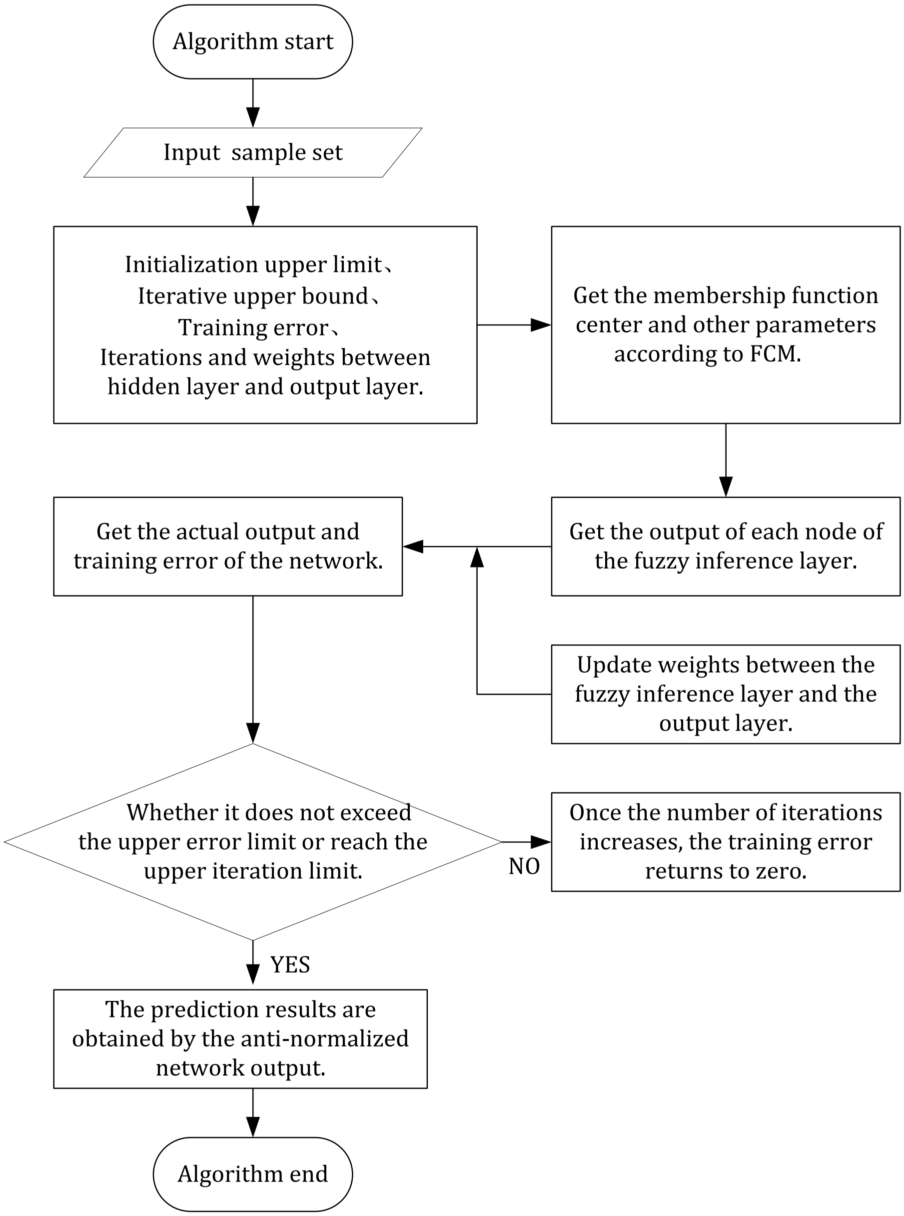

FIGURE 4. Flow chart of the hybrid RBF neural network algorithm.

(6) Update the weights between the fuzzy inference layer and the output layer according to (13)-(14), and then go to step (4).

The whole flow chart of the road speed forecasting algorithm based on hybrid RBF neural network is shown in Figure 4.

V. TEST RESULTS

A. DATA

Based on the traffic road network data (traffic condition data from Amap API) and weather data (from the website of Weather China) of a city, this paper selects the traffic and weather data of one road section from June to August 2018 as the training set data, and selects the data on a day of September as the verification data.

At present, the prediction of traffic congestion always uses the indicator of traffic flow [13]. The traffic flow of a road was trained according to the time statistics, and the congestion prediction was obtained. But for the problem of traffic congestion, there are many factors besides time that can affect it. Such as weather conditions, special road conditions, holidays and so on. At this stage few studies of these factors apply to the traffic congestion prediction, some literature considered these factors, but the method it is considered a qualitative way, set the weight to environmental factors, there is no quantitative to consider these factors on traffic congestion. In fact, quantitative selection of environmental factors is of great help to traffic congestion prediction. For example, a group of data shows that when the intensity of rainfall at night reaches moderate rain or above, the road speed of expressway, trunk road and secondary branch decreases by 8.8%, 4.8% and 5.9% respectively. The result of speed decline means that traffic congestion may occur, so it is very necessary to quantitatively take environmental factors into account in the prediction data set.

The recorded weather conditions of the area where the road is located have been converted to numerical values, as shown in Table 1. The default value is 0.

TABLE 1. Weather condition mapping table.

Weather condition	Numerical Value
Sunny	1
Cloudy	2
Overcast	3
Rainy	4
Snowy	5
Foggy	6

The road speed is different on different grades of roads. In this paper, there are 4 grades, namely expressway, trunk road, secondary trunk road, and branch road. Their impacts on the road speed have been converted to numerical values, as shown in Table 2.

TABLE 2. Road grade mapping table.

Road Grade	Numerical Value
Expressway	1
Trunk road	2
Secondary trunk road	3
Branch road	4

As for holidays, there are four kinds of days - working day, weekend, 3-day mini vacation, and holiday of more than 7 days. They are also converted to numerical values, as shown in Table 3 below:

TABLE 3. Holiday mapping table.

Date property	Numerical Value
Working day	1
Weekend	2
Three-day mini vacation	3
Holiday of more than 7 days	4

B. PROPOSED HYBRID METHOD

The traffic and weather data of one road section from June to August 2018 are used to train the proposed hybrid RBF neural network forecasting model. The FCM-based clustering algorithm uses the training set to obtain the centre of the Gaussian function in the membership function layer. After sufficient trial, the best parameters are determined. The width of the Gaussian membership function is $\sigma = 2.5$, the learning rate $\eta = 0.5$, the momentum factor $\xi = 0.06$, and the initial value of the weight $w_j = 0.01$. Then the trained model is used to predict the data of a certain day in September. The graphs of the actual road speed and the predicted results are shown in Figure 5-6.

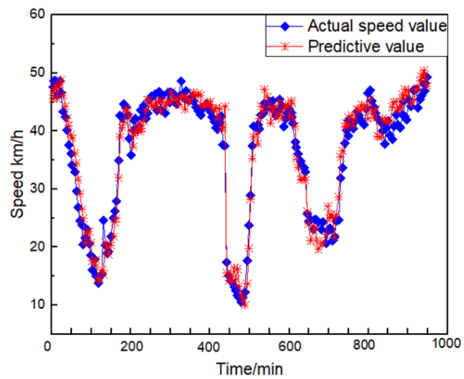

FIGURE 5. Results of short-term urban road speed forecasting using the proposed hybrid algorithm.

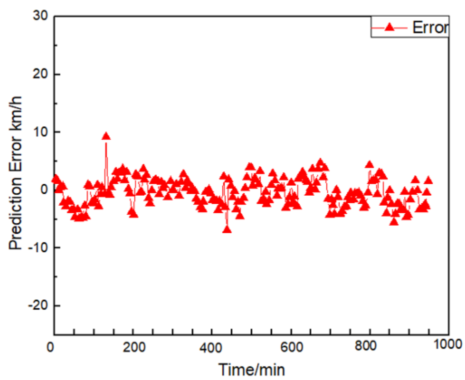

FIGURE 6. Forecasting error of the proposed hybrid algorithm.

From the forecasting results of Figure 5 and Figure 6, it can be seen that the road speed curve forecasted by the hybrid RBF neural network method, with a maximum error of 9.3km/h, well matches the actual road speed curve and that the trend of traffic flow is also well predicted. This fully proves the ability of the proposed hybrid RBF neural network to approximate non-linear curves and shows the trained forecasting model proposed in this paper is capable of forecasting short-term urban road speed.

After the road speed is forecasted, the road congestion conditions in the city can be predicted according to the road congestion criteria given in Table 4.

C. SIMPLEX FORECASTING METHODS

In order to verify the superiority of the proposed hybrid RBF neural network in forecasting of road speed in short-term urban traffic flow, this section also selects three simplex forecasting methods - BP neural network, time series method and RBF neural network for comparison in terms of accuracy, mean absolute error (MAE), root mean square error (RMSE),

TABLE 4. Road congestion level and speed threshold comparisons.

	Unblocked speed (km/h)	Basically unblocked speed (km/h)	Mild congestion speed (km/h)	Moderate congestion speed (km/h)	Serious congestion speed (km/h)
Expressway	>65	(50,65]	(35,50]	(20,35]	≤20
Trunk road	>45	(35,65]	(25,35]	(15,25]	≤15
Secondary trunk road	>35	(25,65]	(15,25]	(10,15]	≤10
Branch road	>35	(25,65]	(15,25]	(10,15]	≤10

mean absolute percentage error (MAPE) and calculation time. The specific expression is as follows:

Mean absolute error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i(i) - y_i'(i)\right| \tag{18}$$

Root mean square error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i(i) - y_i'(i))^2} \tag{19}$$

Mean absolute percentage error (MAPE):

$$MAPE(y, y') = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|y_i - y_i'\right|}{y_i} \tag{20}$$

where, y_i is the actual value and y_i' is the predicted value.

The forecasting results obtained by the time series method are shown in Figure 7 and Figure 8.

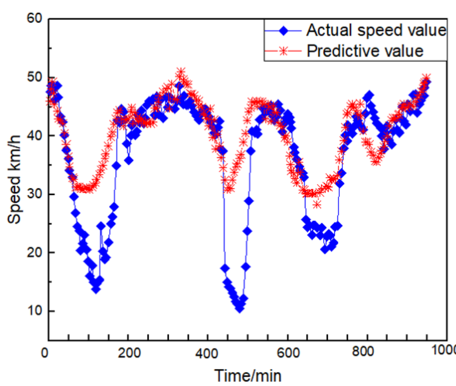

FIGURE 7. Results of short-term urban road speed forecasting using the time series algorithm.

The forecasting results obtained by the BP neural network are shown in Figure 9 and Figure 10.

The forecasting results obtained by the RBF neural network are shown in Figure 11 and Figure 12.

From the Figure 7-12, we can see that the time series algorithm cannot forecast short-term urban road speed well, which is the worst prediction performance among the four forecast algorithms. Th BPNN and RBFNN can forecast the variation trends of the short-term urban road speed well but not the values. The forecasting errors of the three algorithms are all greater than the proposed hybrid algorithm.

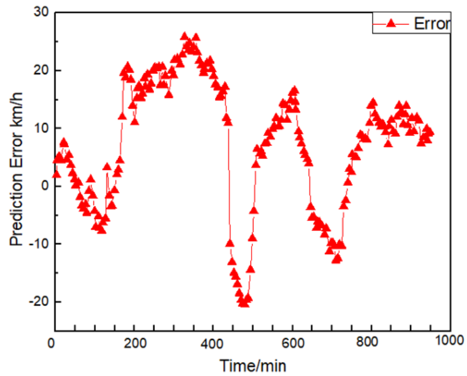

FIGURE 8. Forecasting error of the time series algorithm.

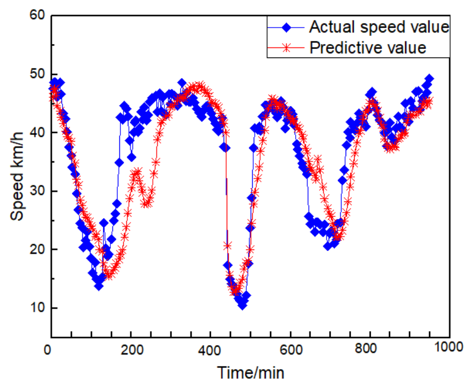

FIGURE 9. Results of short-term urban road speed forecasting using the BP neural network algorithm.

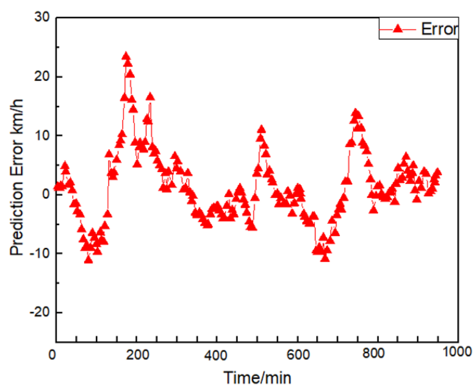

FIGURE 10. Forecasting error of the BP neural network algorithm.

The forecasting results of short-term road speed in urban traffic flow are evaluated using MAE and RMSE. See Figure 13 for the statistical results.

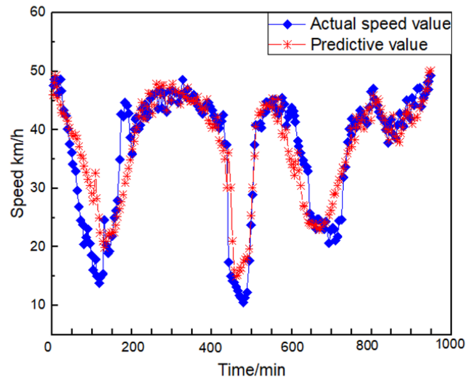

FIGURE 11. Results of short-term urban road speed forecasting using the RBF neural network algorithm.

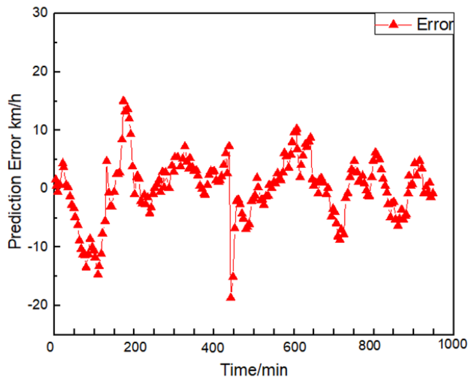

FIGURE 12. Forecasting error of the RBF neural network algorithm.

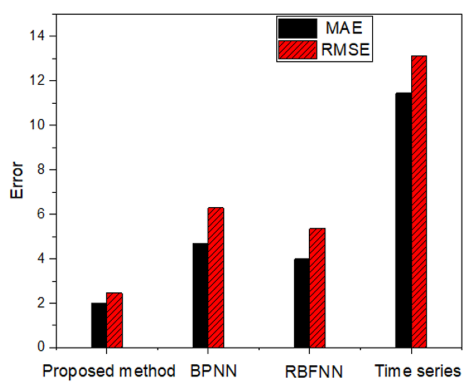

FIGURE 13. Evaluation results of MAE and RMSE.

See Table 5 for the statistical comparison of prediction accuracy. It is found that the MAE and RMSE of the proposed hybrid RBF neural network forecasting algorithm are 1.89 and 2.15, respectively, those of the time series algorithm are 11.39 and 13.25, respectively, those of the BPNN algorithm are 4.67 and 6.29, respectively and those of the RBFNN algorithm are 3.96 and 5.36, respectively. It can be seen that the time series method has the worst forecasting performance, which has something to do with the high nonlinearity of road speed. The hybrid RBF neural network has higher forecasting accuracy than the simplex BPNN and RBFNN. The MAPEs of the BPNN algorithm and the RBF algorithm are 14.92% and 14.21%, respectively, while that of the proposed hybrid RBF algorithm is 6.4%, indicating that it has the highest forecasting accuracy for road speed.

TABLE 5. Comparison of forecasting accuracy and time consumption.

Forecasting algorithm	Accuracy rating		
	MAPE	MAE	RMSE
Hybrid RBF	6.4%	1.89	2.15
Time series	34.16%	11.39	13.25
BPNN	14.92%	4.67	6.29
RBFNN	14.21%	3.96	5.36

VI. CONCLUSION

Regarding the forecasting of short-term road speed in urban traffic flow, this paper proposes a hybrid RBF neural network forecasting method by integrating the fuzzy logic system, fuzzy C-means clustering and RBF neural network. With the aid of the fuzzy logic system, this method constructs a fuzzy RBF neural network. It uses fuzzy C-means clustering to determine the centre of the membership function layer, and adjusts the network weights online using the gradient descent method (error back propagation). The input layer of the network also takes into account factors such as weather, holidays and road grades, which greatly improves the fault tolerance of the method when external influencing factors change. The tests on road speed forecasting using the traffic road network data and weather data in a city verify that the proposed hybrid RBF neural network forecasting algorithm can improve forecasting accuracy. It can predict road congestion based on the road congestion thresholds. In a comparative analysis with simplex forecasting algorithms, such as the time series method [3], the BP neural network [4] and the RBF neural network [18], [24], the proposed forecasting algorithm is found to be the best, with the MAE and RMSE being 1.89 and 2.15, respectively, which are the lowest (the MAE and RMSE of the time series algorithm are 11.39 and 13.25, respectively; those of the BPNN algorithm is 4.67 and 6.29; and those of the RBFNN algorithm are 3.96 and 5.36). Better still, the MAPE of the forecasting results obtained by the proposed algorithm can be reduced to 6.4%, while this indicator is 34.16%, 14.92%, and 14.21% for the other 3 algorithms, showing that the proposed method is really outstanding in terms of forecasting performance. Our next steps will be to optimize the forecasting model, shorten the calculation time, and extend the application of this method to the long-term forecasting of other parameters in urban traffic flow, so as to provide reliable basis for solving urban congestion problems.

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