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IMPROVING PREDICTION ACCURACY OF THE TRAFFIC SPEED USING THE FUZZY NEURAL NETWORK

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Abstract: *The accuracy of the predicted speed is the more important in the efficiency of the traffic management system. The first-order Takagi–Sugeno system is used to complete the fuzzy inference. To train the evolving fuzzy neural network (EFNN), two learning processes are proposed. First, a K-means method is employed to partition input samples into different clusters and a Gaussian fuzzy membership function was designed for each cluster to measure the membership degree of the samples to the cluster centers. When the number of the input samples increases, the cluster centers are modified and membership functions are also updated. Second, a weighted recursive least squares estimator is used to optimize the parameters of the linear functions in the Takagi–Sugeno type fuzzy rules. Furthermore, a trigonometric regression function is introduced to capture the periodic component in the raw speed data. Specifically, the predicted performance between the proposed model and six traditional models are compared, which are artificial neural network, support vector machine, autoregressive integrated moving average model, and vector autoregressive model. The results suggest that the prediction performances of EFNN are better than those of traditional models due to their strong learning ability. As the prediction time step increases, the EFNN model can consider the periodic pattern and demonstrate advantages over other models with smaller predicted errors and slow raising rate of errors.*

Keywords: *cluster, Gaussian, K-means method, weighted recursive least squares estimator, periodic pattern.*

I.INTRODUCTION

The prediction of traffic information is a key step to achieve the performance of Intelligent Transportation System (ITS), especially in Advance Traffic Management System (ATMS) and Advanced Traveler Information Systems (ATIS). By the forecasted information, volume, time and traffic condition, travelers can re-plan the traveling paths to save their time and cost. By which the efficiency of management in traffic system can be improved.An ultrasonic device is placed on the surface of the road, and it can directly detect moving or stationary objects without interrupting traffic flow. It can detect traffic volume, occupancy and speed for multiple lanes simultaneously although sometimes in the severe environment. As its high measurement accuracy compared to single loop detector, travel speed data collected from an ultrasonic device is used as data source to construct prediction model. In the Artificial Neural Network(ANN), the neural network is one of most popular approach to forecasting traffic flow time series. The important branch of ANN is the Fuzzy Neural Network(FNN). The FNN is the combination of fuzzy inference system and network structure of a neural network and shows good performance in traffic flow prediction.

II. MAMDANI-TYPE FIS VS. SUGENO-TYPE FIS

Mamdani method is widely accepted for capturing expert knowledge. It allows us to describe the expertise in more intuitive, more human-like manner. However, Mamdani-type FIS entails a substantial computational burden. On the other hand, Sugeno method is computationally efficient and works well with optimization and adaptive techniques, which makes it very attractive in control problems, particularly for dynamic nonlinear systems. These adaptive techniques can be used to customize the membership functions so that fuzzy system best models the data. The most fundamental difference between Mamdani-type FIS and Sugeno-type FIS is the way the crisp output is generated from the fuzzy inputs. While Mamdani-type FIS uses the technique of defuzzification of a fuzzy output, Sugeno-type FIS uses the weighted average to compute the crisp output. The expressive power and interpretability of Mamdani output are lost in the Sugeno FIS since the consequents of the rules are not fuzzy [7]. But Sugeno has better processing time since the weighted average replaces the time-consuming defuzzification process. Due to the interpretable and intuitive nature of the rule base, Mamdani-type FIS is widely used in particular for decision support application. Other differences are that Mamdani FIS has output membership functions whereas Sugeno FIS has no output membership functions. Mamdani FIS is less flexible in system design in comparison to Sugeno FIS as latter can be integrated with ANFIS tool to optimize the outputs.

III. DATA DESCRIPTION

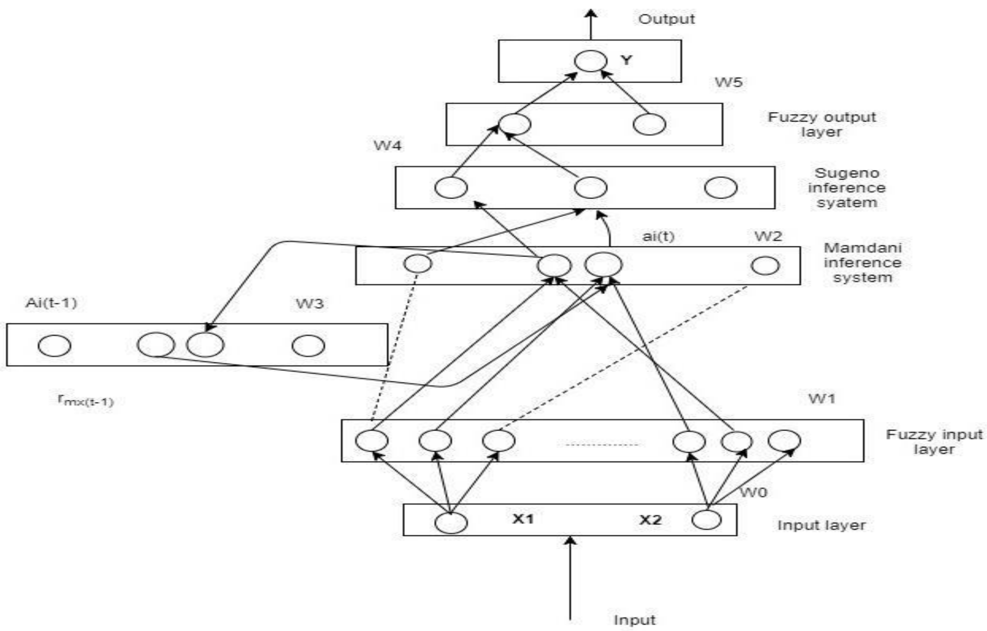


Figure:3.1 Architecture for speed detection

A. Input Layer
In this layer, the input gets passed to the system using a remote sensor which is placed along the road side. The inputs are the speed of the vehicle that passing on that road. In our proposal instead of the traffic speed, the traffic volume is being taken as the input for the system. The input can be of multiple values since the sensor can detect the speed of the multiple lanes.

B. Fuzzy Input Layer
This layer consist of the variables that can be used to the input which are passed to the input layer from the remote sensor.

The sensor transmits the input to the system. And this input is further passed to the many layers where the actual process will be taken to predict the traffic speed.

C.Mamdani Inference System
This is the algorithm that is used to get some values for the system and these values are being generated using the algorithm. This system is used to produce some sets of values as the result. And this kind of set of values is called as the fuzzy sets (i.e. the Mamdani inference is used to produce the fuzzy sets as the result of the input transmitted.)

D.Sugeno Inference System
This inference system is another method which is used to produce the result. When compared to the Mamdani system the Sugeno inference system is used to produce a linear or constant value as the output. In our proposal, the two systems are introduced to bring the accuracy of the traffic speed prediction.

IV.METHODOLOGY

Evolving Fuzzy Neural System The evolving fuzzy neural network model (EFNN) was presented in Nikola .An EFNN is an improved structure from the fuzzy neural network (FNN), and it can evolve its structure and functionality from a continuous input data source in an adaptive, life-long, modular way. Furthermore, all nodes in n EFNN are created during the learning process and the nodes representing membership functions can be modified during learning. The first layer is the input layer, in which the input variables are stored and each node represents a variable. The second layer of nodes quantifies the fuzzy values of the input variables by transforming the input values into membership degrees to which they belong to the membership functions. Each node in the second layer represents a membership function. The number of membership functions and the formulation of each can change during the learning process. In the third layer, the rule nodes can evolve through supervised or unsupervised learning. For this layer, A denotes the activation of the rule nodes, and each rule node r is defined by two vectors of connection weights: W1(r) and W2(r). The former can be adjusted by unsupervised learning based on similarity measures, and the latter can be adjusted by supervised learning based on the output errors. Between the second and third layers, there is a short-term memory layer which connects to the rule layer and can be used to provide information to it via a feedback loop. The fourth layer of nodes represents fuzzy quantification of the output variables. Finally, the fifth layer represents the real values of the output variables.

Comparing to a traditional FNN, an EFNN makes use of improved learning processes, which include two parts: the unsupervised learning process and the supervised learning process. In the unsupervised learning process, the main purpose is to determine parameters in fuzzy variables' membership functions. The supervised learning process is then used to adjust weights in the fuzzy inference system.

1) Clustering Based on K-Means Method: The aim of the K-means method is to classify the l input samples which take the form of m-vectors xi ={xi1, xi2,..., xil}, i = 1, 2,..., m, (here m is the dimension of input data , l is the number of samples) into n clusters, and determine the cluster centers for each cluster under the condition of minimizing an objective function J. The a distance between Xi and the cluster center CJ is first defined in the following equation:

d(xi, c j) = l k=1 xik − c where, |·| represents the general Euclidean distance. Then the objective function is defined as:
J = m i=1 n j=1 d(xi, c j) (2)

The algorithm for determining the cluster centers with the K-means clustering method can be divided into three processes. First, initialize the cluster center CJ. Second, iteratively modify the partition to reduce the sum of the distances for each sample from the centers of the cluster to which the samples belong. Finally, the process terminates if one of following conditions is satisfied: the value of an objective function is below a certain tolerance; the difference in the values of the objective function between adjacent iterations is less than a preset threshold; or the iteration process is complete. As the cluster number can definitely influence the prediction results, we will discuss it in the later sections.

2) Structure of Fuzzy Inference System: In the EFNN, a Takagi-Sugeno type fuzzy inference system is used to construct fuzzy rules. As each sample, x = [x1, x2,..., xm], has n memberships describing the degree to which it belongs to each cluster, the number of rules is equal to the number of clusters K. The rules are shown as follows:

if x1 is R11 and x2 is R12 and ... and XM is R1m,
then is f1(x1, x2,..., XM)
if x1 is R21 and x2 is R22 and ... and XM is R2m,
then y
is f2(x1, x2,..., xm)... ...
if x1 is RK1 and x2 is RK2 and ... and XM is RKm,
they is FK(x1, x2,..., XM)

where Rij indicates a fuzzy set defined by its membership function, xj is the antecedent variable, and fi is the inference consequence of variable y when the ith rule is employed. In this study, the fuzzy membership functions were selected to be of the Gaussian type with two parameters defined as follows:

m f (x) = e −(x−μ)2 σ2 (3)

where, MF is defined as membership function, μ is the value of the cluster center on the x dimension, σ2 is the variance of the distance between input samples and the cluster center on the x dimension. Overall, the total number of membership functions is n × m. In the model, a first-order Takagi-Sugeno is used in fuzzy inference system, which means the function fi (x1, x2,..., cm), i=1,2,... K, is a linear function. So, for an input data point x 0 = [x 0 1 , x 0 2 ,..., x 0 m], the inferring results of the system, y0, can be calculated as the weighted average of outputs from each rule:

y0 = K i=1 wi · fi(x 0 1 , x 0 2 , ..., x 0 m) K i=1 (4)
where, wi = m j=1 m fRij (x 0 j); i = 1, 2,..., n, j = 1, 2,..., m. In the learning process, a least squares estimator (LSE) in [43] and [44] is used to train the linear functions. Each of the linear function can be described as follows:

y=α0+α1x1+α2x2+..+αmxm (5)

The training dataset included p data pairs, {([xi1, xi2,..., xim], yi), i = 1, 2,..., p}, and was used to calculate the coefficients a =[α0 α1α2 ...αm]

Furthermore, an improving weighted least squares estimation method in [43] and [44] is used to optimize the parameters.

$$aw = (ATWA)-1ATWy \quad (6)$$

Where w represents the distance between the jth sample and the corresponding cluster center, j = 1, 2,..., p. Equation (6) can be rewritten according to the following:

$$Pw = (ATWA)-1$$
$$aw = PwATWy \quad (7)$$

Define the kth row vector of matrix A in equation (6) to be bT k = [1xk1 xk2 ... xkm] and denote the kth element of y as yk. Then the vector of the coefficient a can be iteratively calculated by equation (9) shown in the following. The calculation process uses a recursive, improved weighted LSE method [42], [43] This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination. to complete the optimization.

$$ak+1 = AK + wk+1Pk+1bk+1(yk+1 - bT0ak)$$

$$Pk+1 = 1\lambda\,(Pk - wk+1Pkbk+1bTk+1Pk\lambda + bTk+1Pbk+1)\ k = t,t+1,..., p-1 \quad (8)$$

where λ is the forgetting factor and with a value is generally between 0.8-1.0, at and Pt are the initial values of a and P, which can be calculated in equation (8) by using the first t data pairs from the training dataset. Here, the r is defined as the split ratio, if p represents the total number of training samples, then r ∗ p is the number of samples used in the first step and (1−r)∗ p indicates the number of samples used in the second step. Similarly, we will discuss the selection of in the later sections.

B. Cyclical Patterns

The periodicity of traffic flow in this study means daily similarity. We can observe similar distribution between days (peaks and trough hours) under normal traffic state. So, the length of period T in prediction is one day. Usually, a periodic function γ (t) with period T can be expanded into a Fourier series as follows:

$$\gamma (t) = +\infty$$

$$k=-\infty\ \beta k \bullet e\ jk(\ 2\pi\ T\ )t \quad (9)$$

where, βk is the coefficient, and it can be defined as:

$$\beta k = 1TT\varphi(t) \bullet e-jk(\ 2\pi T\ )tdt \quad (10)$$
$$e\ j\ \theta = \cos\theta + j \bullet \sin\theta \quad (11)$$

Therefore, the Fourier series can be described as a trigonometric polynomials series:

$$g(x) = +\infty-\infty\ \beta 1k \bullet \cos(kx) ++\infty-\infty\ \beta 2k \bullet \sin(kx) \quad (12)$$

To model the periodic component observed in Fig.2, a combination of sinusoids and cosinusoids is used, which is referred to as the trigonometric regression function. This approach can describe regular cyclical patterns or periodic variations and has been used for in various time series data analysis [45]. Using the observed 2-minute average travel speed values, the daily average 2-minute speed at each station is calculated. 2-minute average speed at time t on day d; t = 1, 2,..., 720 (As we use daily similarity to express periodicity of traffic flow, the total number of data samples collected in one day is 720); and d = 1, 2,... 21 is the number of training days in a month used to estimate the coefficients in equation (14). Considering equation (12), a limited number of trigonometric polynomials with sufficient accuracy is used to represent the period component of the travel speed time series:

$$Mu=m0+m1\sin(2\pi u720)+m2\cos(2\pi u720\ )+...+m2n-1\sin(2n\pi u720)+m2n\cos(2n\pi u720)(13)$$

where Mu is the estimated periodic component at time u, u = 1, 2,... 720, n is the number of trigonometric polynomials, m0, m1,..., m2n are the coefficients. For the daily average 2-minute speed, a least squares estimation method is used to determine the parameters in Equation (14). As the number of trigonometric polynomials can affect the prediction performance of the model, the selection of number of trigonometric polynomials will be discussed in the results section.

C. Structure of the Proposed EFNN+CP Prediction Method

As we discussed in Section two, speed values often have a daily periodic pattern. Thus, in this study, original data are divided into two parts. The hybrid prediction process in the study includes following several steps:

Step1 The training dataset, speed data collected in first 21 days at 2-min time scale, was used in trigonometric regression function to fit daily periodic pattern based on Equation (14)

Step2 Considering raw speed data contain periodic component and residual part:

$$St=Mt+Srt \tag{15}$$

where St is the speed at time t at a selected station, Mt is the periodic component, Srt is the residual part after removing the periodic component. We use raw speed data minus periodic component, and then obtain residual errors. One is the cyclic component and represents the periodic trend of speed, and the other is the irregular component or residual component.

Step3: The residual errors are used as the training dataset to optimize parameters in EFNN model, and then predict residual errors in future steps.

Step4: Through combing predicted residual errors and periodic component, the predicted values for real speed data .

Centroid of the area (COA)

Defuzzification method returns the output by calculating the centroid of the area formed by the aggregated fuzzy sets of the consequents.

$$y = \frac{\int_v \; y.\mu_{B\,(y)dy}}{\int_v \; \mu_{B\,(y)dy}}$$

The bisector of the area (BOA)

The vertical line corresponding to the output generated by BOA splits the aggregated fuzzy sets into two sub regions of equal area.

$$\int_{\alpha}^{y_{BOA}} \mu_{B}\,(y)dy = \int_{y_{BOA}}^{\beta} \mu_{B(Y)DY}$$

Smallest of maximum (SOM)

This method generates the crisp output by taking the smallest value that gives the maximum membership degree of the aggregated fuzzy set.

$$y_{SOM} = min\{y|\mu_B(y) = max(\mu_B(y))\}$$

Largest of maximum (LOM)

Instead of smallest value as SOM, LOM takes the largest value corresponding to the maximum membership degree to yield the final crisp output.

$$y_{lOM} = max\{y|\mu_B(y) = max(\mu_B(y))\}$$

Mean of maximum (MOM)

In this defuzzification, the mean of maxima is taken as the crisp output.

$$y_{MOM} = \frac{y_{SOM} + y_{LOM}}{2}$$

Methods of Sugeno System:
I.Weighted Average(WA)
II. Weighted Sum (WS)

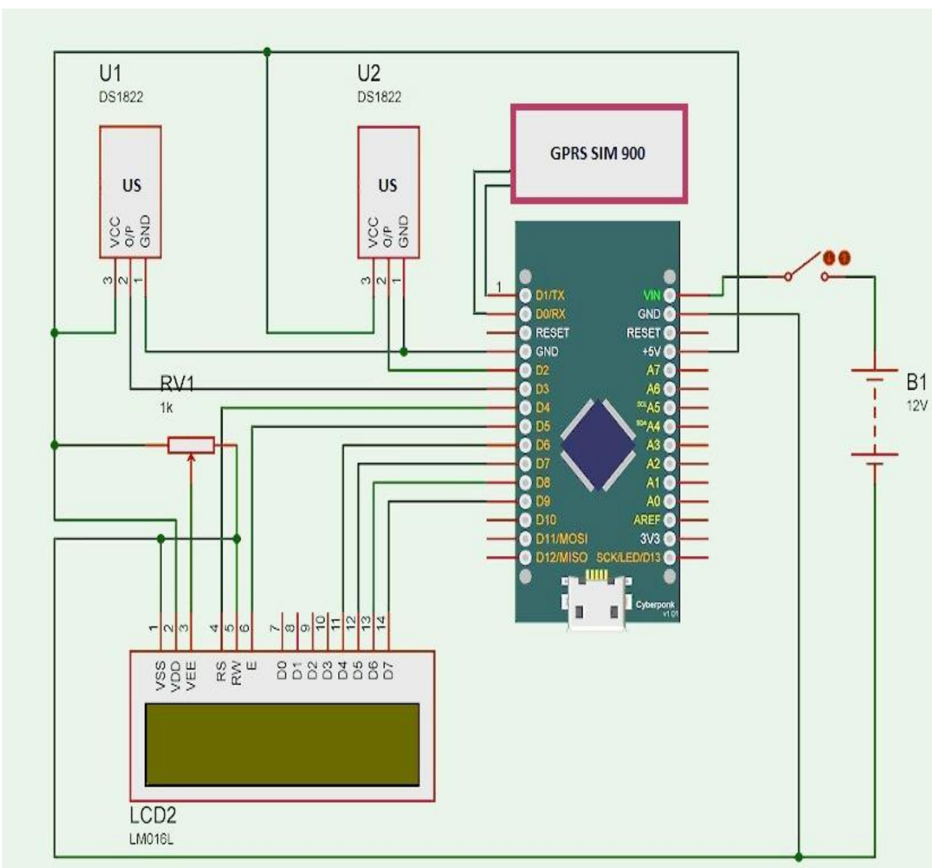
Weighted average(WA)
This defuzzification method generates the final output for a Sugeno FIS by averaging the weighted rule outputs.

$$y_{WA} = \frac{\sum_{I=1}^{M} W_i y_i}{\sum_{i=1}^{M} Wi}$$

Weighted sum (WS)
To reduce the computation of WA, the WS method takes only the sum of the weighted rule outputs.

$$y_{ws} = \sum_{I=1}^{M} W_i y_I$$

Circuit Diagram:



The Evolving of Fuzzy Neural Network (EFNN) is based on two learning process.

I. K means method
II. Weighed least square estimator
K means method:
The aim of the K-means method is to classify the l input samples which take the form of m-vectors xi ={xi1, xi2,..., xil}, i = 1, 2,..., m, (here m is the dimension of input data, l is the number of samples) into n clusters, and determine the cluster centers for each cluster under the condition of minimizing an objective function J . The distance between Xi and the cluster center CJ is first defined in the following equation: d(xi, c j) = l k=1 xik − c j where, |•| represents the general Euclidean distance. Then the objective function is defined as: J = m i=1n j=1 d(xi, c j) (2) The algorithm for determining the cluster centers with the K-means clustering method can be divided into three processes. First, initialize the cluster center CJ. Second, iteratively modify the partition to reduce the sum of the distances for each sample from the centers of the cluster to which the samples belong. Finally, the process terminates if one of following conditions is satisfied: the value of an objective function is below a certain tolerance; the difference in the values of the objective function between adjacent iterations is less than a preset threshold, or the iteration process is complete. As the cluster number can definitely influence the prediction results, we will discuss it in the later sections.

V.DIFFERENCE BETWEEN EXISTING AND PROPOSAL

In the existing system, the process of calculating the speed of the vehicle is done by the RTMS (i.e. a sensor device that s used to calculate the speed of the vehicle effectively). The accuracy was the major limitations that have been processed. And the device had been placed on the side of the road with some proper calculation of the position. In the proposed system the ultrasonic device is used to detect the speed of the vehicle instead of the RTMS sensor. And the device is to be placed on the surface of the road to detect the speed. The device produces ultrasonic waves using which the speed of the vehicle is getting calculated. And the device consists of the antenna by which the detected speed is transmitted to the software.

VI.CONCLUSION

In this paper, a new model of travel speed prediction method has been developed based on a fuzzy neural network by using traffic speed data collected from the ultrasonic device on the surface of the road in the city. This EFNN model is based on the Takagi-Sugeno fuzzy inference system, in which n fuzzy rules are activated to calculate the output vectors for a given set of input vectors. In the training process, a K-means method was first used to cluster the input vectors and calculate the cluster centers. Then, the Gaussian-type fuzzy membership functions were designed to evaluate the membership degree of the input samples to each of the clusters. Finally, an improved weighted recursive LSE was used to optimize the parameters in the linear Takagi-Sugeno fuzzy inference functions. In the model's performance comparison, six traditional methods are selected as candidates: BPNN, NARXNN, SVM-RBF, SVM-LIN, ARIMA, and VAR. First, the prediction accuracy of speed decreased as the prediction time steps increased for all models. Second, the EFNN was superior to ANN, SVM and SM models. Third, the EFNN considering CP model could significantly improve the multi-step-ahead prediction accuracy. Fourth, machine learning models outperformed two traditional statistical models. Among the machine learning models, the prediction performance of ANN was better than that of SVM.

For the further processing, the following can be the considerations:
(1) The spatial-temporal features of speed in the prediction model. A lot of works have been demonstrated that speed variation patterns at one station show high spatial and temporal correlation with that at adjacent stations. This spatial-temporal property can be used to modify the prediction patterns of speed in a specific location from other related locations.

(2) The speed prediction for arterial roads or networks becomes more applicable in traffic management and control. It is useful to quickly respond to some special events and improve managing efficiency by perceiving future patterns of speed in the arterial or local network based on accurate prediction results. One practical future research will focus on how to apply the proposed method from a single station to roads or network level.

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