Variation Based Online Travel Time Prediction Using Clustered Neural Networks

Jie Yu, Gang-Len Chang, H.W. Ho and Yue Liu

Abstract-This paper proposes a variation-based online travel time prediction approach using clustered Neural Networks with traffic vectors extracted from raw detector data as the input variables. Different from previous studies, the proposed approach decomposes the corridor travel time into two parts: 1) the base term, which is predicted by a fuzzy membership-value-weighted average of the clustered historical data to reflect the primary traffic pattern in the corridor; and 2) the variation term, which is predicted through the calibrated cluster-based artificial neural network model to capture the actual traffic fluctuation. To evaluate the effectiveness of the proposed approach, this paper has conducted intensive numerical experiments with simulated data from the microscopic simulator CORSIM. Experimental results under various traffic volume levels have revealed the potentials for the proposed method to be applied in online corridor travel time prediction.

I. INTRODUCTION

AS is well recognized, travel time information plays an important role in the Advanced Travelers Information Systems (ATIS), which has the potential of providing dynamic route guidance for travelers, increasing the reliability in road networks, and alleviating congestion and its negative environmental/social side effects [1]. Travel time prediction, which refers to the calculation of the travel time at the time the vehicles start their trips, is a highly complex and challenging problem, as travel times are the results of complex nonlinear interactions of heterogeneous groups of driver-vehicle combinations. Furthermore, exogenous factors (such as availability of vehicle detector system, traffic delay and missing of real-time data) are often beyond control of the prediction model.

In review of the literature, researchers have attempted to implement both parametric and nonparametric approaches to forecast travel times. Among parametric models, promising results were achieved using regression models [2], time-series models [3], and Kalman Filter models [4]. Meanwhile, lots of researchers have devoted considerable

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attention to nonparametric models, which include artificial neural network (ANN) models [1, 5, 6, 7, 8], nearest neighborhood models [9], and simulation models [10, 11, 12], due to their robust performance. Many studies have demonstrated that ANNs have the potential to accurately predict travel time on freeways, including modular neural network model [5], spectral basis neural network model [6], and state-space neural network model [1, 7] etc. Nearest neighborhood model can provide reasonably good performance when a sufficient number of similar historical cases can be obtained. Simulation-based approaches (e.g., SBOTTP [10], DYNAMIT [11]) can also be used as a cost-effective tool for travel time prediction.

Despite the promising work by previous studies, the following drawbacks remain to be further addressed:

- Most studies predicted travel times in a link-based way assuming that corridor travel time is the addition of the travel times on its consisting links during the prediction period. However, those approaches may not be reliable due to the neglect of time lag between prediction periods of different links and accumulation of link prediction errors;
- Some studies use travel times in previous time periods as inputs, which limits them to be applied online because travel times in previous time periods may not be available before they are realized;
- Previous studies treated the travel time as a single component and predict it directly, which may have large prediction errors.

To accommodate the aforementioned issues, this paper presents a variation based approach for real-time travel time prediction focus on the following specific issues:

- The proposed prediction model predicts travel time at the entire corridor level rather than the link-based level to overcome the accumulation of link travel time prediction errors, as well as to fully take advantage of the historical corridor travel time data;
- The proposed prediction model takes detector data instead of travel time in previous intervals as inputs and is more suitable to be eligible for online application;
- The proposed prediction model tries to make the prediction results more robust by decomposing the corridor travel time into a base term and a variation term. The base term can make full use of the historical data to capture the primary traffic pattern in the corridor, while prediction of the variation term will represent the traffic

fluctuation.

This paper is organized as follows. A model framework that consists of online and offline procedures will be introduced in Section II. Section III presents five key functional modules of the proposed model, including data collection module, data processing and pattern identification module, base travel time prediction module, travel time variation prediction module, and final travel time output module. Section IV evaluates the performance of the proposed model on a segment of US50 eastbound to Ocean City, Maryland under different demand scenarios using data from CORSIM. Finally, a concluding discussion follows in Section V, including a summary of the proposed approach and future extensions.

II. MODEL FRAMEWORK

This section presents the model framework (see Fig. 1) for the proposed online travel time prediction approach.

As shown in Fig. 1, the entire framework for online travel time prediction consists of two main procedures:

- Off-line procedure: Integrated with a comprehensive historical database, the off-line procedure functions to 1) collect, store and provide required traffic data (i.e. volume, speed, and historical travel time); 2) classify different traffic patterns based on clustering techniques

and calculate the mean travel time for each cluster; and 3) calibrate ANN models for each cluster;

- On-line procedure: Based on the clustering results and calibrated models from the off-line procedure, the on-line procedure serves to fulfill the following five tasks. 1) Process real-time detector data and extract the input traffic vector; 2) Calculate fuzzy membership values of the extracted traffic vector for all clusters; 3) Predict the base travel time term based on the membership-value-weighted average of all cluster means; 4) Apply the clustered ANN model to predict the variation term for each cluster, and calculate their membership-value-weighted average as the travel time variation term; 5) Sum up the base term and variation term to output the total predicted travel time.

During the real-world operation, the offline and online procedures will interact with each other through various seamlessly integrated modules, including data collection module [(A), (B), and (F)], data processing and pattern identification module [(C) and (G)], base travel time prediction module [(D) and (H)], travel time variation prediction module [(E) and (I)], and final travel time output module [(J)]. Each of its five functional modules will be elaborated below.
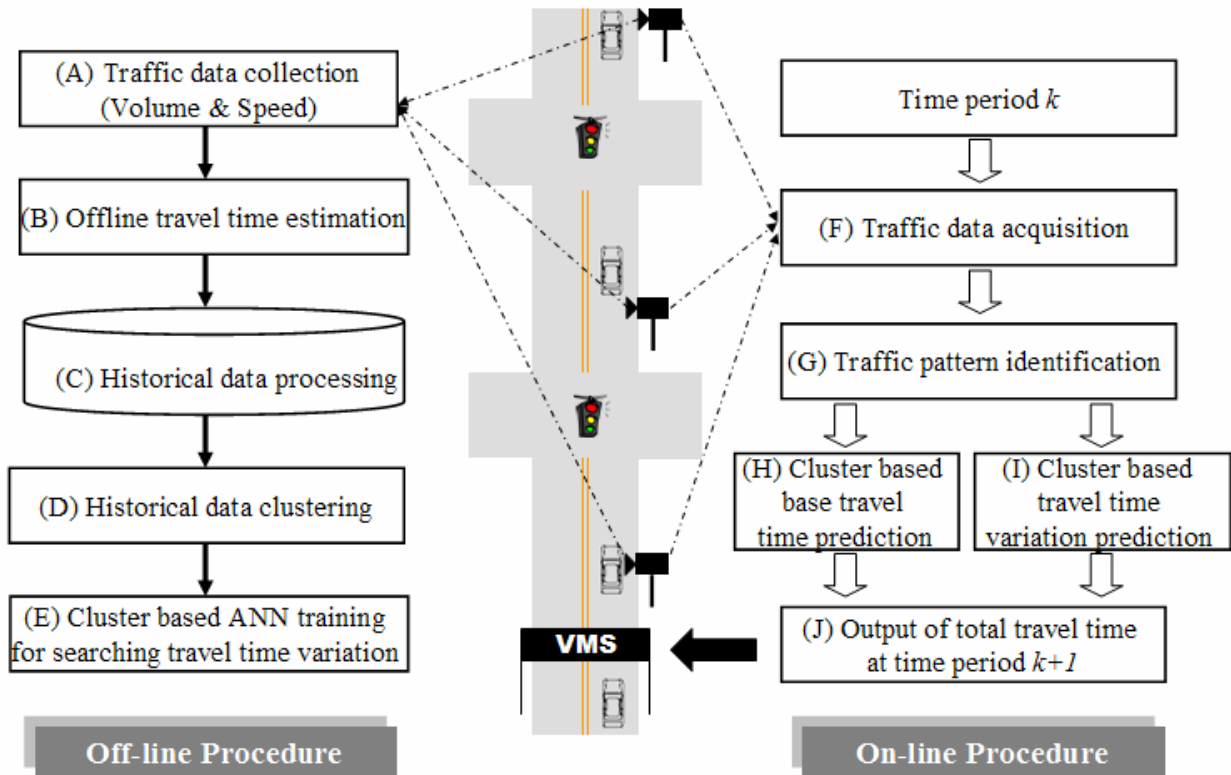

Fig. 1 A conceptual framework for online travel time prediction

III. KEY MODULES

A. Data Collection Module

This module provides basic input information to both online and offline models for travel time prediction. It includes two parts: historical data archiving and real-time detector data collection.

A comprehensive offline database plays a key role in archiving and organizing historical data, including the following information:

- Historical traffic volume & speed data (from roadside detectors) representing different traffic patterns at the target corridor in different time periods;
- Historical corridor travel time in one time period ahead (either from direct measurement or offline estimation approaches). For example, for the record of historical speed and volume data collected in the time period k, historical corridor travel time in time period k+1 will be matched with it.

This module is also responsible for collecting real-time traffic volume & speed (from detection equipment) in each time period to represent the current traffic pattern on target corridor and update the prediction results.

B. Data Processing and Pattern Identification Module

Traffic data collected from the entire corridor in the preceding time periods are important parameters for identifying future travel time patterns. However, it is difficult to directly apply those raw data to represent the traffic pattern when the number of detectors and selected preceding time periods is large.

This module functions to efficiently reduce the dimensionality of raw data by extracting one traffic vector which can represent the dynamic traffic patterns for the target corridor, as shown in Equation (1) - (2):

$$\vec{\varphi}(k) = \{\vec{\varphi}_1(k), \cdots, \vec{\varphi}_i(k), \cdots, \vec{\varphi}_n(k)\} \tag{1}$$

$$\vec{\varphi}_i(k) = \frac{\sum_{j=1}^{\Delta k_i} \vec{s}_i(k-j+1) \cdot w_i(j)}{\sum_{j=1}^{\Delta k_i} w_i(j)} \tag{2}$$

Where,

i : Index of link;

k : Index of time periods;

j : Index of previous time intervals from 1 to Δk_i;

n : Number of links in the target corridor;

$\vec{\varphi}(k)$: A 2n-dimensional vector at the time period k;

$\vec{\varphi}_i(k)$: A 2-dimensional vector (volume, speed) on link i at the time period k;

$\vec{s}_i(k)$: A 2-dimensional traffic data vector (volume, speed) for the ith detector at the time period k;

$w_i(j)$: Weight of previous time period j for link i;

Δk_i : Num. of the preceding time periods used for link i.

In this module, the 2n-dimensional vector $\vec{\varphi}(k)$ which consists of those different 2-dimensional vectors $\vec{\varphi}_i(k)$ represents the specific traffic pattern for the entire corridor up to time period k (including both current and previous time period). $\vec{\varphi}_i(k)$ is a weighted measure of traffic status of link i up to the time period k. To account for the maximal possible impact of previous traffic data, the number of previous time periods (Δk_i) used for calculating $\vec{\varphi}_i(k)$ is chosen to be the maximal estimated travel time from detector i to destination based on historical data, as shown in Fig. 2.

It would be reasonable to expect that weights for traffic data in the more recent time period are higher, based on the assumption that the more recent information would influence the future states more. Fig. 3 demonstrates the potential weight functions used for different time periods. In this module, we take the linear form weight function as shown in Equation (3):

$$w_i(j) = w_{min} + \frac{[\Delta k_i - j]}{[\Delta k_i - 1]} \cdot [w_{max} - w_{min}] \quad \forall j \in [1, \Delta k_i] \tag{3}$$

Where,

w_{max} : Maximal weight (1.0 in this paper);

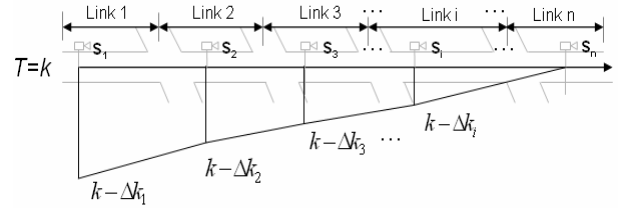w_{min} : Minimal weight (0.1 in this paper).

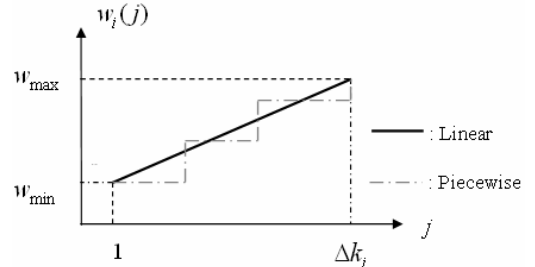Fig. 2 Num. of the preceding time periods used for different links

Fig. 3 Weight functions for different time periods

C. Base Travel Time Prediction Module

This module functions to predict the base travel time in order to capture the primary traffic pattern at the target corridor. As is reported in the literature and observed in the field survey, traffic patterns on a corridor may vary significantly during the morning peak hours, evening peak hours, and off-peak hours due to the complex interactions of many factors with time-varying natures. Therefore, it would be more accurate to predict the base travel time by pre-classifying the traffic patterns into several simpler classes.

Considering the actual classification scheme is not known as a priori, an unsupervised learning model may be more suitable for clustering traffic patterns. This module employs a fuzzy c-means clustering algorithm, which had given outstanding results in previous related studies [5]. As shown in Fig. 4, the procedure for base travel time prediction includes both off-line and on-line parts. Based on the comprehensive historical database provided by data collection module, the off-line procedure aims to identify cluster centers, and as well as calculate the mean travel time $\overline{TT_c}$ for each cluster, which is a fuzzy membership value weighted average of historical travel time samples. On the other hand, the on-line part first acquires real-time traffic pattern vectors at time period k, and then calculates cluster membership values $\mu_c(\varphi(k))$, which defines the degree to which the vector $\vec{\varphi}(k)$ belongs to the cth cluster. Finally, this module predicts the base travel time by conducting a $\mu_c(\varphi(k))$ weighted average of each cluster mean $\overline{TT_c}$, as shown in Equation (4):

$$TT_b(k+1) = \frac{\sum_{c=1}^{C} \overline{TT_c} * \mu_c(\varphi(k))}{\sum_{c=1}^{C} \mu_c(\varphi(k))} \tag{4}$$

Where,

$TT_b(k+1)$: Predicted base travel time at time period $k+1$ for the corridor;

$\overline{TT_c}$: Mean travel time corresponding to cluster c;

$\mu_c(\varphi(k))$: Fuzzy membership value of vector $\vec{\varphi}(k)$ corresponding to cluster c;
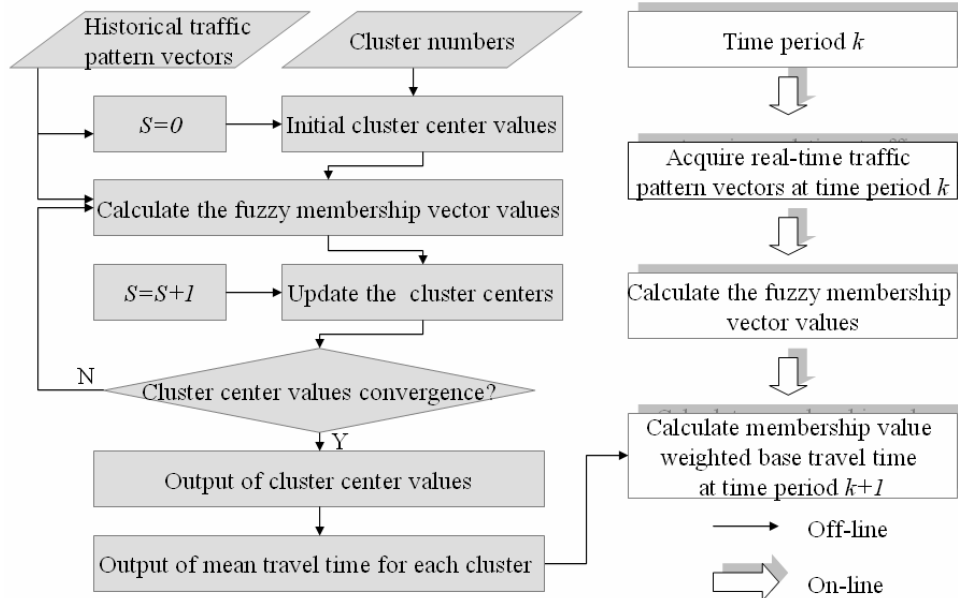
C : Number of clusters.

Fig. 4 Procedures for base travel time prediction using fuzzy c-means clustering algorithm

D. Travel Time Variation Prediction Module

This module aims to predict the variation of travel time to reflect the real-time traffic fluctuation in the target corridor through pre-calibrated clustered Neural Network models. For each cluster, the feed-forward Multilayer ANN was selected and the back-propagation algorithm was implemented to train the neural network in order to minimize the errors between the actual and desired output. Fig. 5 illustrates the topology of the Neural Network model for each cluster. Each neuron in the input layer receives inputs from $\vec{\varphi}_i(k)$, and the output layer consists of one neuron which is the predicted travel time variation on the target corridor at time interval $k+1$ for each cluster. One hidden layer was determined for the back-propagation structure.

Similar to the procedure of calculating the base travel time, the travel time variation is predicted as a fuzzy-membership-value-weighted average of the outputs from all cluster based ANNs, as shown in Equation (5):

$$\Delta TT(k+1) = \frac{\sum_{c=1}^{C} \Delta TT_c(k+1) \cdot \mu_c(\varphi(k))}{\sum_{c=1}^{C} \mu_c(\varphi(k))} \tag{5}$$

Where,

$\Delta TT(k+1)$: Predicted travel time variation at time period $k+1$;

$\Delta TT_c(k+1)$: Predicted travel time variation at time period $k+1$ for the cth cluster.

E. Final Travel Time Output Module

The total predicted travel time at time period $k+1$ is the sum of base travel time and travel time variation, given by the following Equation:
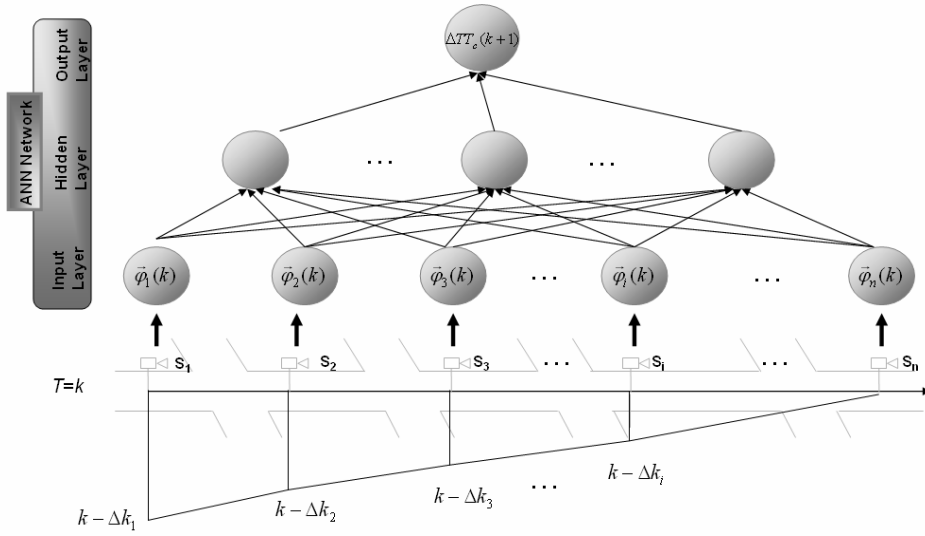
Fig. 5 Topology of the Neural Network model for travel time variation prediction

$$TT(k+1) = TT_b(k+1) + \Delta TT(k+1) \qquad (6)$$

IV. NUMERICAL EXPERIMENT

A. Test Network

An approximately 7.1 mile section of US50 eastbound to Ocean City, MD was modeled in CORSIM (see Fig. 6) to generate the data for clustering, ANN training, and testing. This arterial section was comprised of 11 2-lane links and 10 signalized intersections with speed limits varying between 35 and 55 miles per hour. 11 detectors, which programmed to record flow and speed data, were located at the upstream of each link.

Fig. 6 Illustration of the study area

B. Experiment Design

To create a training and testing dataset under different traffic conditions, the travel demand loadings on the network lasting from 7:30am to 8:30pm were varied hourly based on the observed real world traffic pattern, as shown in Table I, in which free-flow traffic, moderated congested traffic, and heavily congested traffic are all considered. As the first 30 minutes of simulation is used to warm-up and some of the vehicles departure in the last 30 minutes could not arrive the destination before the end of the simulation, 12-hour (8:00 am ~ 8:00 pm) detector data and travel times are used for analysis. 7200 data records (10days x 12 hours/day x 60 time periods/hour) are generated for training and testing the proposed models.

Among these 7200 data records, nearly 6,500 samples (9 days x 720 periods a day) were employed to 1) identify cluster centers (the number of cluster we chose in this paper is

10) and calculate the fuzzy-membership-value-weighted mean travel time for each cluster; and 2) calibrate ANN models for each cluster. Meanwhile, 720 samples were used to validate the performance of the proposed models.

TABLE 1
HOURLY VARIED TRAVEL DEMAND LOADING

Time Duration	Volume (vph)	Time Duration	Volume (vph)
7:30am~8:30am	1200	2:30pm~3:30pm	1600
8:30am~9:30am	2000	3:30pm~4:30pm	1600
9:30am~10:30am	2000	4:30pm~5:30pm	2000
10:30am~11:30am	1600	5:30pm~6:30pm	2000
11:30am~12:30pm	1600	6:30pm~7:30pm	1600
12:30pm~1:30pm	1200	7:30pm~8:30pm	1600
1:30pm~2:30pm	1200		

C. Performance Evaluation

Fig. 7 shows the comparison of the predicted travel time and the CORSIM results. The x-axis denotes the departure time of day (i.e. from 8:00am~8:00pm) whereas the y-axis denotes the travel times in minutes. From the figure below, we can see that the predicted travel times showed a very similar trend to the simulated results.
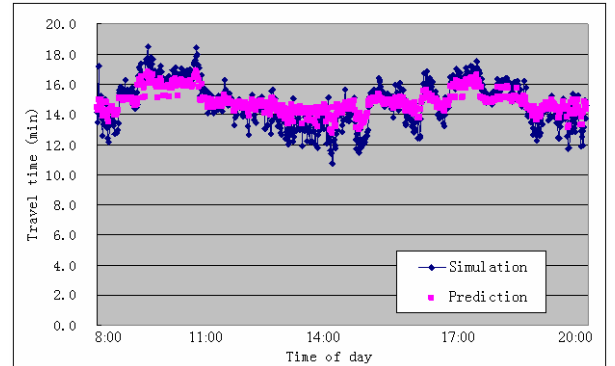

Fig. 7 Comparison of predicted travel time with CORSIM simulation results

Table II evaluates the performance of the developed models by two indices: Root Mean Square Error (RMSE) and

Root Mean Square Percentage Error (RMSP). As indicated in the table below, one can reach the following findings:

- As a whole, the proposed models produce reasonably good results with 1.29 minute RMSE and 0.087 RMSP; and
- For the peak hours in which predicting travel time reliably is a challenge, the proposed models can provide promising prediction accuracy (with RMSP equal to 0.083) due to the embedded base term which is capable of capturing primary traffic patterns.

TABLE II
PERFORMANCE EVALUATION FOR TRAVEL TIME PEDICTION

Time Period	RMSE	RMSP
Whole	1.29	0.087
Peak hour	1.30	0.083
Off-peak hour	1.29	0.089

V. CONCLUSION AND FUTURE EXTENSIONS

This paper proposes a variation-based online travel time prediction approach using clustered Neural Networks with traffic vectors extracted from raw detector data as input variables. The total predicted travel time is comprised of two parts: base travel time and travel time variation. The base term is predicted by a fuzzy-membership-value-weighted average of the clustered historical data to reflect the primary traffic pattern, while the variation term is predicted through the calibrated cluster-based artificial neural network model to capture the actual traffic fluctuation. Numerical experiments on a segment of US50 eastbound to Ocean City, Maryland under different demand scenarios using data from CORSIM illustrate that the proposed appoach is capable of reliably predicting corridor travel time.

Although the results of the proposed approach are promising, a number of issues still need to be resolved in future studies:

(1) The proposed models will be tested with field data under more complex real world traffic conditions;

(2) Advanced ANN structures could be employed to achieve better prediction performance;

(3) Sensitivity analysis of the number of cluster should be taken into account to obtain the optimal number of clusters with the minimal prediction errors.

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