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An Adaptive Neural Fuzzy Inference System model for freeway travel time estimation based on existing detector facilities

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ABSTRACT

While volume-counting detectors are currently installed in many freeways and have the capabilities of collecting high-resolution traffic information, travel time estimations are usually only based on spot speeds collected by the detectors, which could only produce rough estimates of travel time during peak hours when roadways are congested. In addition to spot speeds, these detectors provide directional volume counts and occupancy, which are useful for a better travel time estimation. This research used data from volume counting detectors and made Adaptive Neural Fuzzy Inference System (ANFIS) to automatically estimate real-time travel times. ANFIS's ability to learn traffic patterns allows accurate and reliable real-time travel time estimation even with missing or corrupted data. ANFIS also proves to be a powerful tool for estimating future travel times on freeways. For easier use by practitioners and researchers, the method used in this study was implemented into a software package, named FTTE (Freeway Travel Time Estimator). Finally, a case study was conducted using the new approach and the results were compared for both congested and uncongested traffic conditions.

1. Introduction

Obtaining condition of streets and especially freeways is essential to operating agencies for timely managing different unpredicted events and provide accurate travel time estimates to users through Variable Message Signs (VMS). While loop detectors are widely popular all around the world (Appendix A demonstrates a sample of detector data from the existing freeway detectors in Reno, Nevada and Golestan, Iran), these detectors estimate only spot speed at detector locations and obviously not between detectors. Hence, travel times directly calculated from spot speed of detectors produce rough estimates of travel time especially during peak hours.

To respond to this issue, some researchers have proposed predictive travel time methodologies using traffic flow theory, filtering algorithms, data mining and machine learning methods. Vanajakshi et al. (2009) modified an existing traffic flow theory based model to predict travel time on freeways. Their modified model could estimate travel time at transition periods which traffic flow gradually moves from normal to congested flow conditions. Later, Yildirimoglu and Geroliminis (2013) also provided travel time prediction by using traffic flow fundamentals and real time and historical traffic information. To estimate travel time, this approach clusters traffic data based on traffic regimes, develops a stochastic congestion maps, and combines real time and historical traffic information, and identifies bottlenecks. Wang et al. (2006) and Paterson and Rose (2008) presented macroscopic models to predict a freeway travel time. Paterson and Rose (2008) drew on queuing theory to show how vehicles pass through sections of the freeway in order to overcome the limitations of 'instantaneous' speed models. This model considers condition of bottlenecks, geometry, speed limits, distribution of vehicles along the freeway, and ramp flows. Nam and Drew (1996) also used queuing theory for freeway travel time estimation.

Fei et al. (2011) created a Bayesian inference-based dynamic linear model (DLM) used to predict short-term travel time on freeways. This method is able to recognize the primary travel time pattern. Yeon et al. (2008) used the Markov Chain and later Qi and Ishak (2014) proposed the Hidden Markov Model (HMM) for short-term freeway traffic prediction during peak periods. The HMM creates a two-dimensional space consisting of mean and contrast of speed observations to define traffic states. It can be seen that Zou et al. (2014) also used a space–time diurnal (ST-D) method which obtains accurate short-term travel time predictions by merging the spatial and temporal travel time information. This method considers diurnal pattern and spatial and temporal

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correlation. Other use of filtering methods for real-time short to medium-term travel time estimation can be seen in Chen and Rakha (2014) that proposed a particle filter approach and Dion and Rakha (2006) that obtained automatic vehicle identification (AVI) data to use an adaptive filtering algorithm.

Some research is focused on data mining and machine learning methods to estimate the travel time. Li and Chen (2014) used K-means clustering, decision trees, and neural networks, Dharia and Adeli (2003) used counter propagation neural (CPN) network, Elhenawy et al. (2014) used clustering and genetic programming (GP), Khosravi et al. (2011) automated the neural network hyper parameter by using the neural network and adopting a genetic algorithm, and Wei et al. (2010) and Wei and Liu (2013) applied Least-Square Wavelet-Support Vector Machine (LSWSV) and support vector regression (SVR).

Soriguera et al. (2010) developed a method for estimation of travel times from data used for toll collection on closed toll highways where toll plazas are located on the entrance and exit ramps. In contrary to the most methods which use a unique data source, Soriguera and Robusté (2011) proposed a data fusion algorithm that uses both inductive loop detectors and toll tickets for the short-term prediction of travel times.

Li et al. (2006), van Lint et al. (2008), Arezoumandi (2011), and Tu et al. (2012), have studied the reliability of freeway travel time estimations. Other research about travel time that can be reviewed include Coifman, and Cassidy (2002), Deniz et al. (2013), Celikoglu (2013), and Dong et al. (2014).

Though some researchers, such as van Lint et al. (2005), Khosravi et al. (2011), Celikoglu (2011), and Li and Chen (2014), have used the neural networks for travel time estimations, and some researchers, such as Coifman (2002), van Lint and van der Zijpp (2003), Paterson and Rose (2008), Coifman and Krishnamurthy (2007), and Martchouk et al. (2011) have used different detector data for estimations, the application of ANFIS has not yet been studied. ANFIS has the ability to learn patterns and since volume-counting stations provide different data, it can learn the traffic pattern and based on those patterns, produces a real-time estimation.

The objective of this research was to propose a simple and cost-effective method and its related software for estimating freeway travel time using ANFIS and existing detection devices in such a way that travel times can be continuously calculated at low cost, which fulfills the need for various transportation studies. The method proposed here does not need complex data preparation and calculations by practitioners and can be used with different data collection methods such as loop detectors (Gholami and Tian, 2016; Bielli and Reverberi, 1996), Bluetooth detectors (Haghani et al., 2010), video cameras (Giannopoulos, 2004), automatic vehicle location (AVL) systems (D'Acierno et al., 2009), cellular phone data (Pathirana et al., 2006; Astarita et al., 2006) etc.

Though many other speed estimation methods are already developed for freeways, this paper tries to focus on a simple and practical method which is easy for application. The method proposed here uses only simulation VISSIM data for training. By using COM interface of VISSIM, practitioners can prepare training data easily, in contrary to other methods which training data preparation is burdensome and time-consuming. The prepared trained model uses only existing loop detectors along freeways as the main source of data for travel time prediction. Some other modern travel time estimations can definitely provide more detailed information, but a broad deployment of such devices and methods still involves a significant cost. Since many DOTs (Department of Transportation) have installed many loop detectors along major freeway and arterial routes and have the capabilities of archiving high-resolution detector information, there is a great payoff potential for providing continuous travel time estimates without considerable additional costs. Also, the software package provided in this paper, can be used to make the whole process of the methodology ready and easy for practitioners.

2. Methodology

The methodology provided in this section tries to use only existing detector information along freeways to estimate travel time at a freeway section which have two sets of detectors at its two ends. As described in the research background, such data are available in many freeways. The method proposed here develops a prediction model using Adaptive Neural Fuzzy Inference System (ANFIS) whether or not the link is congested. Fig. 1 shows the flowchart of the proposed method.

The first step in this methodology is to make a calibrated simulation model to produce the required training data for ANFIS. This data set contains different volumes and their correspondence travel time, spot speed and occupancy. In reality, volumes, spot speed and occupancy (independent variables) can be obtained from detectors but their corresponding speed (dependent variable) needs to be obtained manually and since ANFIS needs a considerable number of records (each record is comprised of travel time and its corresponding volume, spot speed, and occupancy), real variables are not practical to be obtained from the field to make the required data for training model. To produce such a data set, VISSIM was selected for simulation due to ability to produce high-resolution outputs and model any specific situation. To obtain required data from VISSIM, sensors at two ends of the section should be placed in the model in exact locations of real sensors. The model needs to be run under different volumes and since this is very time consuming, VISSIM COM interface was used to automatically change volumes after each run and save the output. After preparation of data, ANFIS was used to learn the behavior of the freeway section in terms of travel time under different conditions. In ANFIS, travel time along the section was used as a dependent variable and spot speed, volume and occupancy were used as independent variables.

Given the collinearity with spot speed, volume of traffic, and occupancy, the time-of-day is not included as a predictor, to avoid biasing parameter estimates towards "normal conditions".

ANFIS takes advantage of both the Fuzzy Inference System (FIS) and the Artificial Neural Networks (ANN). The FIS models relationship of variables in a fuzzy perspective and ANN optimizes parameters of membership functions. Therefore, ANFIS is actually an automated FIS that follows the process of theory of fuzzy sets and uses ANN to automatically define the rules and membership functions of fuzzy sets and adjusts the different weights during the FIS process (Negnevitsky (2004)).

The ANFIS architecture designed in this paper has five layers (Fig. 2). For sake of simplicity, only the variables of first detectors at location i (upstream detector) are shown in this figure. Layer 1 gets the

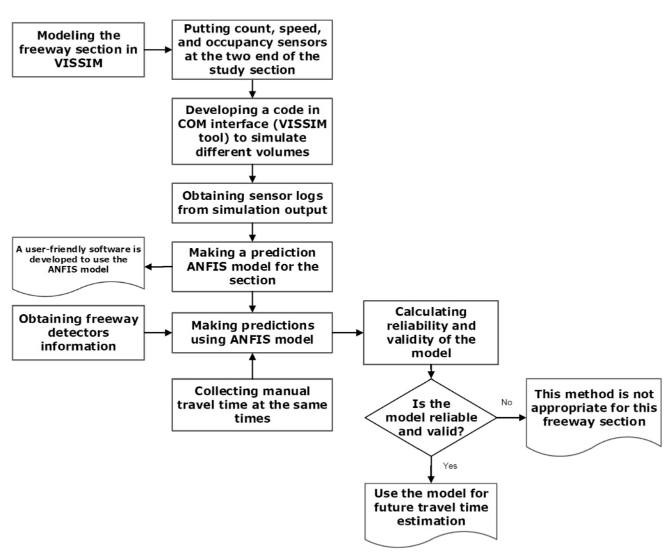

Fig. 1. Methodology flowchart.

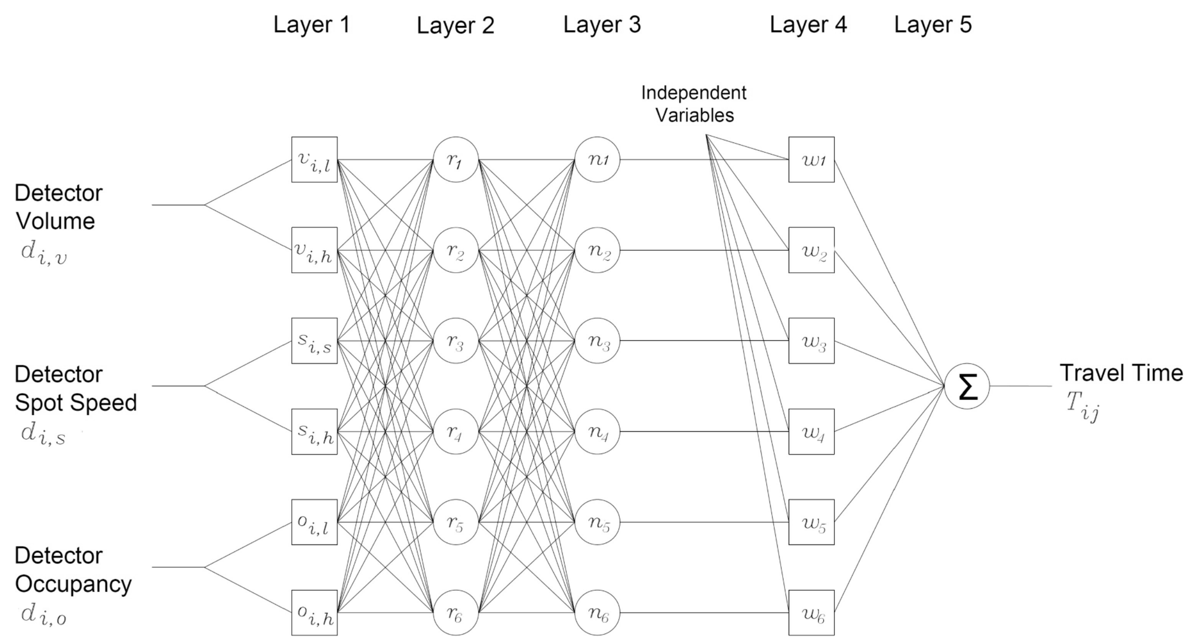

Fig. 2. ANFIS of freeway travel time prediction. Note: At Layer 1, the model applies more than two fuzzy members per input. For simplicity, only two are displayed here, low (l) and high (h).

independent variables and makes them fuzzy. Three independent variables are usually available from detectors: volume, spot speed and occupancy (Appendix A-a). However, some detectors do not record occupancy (Appendix A-b). In this case, independent variables should be volume and speed. At layer 1, variables of both detectors at the section under study should be entered. The variables of first location detectors are $d_{i,v}$ (detector volume), $d_{i,s}$ (detector spot speed) and $d_{i,o}$ (detector occupancy). The variables of second location detectors (j) (downstream detectors) are similar to the first one by notations of $d_{j,v}$, $d_{j,s}$, and $d_{j,o}$. The output (T_{ij}) is travel time between two location detectors.

This layer calculates how much each input belongs to all fuzzy members. While actual number of fuzzy members is more, Fig. 2 depicts only two fuzzy members for each variable. For example, fuzzy members shown in Fig. 2 for variable volume ($d_{i,v}$) are shown as low volume ($v_{i,l}$) and high volume ($v_{i,l}$), fuzzy members of spot speed ($d_{i,s}$) as slow speed ($s_{i,s}$) and high speed ($s_{i,h}$), and fuzzy members of occupancy ($d_{i,o}$) as low occupancy ($o_{i,l}$) and high occupancy ($o_{i,h}$). The actual fuzzy members for variables are more than two. For example, for variable volume, fuzzy members can be defined as very low volume, low volume, medium volume, high volume, and very high volume. For fuzzification of variables, different functions can be used. Depending on the function which is used, a variable can be a member of one or more of these fuzzy sets. For example, volume 3000 vehicle per hour can be both a member of high volume and very high volume by degrees of 0.6 and 0.8 respectively. Trapezoid activation function and bell shaped activation function were used in this study. For example, the fuzzy value of $d_{i,v}$ by a bell activation function for fuzzy set of "low volume" is calculated as follows:

$$v_{i,l} = \frac{1}{1 + \left(\frac{d_{i,v} - c_{i,v}}{g_{i,v}}\right)^{2w_{i,v}}} \tag{1}$$

where

$v_{i,l}$: degree of fuzzy value of $d_{i,v}$ for fuzzy set of "low volume"

$d_{i,v}$: detector volume at location i (veh/h)

$c_{i,v}$, $w_{i,v}$ and $g_{i,v}$: parameters which define the center, width and slope of the bell of variable $d_{i,v}$for fuzzy set of "low volume"

Four corners of the trapezoid activation function should be specified. At this layer, the value of all variables change to membership degree which they belong to fuzzy sets.

In Layer 2 the truth values of rules are defined. A typical rule can be similar to the following form:

IF	First detector spot speed	is	Slow
AND	First detector volume	is	High
AND	Second detector spot speed	is	Slow
AND	Second detector volume	is	High
THEN	Travel time	is	High

In layer 2, the values of Layer 1 which are related are multiplied to determine the acceptance threshold of each rule. For example, if the above mentioned rule is the first rule in Layer 2, then it can be calculated as follows:

$$r_1 = \prod_{k \in C} f_k = s_{i,s} \times v_{i,h} \times s_{j,s} \times v_{j,h} \tag{2}$$

where

r_1: acceptance threshold of rule number 1

f_k: fuzzy values of r_1 from set of conditions

C: set of conditions specified for a given rule

$v_{i,h}$, $v_{j,h}$: degree of fuzzy value of $d_{i,v}$ and $d_{j,v}$ respectively for fuzzy set of "high volume"

$s_{i,s}$, $s_{j,s}$: degree of fuzzy value of $d_{i,s}$ and $d_{j,s}$ respectively for fuzzy set of "slow speed"

Fig. 2 shows only 6 rules, but the actual number of rules can be more. Layer 3 just normalizes all neurons in the previous layer. This means it calculates the normalized acceptance threshold of a given rule by following equation:

$$n_r = \frac{r_r}{\sum_{p=1}^{R} r_p} \tag{3}$$

where

n_r: normalized acceptance threshold of rule r

r_r: acceptance threshold of rule r

r_p: rule acceptance thresholds of rule number p

R: the total number of rules.

Layer 4 defuzzifies each neuron. In addition to previous layer neurons, this layer also receives initial independent variables to calculate the weighted value of a rule as follows:

$$w_r = n_r\left[c_r + c_{r,i,v}d_{i,v} + c_{r,i,s}d_{i,s} + \cdots + c_{r,j,o}d_{j,o}\right] \quad (4)$$

where

w_r: weighted value of rule r

n_r: normalized acceptance threshold of rule I from Layer 3

$c_r, c_{r,i,v}, c_{r,i,s}, \ldots, c_{r,j,o}$: coefficient of variables for rule *r* subscripts i, j, v, s, and o stands for location i, location j, volume, speed and occupancy respectively.

Layer 5 calculates the sum of all defuzzified neurons from Layer 4. The result of this layer gives the dependent variable travel time (T_{ij}) as follows:

$$T_{ij} = \sum_{r=1}^{R} w_r \quad (5)$$

where

T_{ij}: travel time from location i to j.

In contrary to ANN, a modeler does not need to engage into defining the rules for the ANFIS model. ANFIS has this big advantage that automatically learns the required parameters for rules and makes the proper rules.

After training the ANFIS model using VISSIM simulated data, the model reliability (precision) was tested using a different test data set.

After the model is trained, actual freeway detector information can be used for travel time estimation in ANFIS model. However, due to different loop placement, layout, and wiring among transportation agencies and also loop maintenance issues, usually inductive loop data is not accurate. Before using a detector data, method proposed by Gholami and Tian (2017) can be applied to increase the accuracy of the data. In their research they proposed two methods to increase the accuracy of loop detector counts using ANFIS and Genetic Programming (GP) based on detector volume and occupancy. To verify the validity (accuracy) of models, real travel times (obtained from probe vehicles or other manual speed data collection) are compared with model outputs. Since the parameters obtained from the detectors are estimators of the model, if any event affects these parameters, in the form of changing the spot speed, occupancy, and volume, the model can predict the resulted travel time. Therefore, the location of the detectors are important for an accurate and sensitive prediction. If accuracy is satisfactory, the model can be used for speed predictions of the freeway section.

To facilitate usage of this process, a software package was developed, named FTTE (Freeway Travel Time Estimator). Fig. 3 shows a snapshot of this software package. By following the four steps of FTTE, an ANFIS model can be made for a section of a freeway. The first step of FTTE implements COM code to open VISSIM file of freeway section and run it by different volume scenarios. The user loads the VISSIM model and after VISSIM finishes all runs (each run is under one volume scenario), user loads the VISSIM output RSR files at Step 2. Appendix B shows the raw data in VISSIM output RSR file. RSR file records travel time of each vehicle between two detectors. Step 3 prepares required data for ANFIS using the RSR file. Two files will be prepared at this step. One is an Excel file and another one is a DAT file that can be used directly at the next step. Step 4 has implemented the ANFIS toolbox of MATLAB. Fig. 4 shows the Neuro-Fuzzy Designer toolbox of MATLAB after clicking Step 4 push button of FTTE. After opening of this toolbox, the model can be trained and tested.

3. Case study

A 11,050 ft. long section of I-80 east in Sparks, Nevada was selected for case study (Fig. 5). This section of I-80 connects to I-580 and experiences delays during peak hours due to insufficient off-ramp capacity from I-80 east to I-580 south.

First, a calibrated simulation model was made using VISSIM for this section. For the methodology of simulation model calibration one can refer to Antoniou et al. (2014), Abuamer et al. (2016), and Sadat and Celikoglu (2017). After running the prepared calibrated VISSIM model using FTTE (Step 1 of the FTTE), the VISSIM output RSR file was converted to a DAT file (Step 2 and 3 of the FTTE). By pushing the Step 4 button of the FTTE, the Neuro-Fuzzy Designer toolbox of MATLAB opens and from the "Load Data" section of this toolbox the DAT file was loaded. This toolbox produces a fuzzy inference system (FIS) that can be used for prediction. The function *evalfis* in MATLAB does the prediction based on the produced FIS and detector information.

Precision and accuracy of the model can be expressed using Mean Absolute Percent Error (MAPE) as follows:

$$MAPE(\%) = \frac{\sum_{i=1}^{n}\left|\frac{P_i - B_i}{B_i}\right|}{n} \quad (6)$$

where

MAPE: Mean Absolute Percentage Error

P_i: predicted travel time at time interval *i* (min)

B_i: value of base (reference) data at time interval *i* (min)

n: number of study intervals

Time intervals can be selected 1, 5, 10, or 15 min. During each time interval, predicted travel time (P_i) of model compares with the reference travel time. For determining precision and accuracy, two different data sets are used.

For calculating precision of the model, $P_i$is compared with travel times obtained from simulation runs (B_i). Overfitting of the model can be determined here. If the MAPE of the model using training data is

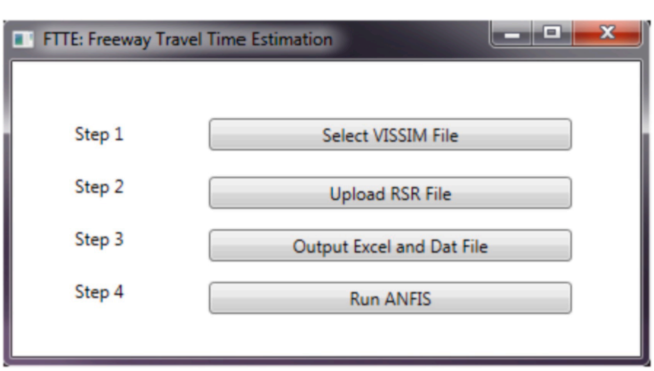

Fig. 3. Snapshot of FTTE.

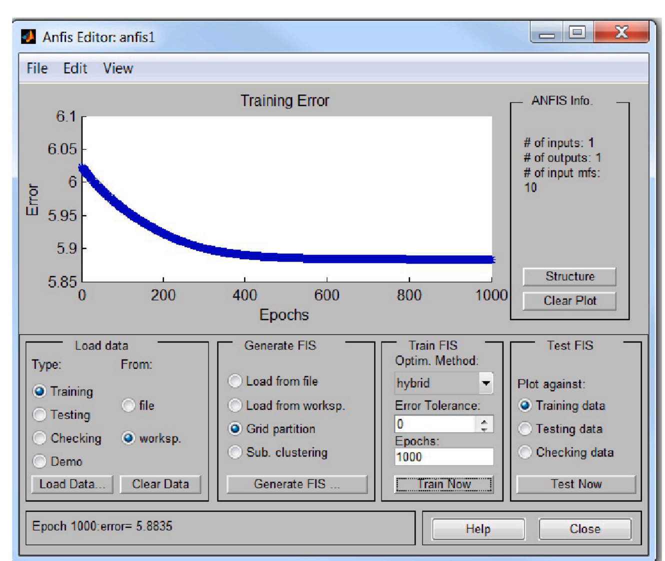

Fig. 4. Snapshot of Neuro-Fuzzy Designer toolbox of MATLAB.

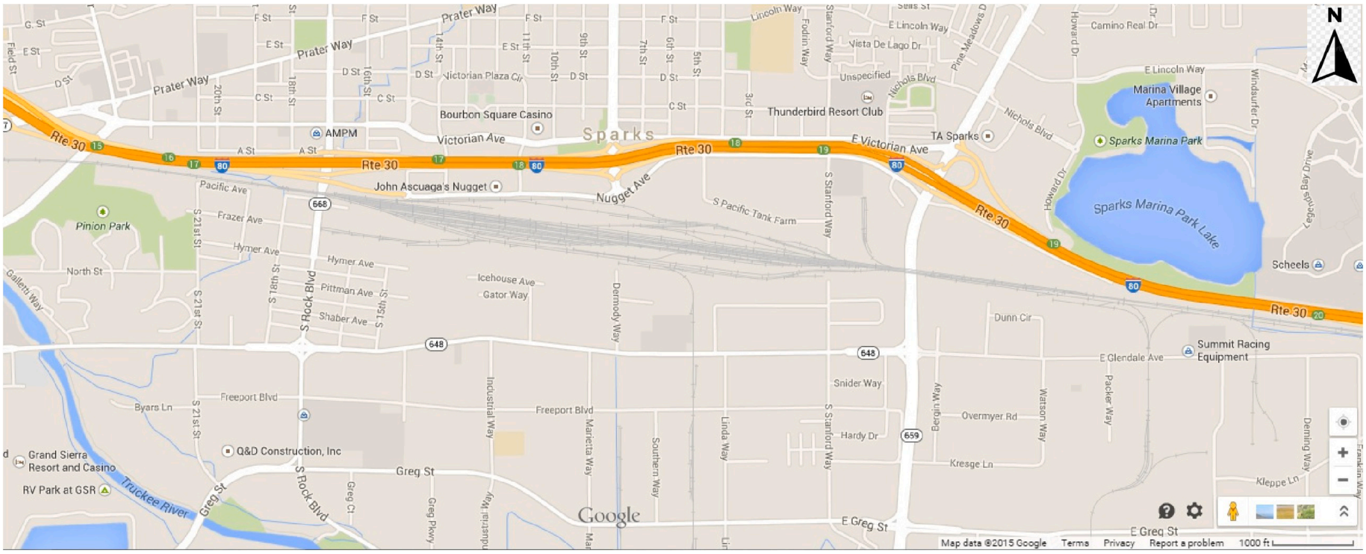

Fig. 5. Simulation case study (I-80).

significantly lower of the MAPE of the model using tested data, the model suffers from overfitting. If both errors are high, then the model is under-fitted. If the model is adequately precise, then $P_i$is also compares with actual travel times obtained from the field to calculate the accuracy of the model. Here, for each field travel time (B_i), its corresponding model prediction (P_i) is compared and from n (around 30 field run) field travel times, MAPE of the model can be calculated. Probably acceptable MAPE can range 5% to 15% depending on the travel time usage purpose and agency standards.

4. Results

Fig. 6 (left) shows the comparison of simulation and ANFIS prediction travel time estimations with training data set. The right diagram of this figure demonstrates the MAPE of training predicted travel time for different volumes. As it can be seen from these two diagrams, ANFIS predictions are very good at the low volumes. Though the predictions for higher volumes are not as good as lower volumes, they are still in an acceptable range. While the maximum MAPE is under 15%, the average MAPE is 1.51%. For example, for a 5-mile stretch of freeway with a speed limit of 60, the maximum error of travel time is ±45 second, and in average the error is ±4.5 seconds.

The results of reliability test of the ANFIS model (precision of the model) using test data are shown in diagrams in Fig. 7. Here, similar to training data set, the model predictions for lower volumes are perfect

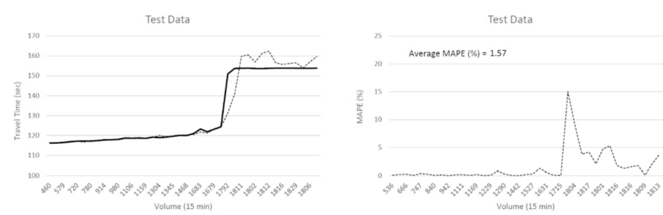

Fig. 7. ANFIS prediction comparison for different volumes (left); MAPE of predicted travel time for different volumes (right).

and for higher volumes, they are lower than 15%. The average MAPE is 1.57%. As can be seen, the MAPE calculated from training and testing data sets are very similar and as a result, can conclude that model is precise and is not over-fitted. The sharp rise of travel time between low and high flow is due to the low capacity of the off-ramp from I-80 east to I-580 south that after a certain volume, the queue spills out to I-80 east and affects almost all lanes significantly.

For validation, a probe car recorded travel time at different times independent variables (volume, spot speed, and occupancy) were obtained from freeway detectors. Fig. 8 shows a sample of trajectories obtained from floating car using TranSync-M along test section of I-80 east. Since TranSync-M is basically for coordinated intersections, the

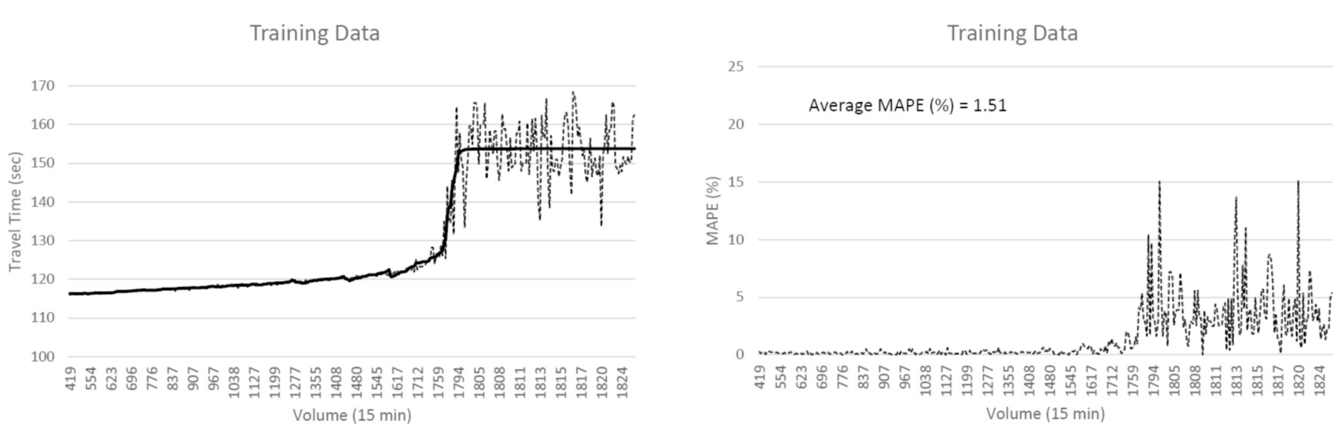

Fig. 6. Simulation vs. ANFIS prediction (left); MAPE of training predicted travel time for different volumes (right).

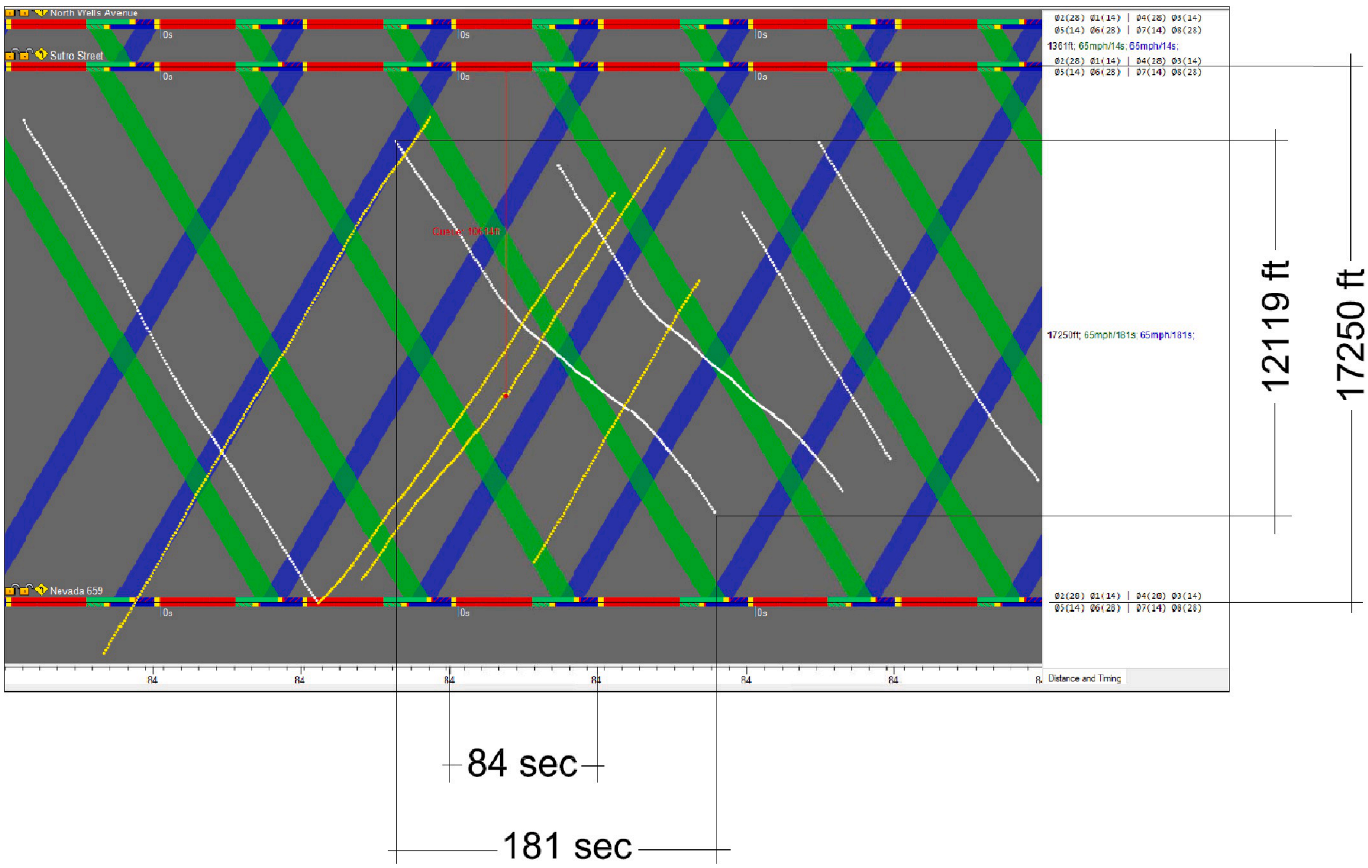

Fig. 8. A sample of trajectories obtained from probe car using TranSync-M.

depicted figure is similar to a coordinated corridor. However, the trajectories along the tested section fits the purpose of this study. The white trajectories are for I-80 east bound and the other ones for I-80 west. From comparing the east bound and west bound trajectories, it can be seen that while there is a congestion on east bound, west bound speed is as high as the speed limit (65 mph). The example trajectory shown in Fig. 8, has 12,119 ft distance and 181 sec travel time. Trimming this trajectory to the study section (1150 ft long section), gives 165 sec travel time along the study section. The MAPE for this travel time is 6.7%. Repeating this process for all other trajectories, travel times at different times and then average validation MAPE were calculated. The MAPE was lower than 10% for all congested runs and lower than 5% for low flow conditions.

5. Summary and conclusion

Travel time is an important indicator for showing freeway and highway traffic conditions. Dissemination of travel time information to travelers can change drivers' behavior in changing their routes and as a result can reduce congestions and improve overall network efficiency.

In recent years many detectors were installed along freeway and arterial routes with the capabilities of archiving high-resolution information. However, these detectors provide spot speed and are not able to estimate actual speed and travel time between detectors. Therefore, operational systems commonly estimate travel times from spot speed using simple algorithms. Since counting stations provide other measures such as directional volume counts and occupancy, there is the possibility to provide more sophisticated models for a better travel time estimation.

This research obtained data from volume-counting stations along a major freeway and used Adaptive Neural Fuzzy Inference System (ANFIS) to automatically estimate real-time travel time. Since continuous real travel time is not practical to be obtained from the field, the methodology used a VISSIM simulation model for generating the required training data. COM interface was used to automatically change volumes after each run and save the output. After preparation of data, ANFIS was used to learn the travel time patterns of the freeway section under different conditions. Two software packages were developed to implement COM code and ANFIS prediction.

The model reliability (precision) and validity (accuracy) were tested with different data sets. For reliability, a different set of simulation data and for validity several actual trajectories and GPS data obtained from probe car were used. For all three sets (training data, test data, and validation data), up to 1650 veh/15 min travel time is around 120 s and more than 1800 veh/15 min travel time is around 150 s. The results show that ANFIS predictions are very good at low volumes. For higher volumes however, the predictions are not as good as lower volumes but the MAPE still remains below 15%. The average MAPE was 1.51% for training data set and 1.57% for testing data set.

This research meets the immediate needs of several DOT's programs such as Arterial Performance Measures in Traffic Operations, the states Connecting Initiative for developing regional and state-wide travel demand forecasting models, and the Highway Safety Manual implementation in Safety Engineering. All these programs require a significant coverage of roads where traffic travel times need to be regularly collected. Local agencies also benefit from this research by reducing the costs associated with manual obtained travel time data (such as probe vehicle) needed for various transportation studies.

Data availability

The software package FTTE can be downloaded using the QR code and the link address provided in Appendix C.

All data used for the case study were provided by City of Reno. Direct requests for these materials may be made to the provider as indicated in the Acknowledgements.

CRediT authorship contribution statement

Ali Gholami: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration. **Daobin Wang:** Software, Methodology, Visualization. **Seyed Rasoul Davoodi:** Data curation. **Zong Tian:** Resources, Validation, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cstp.2021.08.009.

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