Short-term Direct Travel time Prediction for Freeway Segments

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ABSTRACT

This research examines the short-term travel time prediction problem on a link level basis (section of freeway between adjacent traffic sensors). The prediction problem can be abstracted as one of finding a mathematical relationship between the response variable (actual vehicle travel time) on the explanatory variables (detector measurements of speed, flow and occupancy). We use a neuro fuzzy logic approach which gives better extrapolation capability to the models and performs significantly better than purely data driven models such as neural network. Further analysis showed that the inherent variability in travel times limits the accuracy that the models can achieve.

1 Introduction

There is considerable demand for real time and future travel time information, to assist commuters in making travel decisions. Such information would enable the driver to optimize his or her driving strategy according to traffic conditions and the disruptions that he or she is likely to encounter on his or her journey, and this inherently would lead to increased efficiency in the use of road facilities. Travel times are the most appropriate interpretation of traffic conditions because from the traveler perspective it is a natural measure of freeway efficiency and easily interpretable [1]. With the advent of Intelligent Transportation Systems (ITS) it has become more critical for transportation researchers and operators to provide accurate traffic information to travelers. ITS utilizes a range of wireless and wired communication-based information, control, and electronic technologies to improve safety and mobility on roadways [2]. Components typically used in ITS applications for gathering traffic information are dual loop detectors. These detectors are often part of a network continuously monitoring roadway conditions on a 24/7 basis and providing updates to a

Traffic Management Center (TMC) in real time. Installed along major highways, these digital sensor networks gather lane-by-lane data on traffic variables including average travel speeds, lane occupancy, and vehicles counts. Occupancy is the proportion of an observational period during which the loop senses the presence of a vehicle and is indicative of the density of vehicles on the roadway. These traffic variables are point estimates and the travel time modeling research concerns itself with building a mathematical relationship between the point estimates of these traffic variables and average travel time for vehicles to transit between the points. In the context of methodologies developed, most of them have been data driven techniques including regression [3], time series analysis [4], Kalman filtering [5], and ANN models [6, 7]. The travel time modeling process involves building a mathematical relationship between the average travel time and the sensor data. The limited availability of travel time data has been a major constraint in the travel time modeling research. Actual travel times are difficult to obtain, because most loop detectors do not possess vehicle re-identification capability [8]. The danger of pursuing data driven modeling when travel time data are scarce is that the model may work well in one traffic setting, but may fail to operate correctly in a different one because that particular setting (data) was not fed into the model while building (training) it. The purpose of this paper is twofold. The first objective is to compare a gray box modeling technique like neuro fuzzy logic to a purely data driven model (black box) like neural network. The neuro fuzzy logic travel time modeling methodology incorporates the engineer's knowledge into the model and is particularly useful when travel time data are scarce, which is often the case. The second objective of the present study is to demonstrate that the inherent travel time variability sets a limit to the accuracy of the modeling exercise. The paper is structured as follows. Section 2 describes the location site and data collection procedures. Section 3 discusses the application of neural networks to travel time prediction based on the work done by Rilett et al [9]. Section 4 describes the proposed neuro fuzzy Logic methods and section 5 discusses the significance of travel time variability to the total model error. Finally, in Section 6, major conclusions are summarized, and future research directions are discussed.

2 Study location and data

The experimental study route is a section of US 202 S freeway located near King of Prussia, PA. A schematic of the route is shown in Figure 1. The route is equipped with densely populated sensors and cameras, and typically experiences congestion during morning (6:30 a.m. to 9:30 a.m.) and evening peak hours (15:30 p.m. to 18:30 p.m.). The section under study was a 4-mile long freeway consisting of four dual loop sensors and three cameras. The dual loop sensors monitor speed, flow and occupancy on a lane-by-lane basis every minute. Mobility Technologies Inc, Transportation Information Systems Company, provided the sensor data. PennDOT maintains the cameras along the freeway. For the purposes of this paper, a link is defined as the road section between adjacent sensors; three links were used for analysis.
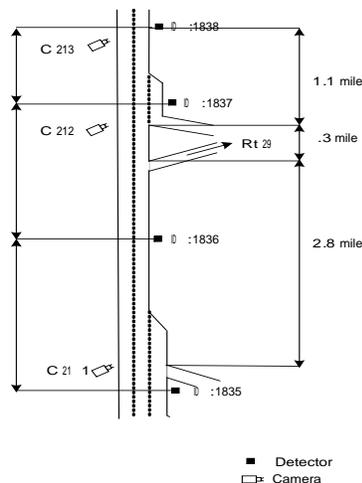

FIGURE 1 US 202 South freeway

Link travel time data were collected through manual vehicle reidentification using camera images. Access to images from cameras on US 202 S freeway was made available through PennDOT. The majority of the travel time data collection effort was carried out under non-free flow traffic conditions. The travel time data

were collected on June 2 and June 3, 2004. There were no accidents reported on this freeway section on these two days. The detection of bad data from the sensors on US 202 S freeway was carried out in two phases. The first phase involved passing each line of data through an algorithm written in SAS that systematically checks for both improbable values and improbable combinations of value. A simple imputation procedure was adopted to fill in missing and incorrect values that were identified in the first phase of error checking. These data points were replaced the average of correct preceding and succeeding time period values.

3 Neural Networks

A fully connected feed-forward neural network combined with a back-propagation algorithm was used in the forecasting model. The objective function was minimized using a steepest descent algorithm; a hyperbolic tangent sigmoid function was used as a neuron transfer function for the hidden layers and conventional stopping criteria were used to prevent overtraining [10, 11]. It was found that one hidden layer of approximately 5 neurons gave the best results. The learning rate was set to 0.9 and momentum to 0.1. The training period was 10000 epochs. The input to the neural network model includes the average speed, cumulative flow and average occupancy data from the dual loop sensors. As mentioned previously, the sensor updates this data every minute. The speed and the occupancy values were averaged and the flows are added up across the lanes. This transformed sensor outputs are the independent variables and the average travel time is the dependent variable. The input includes sensor data from the previous 5 time periods, from the link for which the travel time is to be predicted, and its upstream and downstream links. The neural network travel time model can be represented in mathematical terms as follows:

$TT(k)= f(spd_u(k),occ_u(k),flow_u(k), spd_u(k-1),occ_u(k-1),flow_u(k-1)\ spd_u(k-5),occ_u(k-5),flow_u(k-5),$
$spd_d(k),occ_d(k),flow_d(k), spd_d(k-1),occ_d(k-1),flow_d(k-1)... spd_d(k-5),occ_d(k-5),flow_d(k-5))$ **-(1)**

Where,
$TT(k)$ is the average travel time to traverse the link for vehicles entering the link at time k,
$spd_u(k)$ is the averaged upstream sensor speed at time k,
$occ_u(k)$ is the averaged upstream sensor occupancy at time k,
$flow_u(k)$ is the total upstream sensor flow during the time period $(k,k-1)$,
$spd_d(k)$ is the averaged downstream sensor speed at time k,
$occ_d(k)$ is the averaged downstream sensor occupancy at time k, and
$flow_d(k)$ is the total upstream sensor flow during the time period $(k,k-1)$.

Approximately two thirds of the available travel time data were used to build/calibrate the neural network and the rest were used to validate it. The prediction results from this conventional neural network model are shown in table 4 and will be discussed in detail in section 4.

4 Neuro Fuzzy logic methodology

Fuzzy systems are motivated by imitating human reasoning processes. Neuro Fuzzy systems makes it possible to incorporate both human reasoning and data, which makes it an ideal tool to model travel times, especially when only limited travel time data are available. Expert knowledge is formulated as a collection of "if–then" rules. In this way, an initial model is created. The parameters of this model (the membership functions and consequent parameters) are then fine-tuned by using the actual travel time data. Two thirds of the available data were used for training and the remaining one-third for validation purpose. The MATLAB software was used to build the neuro fuzzy model. The three critical steps in neuro fuzzy logic modeling namely fuzzyfication, fuzzy inference system and defuzzification are discussed in the subsequent sections.

4.1 Fuzzyfication

Fuzzyfication translates the numerical input into a set of fuzzy classes. Each data point is not rigidly assigned to only one fuzzy class, but rather to a few classes with certain membership values. A *membership function* (MF) is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. A membership value of zero indicates that the element is entirely outside the set, whereas a one indicates that the element lies entirely inside a given set. Any value between the two extremes indicates a degree of partial membership to the set. For the travel time modeling purpose the sensor data are used as an input to determine the traffic condition on the links. The traffic

condition on the link falls into one or more fuzzy classes based on its average upstream and downstream Volume to Capacity ratio. The volume to capacity ratio (v/c ratio) is the measured volume (flow) divided by the capacity of the major downstream bottleneck. The bottleneck capacity for each link was calculated from historical frequencies of measured maximum flows. These fuzzy classes used are based on a "Level Of Service" (LOS), as defined by the Highway Capacity Manual (HCM) 2000 [12]. Table 2 shows the ranges V/C ratio for free flow speeds of 60mph. The speed limit on US 202 S was 55mph at the time of data collection. It is reasonable to assume that the free flow speed is 60 mph. The HCM designates six levels of service for each type of facility, from A to F, with LOS A representing the best operating conditions and LOS F the worst. Each input will be associated with one or two of the fuzzy classes namely free flow (LOS A & B), congested (LOS C & D) and stop and go (LOS E & F) with a membership value attached to it. The membership functions follow the Gaussian distribution with an overlap of 33%. The parameters of the Gaussian distribution are based on the boundary values of the V/C values set forth in the HCM and degree of overlapping between the fuzzy classes. Figure 2 shows Gaussian membership function curves for the V/C ratios.

TABLE 1 V/C ratios for freeway segments based on HCM 2000

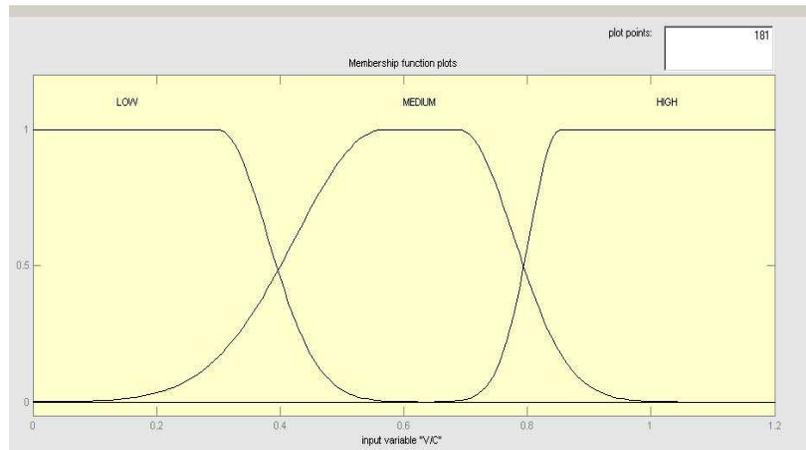| | 60 mph Free-Flow Speed | | |
Density[a] (pc/mi/ln)	Speed[b] (mph)	Maximum[c] V/C	MSF[d] (pcphpl)
≤ 10.0	60.0	0.272/0.261	600
≤ 16.0	60.0	0.436/0.412	960
≤ 24.0	60.0	0.655/0.626	1,440
≤ 32.0	57.0	0.829/0.793	1,824
≤ 41.5/46.0	53.0/50.0	1.000	2,200/2,300
Variable	Variable	Variable	Variable

FIGURE 2 Membership functions of the V/C ratio

4.2 Fuzzy Inference System
The rules, sometimes called the knowledge base, are the heart of the neuro fuzzy logic model. A fuzzy neural network implementing a Mamdani type FIS is used [13]. Basically, a linguistic controller contains rules of the following format. IF <premise> THEN <consequent>. Another factor to consider is that the rule base considers all of the possible input combinations. If the rule base were incomplete, it is possible that no rule would be activated for certain inputs. The rule base was constructed based upon the research done by Bogenberger et al [14], human reasoning and through trail and error. The rules, sometimes called the knowledge base, are the heart of the neuro fuzzy logic model. Basically, a linguistic controller contains rules of the following format. IF <premise> THEN <consequent>. There is also the possibility to combine several premises with operators. IF <premise 1> AND/OR <premise 2> AND/OR <premise 3>..... THEN <consequent>. Table 3 shows the rules base used in the FIS.

TABLE 3 Rule base for Fuzzy Inference System

Current link	Downstream link	Travel time	Membership Function
High	High	High	Gauss
High	Med	High	Gauss
High	Low	High	Gauss
Med	High	High	Gauss
Med	Med	Med	Gauss
Med	Low	Med	Gauss
Low	High	Med	Gauss
Low	Med	Low	Gauss
Low	Low	Low	Gauss

4.3 Defuzzification

For a fuzzy system whose final output needs to be in a crisp (non-fuzzy) form, a conversion from the final combined fuzzy conclusion into a crisp estimate (travel time) is needed. This step is referred to as defuzzyfication. The Centroid Average method [15], which finds the centre of gravity of the solution fuzzy sets, was used to determine the crisp predicted travel time output. The shape of the output membership function is also gauss. Two thirds of the data was used to build/calibrate the model and the remaining one-third to test it.

TABLE 4 MAPE Estimates for models

Link	Neural Network	Neuro- Fuzzy
1835-1836	19.8	15.7
1836-1837	15	13.4
1837-1838	20	16.7

The Mean Absolute Percentage Error (MAPE) estimates were used to compare the models. As shown in table 4, the Mean Absolute Percentage Error (MAPE) estimates from the neuro fuzzy logic models were smaller when compared to the conventional neural network model. This demonstrates that it is possible to increase the accuracy of the travel time model by incorporating physical insight. Incorporating human reasoning into models is effective method to address the non-linear characteristic of traffic flow.

5 Travel time variance

The total error from the model may be divided into two categories namely model error and statistical error. An investigation was carried out to determine if high travel time variability contributed significantly to the total error. The input sensor data were clustered into four groups using Kohonen's clustering algorithm. Each cluster consists of data points representing similar traffic conditions. The mean and the variance of the travel times were computed for each cluster. The coefficient of variation (COV) is defined as the ratio of mean to standard deviation and it was determined for each cluster. The COV is a measure of relative variability. A weighted COV was obtained for each link based on the number of data points in each cluster. Table 5 shows the COV results for each link. The numbers in parenthesis show the percentage of input data points in each cluster. As a general rule of the thumb, the total forecasting error can never be better than the COV. That means if we compare the estimated travel time to a single observation sample point that point would deviate from the mean, on an average, by at least the standard deviation. So if the COV is 0.11, then we expect a minimum 11% error approximately between the observed values and estimated values. This is purely statistical error due to the inherent variability and in general the total prediction error is expected to be greater than this number. The forecasting error from all the models that were discussed is higher than the COV. They were positively correlated, which leads to the conclusion that higher travel time variability increases the MAPE estimate of the model. Even under similar traffic conditions, travel times have been observed to vary significantly. This is essentially a statistical error and sets a limit to the level of accuracy that could be obtained for predicting travel times.

TABLE 5 Coefficient of variation of travel times for each cluster

Cluster	Link 1 1835-1836	Link 2 1836-1837	Link 3 1837-1838
Free Flow	7.55(9%)	4.57(7%)	5.33(12%)
Stable	10.78(28%)	8.22(26%)	10.43(28%)
Congested	10.20(32%)	10.15(34%)	12.55(25%)
Stop and Go	14.66(31%)	12.22(33%)	19.24(35%)
Weighted COV	**11.51**	**9.94**	**13.43**

6 Conclusion and future work

This paper presented and compared the neural network and neuro fuzzy logic techniques for predicting travel times. It was observed that the neuro fuzzy modeling technique performed superior when compared to the conventional neural network model. Neural Network modeling falls under the black box modeling approach where the parameters of the model do not have any physical meaning and the only objective is to find a model that fits the observed reasonably well. On the contrary, Neuro-Fuzzy systems make it possible to incorporate both human reasoning and data which give it a better extrapolation capability than Neural Networks and this makes it an ideal tool to model travel times with limited data It was discovered that the variability in travel times contributed a significant portion to the forecasting error. Hence there is limit to the accuracy that the models can achieve. This research work primarily concentrated on travel time modeling on a link level basis. Future research will focus on the application of these methodologies to a route. Effort would also be diverted towards extending the variance analysis to determine the Confidence Interval (CI) for travel times.

References

[1] Rose, M. "Modeling of Freeway Traffic", Xth International Conference on Computing in Civil Engineering, June 02-04, 2004, Weimar.

[2] Henry X. Liu, Rachel He, Bin Ran, "A Literature and Best Practices Scan: ITS Data Management and Archiving", University of Wisconsin at Madison, submitted to the Wisconsin DOT, May 2002.

[3] Hongyu Sun, Heng Xiao, and Bin Ran, "Real-time spatiotemporal data mining for short-term traffic forecasting", Tran. Research Record, No. 1748, 80th Annual Meeting, Washington D.C., January 2001.

[4] Ishak, S. and H. Al-Deek, "Performance Evaluation of a Short-Term Time-Series Traffic Prediction Model ", ASCE Journal of Transportation Engineering, Vol. 128, No. 6, 2002.

[5] Greg Welch and Gary Bishop, "An Introduction to the Kalman Filter", TR-95-041, Department of Computer Science, University of North Carolina at Chapell Hill, updated in 2002.

[6] Kisgyorgy, Lajos, and L. R. Rilett, "Travel Time Prediction by Advanced Neural Network", Periodica Polytechnica Ser. Civ. Eng., 2002 ,Vol 46, No1, PP 15-32.

[7] Rilett, L., D. Park, "Direct Forecasting of Freeway Corridor Travel Times Using Spectral Basis Neural Networks", Journal of Transportation Engineering, ASCE, Vol. 125, no. 6 Nov./Dec. 1999..

[8] Chen, C., A. Skabardonis and P. Varaiya, "Travel Time Reliability as a Measure of Service", Transportation Research Record, No. 1855, Paper No. 03-3456, January 2003.

[9] Kisgyorgy, Lajos, and L. R. Rilett, "Travel Time Prediction by Advanced Neural Network", Periodica Polytechnica Ser. Civil Eng., 2002, Vol 46, No1, PP 15-32.

[10] Zhou.C. , Nelson .P, "Predicting Traffic Congestion Using Recurrent Neural Networks", 9th Congress on Intelligent Transport Systems, Chicago, October 14-18, 2002, electronic proceedings.

[11] Lint, van, J.W.C., Hoogendoorn, van, H.J.,"Accurate and Robust Freeway Travel Time Prediction with State-Space Neural Networks", submitted to Transportation research Part C: Emerging technologies

[12] "Highway Capacity Manual", TRB, National Research Council, Washington DC, 2000.

[13] Wang L.X., Mendel J.M., 1992, "Generating fuzzy rules by learning from examples", IEEE Trans. System, Man and Cybernetics, vol. 22, no. 6, pp. 1414-1427.

[14] Bogenberger, K. and H. Keller 2001. "An evolutionary fuzzy system for coordinated and traffic responsive ramp metering". 34th Annual Hawaiian International Conference on System Sciences, USA.

[15] Durkin, *Expert Systems: Design and Development*, New York: Macmillan Publishing Company, (1994).