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Effective long term travel time prediction with fuzzy rules for tollway

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Abstract

Advanced traveller information system is an important intelligent transportation systems application area, which provides information to transport users and managers in order to improve the efficiency and effectiveness of the transportation system, in the face of increasing congestion in urban cities around the world. So far very limited research attention has been focused on long-term travel time prediction (i.e. predicting greater than 60 min ahead). Long-term travel time forecasts can play a critical role in journey planning decisions for both private road users and logistics operators. In this paper, we have considered a fuzzy neural network incorporated with both imprecise and numerical information and developed a hybrid long-term travel time prediction model, which shows the better prediction capability than naive methods and highlights the importance of different data variables. The model combines the learning ability of neural networks and the knowledge extraction ability of fuzzy inference systems. The model was validated by using travel time data compiled from electronic toll tags on a 14 km length section of the CityLink tollway in Melbourne, Australia. The validation results highlight the ability of the fuzzy neural network model to accommodate imprecise and linguistic input information, while providing reliable predictions of travel times up to a few days ahead.

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Title: Effective Long Term Travel Time Prediction with Fuzzy Rules for Tollway

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Abstract:
Advanced traveller information system is an important Intelligent Transportation Systems (ITS) application area, which provides information to transport users and managers in order to improve the efficiency and effectiveness of the transportation system, in the face of increasing congestion in urban cities around the world. So far very limited research attention has been focused on long term travel time prediction (i.e. predicting greater than 60 minutes ahead). Long term travel time forecasts can play a critical role in journey planning decisions for both private road users and logistics operators. In this paper, we have considered a fuzzy neural network incorporated with both imprecise and numerical information and developed a hybrid long term travel time prediction model, which shows the better prediction capability than naive methods and highlights the importance of different data variables. The model combines the learning ability of neural networks and the knowledge extraction ability of fuzzy inference systems. The model was validated by using travel time data compiled from electronic toll tags on a 14 km length section of the CityLink tollway in Melbourne, Australia. The validation results highlight the ability of the fuzzy neural network model to accommodate imprecise and linguistic input information, while providing reliable predictions of travel times up to a few days ahead.

Keywords: Fuzzy Neural Network; Long Term Travel Time Prediction; Fuzzy Rules

Glossary:
ITS: Intelligent Transportation Systems
AVI: automatic vehicle identification
EFuNN: Evolving Fuzzy Neural Network
GPS: global positioning system
BTM: Burnley to Moreland
MTB: Moreland to Burnley
ANNs: Artificial neural networks
ME: mean error
MRE: mean relative error
MAE: mean absolute error
MARE: mean absolute relative error
fuzzy sets: very small (VS), small (S), medium (M), large (L), very large (VL)

1. INTRODUCTION

Reliably predicted travel times can play an important role in assisting drivers to select optimal routes, as well as assisting road authorities in controlling congestion and managing road operations in urban areas around the world. In terms of the prediction horizon, the travel time prediction problem can be categorized as real-time, short term and long term. When predicting travel time for vehicles which depart at the current time (k), the forecast is usually referred to as real-time or online travel time prediction. The short term travel time prediction is usually defined as the forecast of travel time for vehicles departing in future time periods from k to k+60 minutes [1]. The prediction for vehicles departing 60 minutes or more ahead of the current time k is classified as long term travel time prediction. The long term travel time prediction is very different from the real-time or short term prediction problems in terms of the dynamics of the problem and the input data. Current travel time information is of most relevance in short term prediction and its relevance becomes loose as the prediction horizon is extended. Consequently, the relevance of historical travel time information increases as the prediction horizon extends. In this study, we characterize long term travel time prediction as the prediction for vehicles which depart in a future time period such that the traffic information at current time k does not provide any insight into the prospective traffic conditions, which could be expected in that future time period.

It's noted short term travel time prediction for freeways and motorways has been intensively studied over the last two decades [2-8]. In contrast, the researches on long term prediction lagged well behind for many reasons, even though theoretical foundations for long term predictions on generic time series had been laid many decades ago. In other words, there have been sufficient real time data and convincing algorithms, but the reliability of long term prediction remains an open problem to be tackled [9]. As we will point later in this paper, a key hurdle is how to handle the travel time variability, which has only drawn attention and preliminary researches in recent years [10]. In our research, we have paid particular attention to drive-to-driver variability.

Simple historical approaches for long term travel time prediction have been used or tested in the early applications of traveller information system such as AUTOGUIDE [11], LISB [12] and

ADVANCE [13]. [1] proposed a simple long term travel time prediction model based on the neural networks, in which the future travel times are predicted as a function of time of day and day of week. [14] developed a long term travel time prediction algorithm by using a K-nearest neighbour approach. The model has been implemented as part of a Web-based route planning service by the ANWB, the motoring association in the Netherlands. The long term travel time prediction model proposed by [15] was based on the linear relationships between future, instantaneous and historical travel time. Different models were developed for different traffic profiles, which are divided into four groups in terms of day-of-week.

In this paper, a more comprehensive long term travel time prediction model is developed based on a fuzzy neural network platform. The integrated model is applied to the long term travel time prediction problem on the basis of automatic vehicle identification (AVI) travel time statistics collected on the toll road in Melbourne, Australia. This paper contributes in the following ways:

1, By considering the imprecise and linguistic input information recorded in transportation system, the fuzzy techniques could utilize this information and build up a more robust long term travel time forecasts. The data variable fusion between different kinds of information, either imprecise/linguistic or precise/numerical data, shows the importance of fuzzy techniques in long term travel time forecast. Furthermore, the rules extraction is based on variable fusion strategy by taking the linguistic information into account.
2, The model integrates fuzzy techniques with a neural network, making the learning process of the neural network more transparent. In addition, it is able to directly handle linguistic data like the forecasts of weather information, with the detailed records provided by local governmental meteorology bureau. This information utilization strategy could be much more useful and stable when coming across the weather information, holiday information and so on.
3, The fusion of these two approaches provides application scope for the model to obtain knowledge while learning from historical travel time data. The transparency of fuzzy neural network leads to the rules extraction from the model.

The structure of this paper is as follows. Section 2 formulates the model. Section 3 describes the data used in model development and testing. Model implementation issues are described in Section 4. This includes the methods used to predict percentile travel times along with the model validation results. Related work and discussions on driver-to-driver variability are presented in Section 5. The conclusions are outlined in the final section.

2. FUZZY NEURAL NETWORK MODEL

Long term travel time prediction is inherently different from real time or short term prediction, and current traffic conditions generally do not provide reliable insight into travel times up to a few days ahead. Conceptually, a modelling approach, shown as Equation. (1), has to rely on the relationship between historical travel time data and available explanatory variables to make forecasts:

$$y = f(x1, x2, x3, ...) \tag{1}$$

Neural network has proved to be an effective tool in modelling complex non-linear relationships between inputs (explanatory variables) and outputs (dependent variables) [2, 3]. The relationship function f is requisite to be non-linear due to the interrelationship between variables, which contribute to variance in travel times. The incorporation of fuzzy techniques in the model of neural network enables linguistic variables to be handled directly. In addition, the fuzzy rules derived from trained network models make the training of neural network relatively more transparent. In the following sub-sections, we briefly introduce the formulation of the fuzzy neural network.

2.1. Fuzzy Logic and Evolving Fuzzy Neural Network (EFuNN)

As basic of fuzzy neural network, fuzzy logic and its fuzzy system are two key elements to understand and utilize fuzzy neural network. Fuzzy logic is the main element in fuzzy system, which is an extension of traditional Boolean logic. It handles the grey area between “completely true” (1) and “completely false” (0) by incorporating the concept of a membership function. The fuzzy membership value $\mu_A(x)$, which lies between 0 and 1, defines the degree to which point x belongs to fuzzy set A. A fuzzy inference system is a collection of membership functions and fuzzy if-then rules capabilities [16]. These membership functions and rules are used to map data in order to mimic human knowledge and inference.

A typical fuzzy inference system comprises the processes of fuzzification, inference, composition and defuzzification. The observed input data from existing sensors are usually numerical values and need to be fuzzified before being input into the inference engine, because it only deals with linguistic values such as small, medium and large. The fuzzification process involves applying membership functions associated with the input variables to actual numerical values, to determine the degree of truth for the fuzzy rules. The inference engine is a group of logic rules in the form of ‘IF-THEN’ statements, where the mapping from fuzzified inputs to output is undertaken in the form of a fuzzy set. A typical fuzzy rule has the following structure: if x is $A_{x,k}$ and y is $A_{y,k}$ then z is $A_{z,k}$, where x and y are input variables, $A_{x,k}$ and $A_{y,k}$ stand for the fuzzy sets (membership functions) defined on x and y respectively, and z is output variable and $A_{z,k}$ is a membership function defined on z. A good example is, ‘If rain is heavy then congestion is severe’. The ‘IF’ part is considered as the rule’s antecedence, while the ‘THEN’ part is the consequence of the fuzzy rule. In the inference process, the degree to which the antecedent of each rule has been satisfied is computed, and then applied to the output function. The fuzzy set for output variable is then converted to a crisp value in the defuzzification process to produce a single numeric value for final output.

General neural networks are commonly developed with fixed structures. In other words, once the architecture of the neural network has been determined, it would not change during the process of training. [16] proposed an evolving fuzzy neural network (EFuNN), which has an open structure. New neurons in rule layer are dynamically created and adapted depending on the input data. [18] firstly introduced the fuzzy neural network to predict delayed time for process control. Then as presented in [19], an adaptive neuro-fuzzy inference system (ANFIS), which integrates neural network with fuzzy inference system, was deployed to control the speed of a heavy duty vehicle. Not only for control system, but also for mobile learning system, [20,21] incorporated ANFIS as a reasoning engine to deliver learning content for mobile learning system.

In this study we will develop long term travel time prediction models based on EFuNN framework. In an EFuNN, the neurons in each layer are only created and connected to neurons in other layers during the training process, in a way which imitates the operation of the human brain. The typical architecture of a fuzzy neural network comprises five layers (Fig. 1).

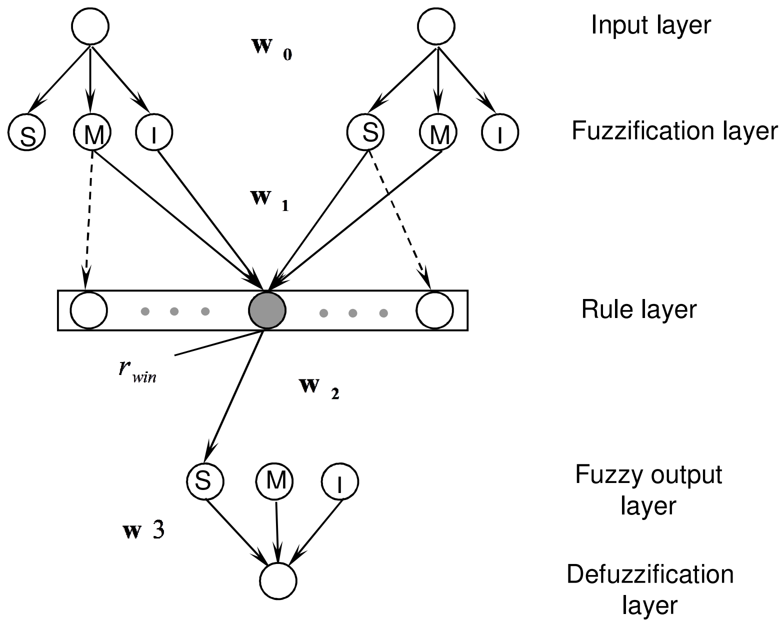

Fig.1 Architecture of EFuNN (Adopted from [1])

The details of the functions in each layer are discussed as follows:

- Layer 1 (Input layer): The first layer is the input layer which only transmits crisp input values to the next layer. The number of neurons in this layer equals to the number of input variables. Each neuron in this layer only connects to the nodes in the next layer, which represents the fuzzy quantification of the corresponding input variables.
- Layer 2 (Fuzzification layer): The second layer performs the fuzzification of the input variables. The nodes in the second layer represent the linguistic terms of inputs and they have different membership functions attached to them. The output values from this layer can be interpreted as the membership grade of the input vector to the fuzzy sets.
- Layer 3 (Fuzzy rule layer): The third layer contains rule nodes. The nodes number in this layer should be equivalent to the rules number. In this way, each rule node represents a mapping from fuzzy inputs to fuzzy outputs, which means the output of each rule nodes will represents the membership of the corresponding fuzzy rules.
- Layer 4 (Fuzzy output layer): The neurons in this fuzzy output layer represent the fuzzy quantification of output variables. The output of the node represents the degrees to which this fuzzy quantification is generated by the fuzzy rule, with which current input data are associated.

- Layer 5 (Defuzzification layer): The fifth layer performs the defuzzification of output variable based on the nodes and the links attached to them. The output of a node is a numerical value.

As in general neural networks, the neurons in the input layer represent the input variables. The neurons apply a linear transfer function in the form of $f(x) = x$ to the input data, resulting in a neuron's output being equivalent to its input. The input data are usually assumed to be normalized in the range of [0, 1]. If the input variable is already fuzzy information like the predicted weather condition (e.g. heavy rain), a four-layer EFuNN that excludes a fuzzy input layer can be employed.

Each output from a neuron in the input layer is fuzzified in terms of the membership functions of its corresponding variable. The commonly used membership functions include triangular, trapezoidal and smoothed (Gaussian and bell-shaped). For the reason of simplicity, herein we set the weights from the input layer to fuzzification layer to unity ($\mathbf{w_0}$ =1) and use triangular membership function. Therefore the net input to neuron i in the fuzzification layer is based on the value of the corresponding input x, and the activation functions ($Act_i^f(x)$) for the neuron are as following Equation. (2-5):

$$Act_i^f(x) = \frac{c_{i+1} - x}{c_{i+1} - c_i} \text{ , if } c_i < x < c_{i+1} \quad (2)$$

$$Act_i^f(x) = \frac{x - c_{i-1}}{c_i - c_{i-1}} \text{ , if } c_{i-1} < x < c_i \quad (3)$$

$$Act_i^f(x) = 1, \text{ if } x = c_i \quad (4)$$

$$Act_i^f(x) = 0, \text{ if } x \le c_{i-1} \text{ or } x \ge c_{i+1} \quad (5)$$

Where c_i, c_{i-1} and c_{i+1} denote the centres of membership functions represented by neuron i and its adjacent neurons. In the case of a triangular membership function, an input signal would only be able to activate a maximum of two neighbouring neurons. The sum of the membership degrees of the input signal to these two neighbouring functions is always equal to 1. The evolving and training scheme of the rule nodes in the EFuNN is the most important characteristic, which distinguishes it from other fuzzy neural networks. [16] provides a detailed description of the training algorithm. Readers are referred to these literatures for further information.

2.2. Knowledge Manipulation in EFuNN

One of the major advantages of EFuNNs is that they have the capability of generating symbolic knowledge in terms of trained connection weights and node activations. The initially crude domain knowledge encoded in the structure of the network can be further refined by rule aggregation [16].

Each rule node in an EFuNN can be interpreted as a fuzzy rule in terms of its connection weights $\mathbf{w}_1$ and $\mathbf{w}_2$. As an example, for a given rule node r in Fig. 2, the fuzzy rule is expressed as follows: If x is small (0.75) and x is medium (0.25) and y is medium (0.82) and y is large (0.18) then z is medium (0.3) and z is large (0.7). The numeric values in brackets represent the membership degrees of input and output to the corresponding fuzzy labels.

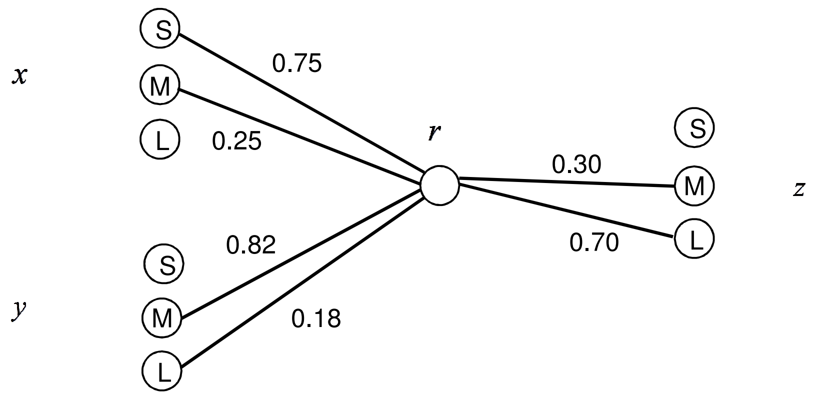

Fig.2. Illustration of a rule node in an EFuNN

2.3. Parameters of EFuNN

Unlike other artificial neural networks, which have to rely on the lengthy trial and error process to determine their optimum structure, the number of layers of EFuNN is fixed while the neurons on each layer evolve automatically based on the learning examples presented to the network. This dramatically reduces the number of running times of the model that are needed to complete the training. The parameters to be set before the training process begins include the initial values for the sensitivity threshold (S_{thr}), initial values for the training rates of w_1 and w_2, and error threshold (Err_{thr}). The parameters related to the knowledge manipulation are the maximum radius $R_{\max}$ for rule aggregation and the threshold values T_{1thr} and T_{2thr} for rule extraction. During the training process, the redundant rule nodes in an EFuNN are combined by rule aggregation. Only the fuzzy sets with membership degrees greater than the threshold values are retained. If the thresholds T_{1thr} (input) and T_{2thr} (output) were set as, say T_{1thr}=T_{2thr}=0.5, then the fuzzy rule in Section 2.3 changes to: If x is small (0.75) and y is medium (0.82) then z is large (0.7).

The sensitivity threshold S_{thr} gives the initial value to determine the activation of a rule node, and it is then adjusted in accordance with the new example associated with that rule node. The error threshold Err_{thr} has a similar function to the objective function in a feed-forward neural network. It defines the error tolerance for the network's output compared with the desired or target output. The values of these parameters influence the performance of model.

The parameters related to training can be determined by a trial and error process. There are no quantified criteria for the determination of rule-related parameters. The setting of these features mainly relies on empirical judgement and is influenced by the size of training data set. For example, rule extraction thresholds T_{1thr} and T_{2thr} are usually set to 0.5. After the training parameters of a model are designed, the next step involves the training and performance evaluation.

Fig. 3. CityLink Study Site in Melbourne, Australia

3. DATA SOURCES AND PREPARATION

To develop reliable travel time prediction models, adequate samples of travel time data are essential for model calibration. The most common approach is to reconstruct the travel times from speed data provided by inductive loop detectors or other point-based sensors, as in [1]. However, this complicates the error analysis because there is an error in the 'assumed' true travel time. Using global positioning system (GPS) enabled probe vehicles is one of the technologies utilized to directly collect travel times, and some other technologies include toll tag readers and automatic license plate recognition. This research focuses on a tollway located in Melbourne, Australia's second largest capital city with a population of about 3.5 million. As a completed free-flow electronic tolling system, the CityLink tollway was the first system in the world, opening in 2000.

The CityLink Tollway comprises the southern link and the western link, which connect three major Melbourne freeways as shown in Fig. 3. The section considered in this research is a stretch from toll gantry 1 located between Moreland Road and Brunswick Road to toll gantry 5 near Burnley Street. The travel time data used in this study were collected from 2003 and 2004 for both the Burnley to Moreland (BTM) and Moreland to Burnley (MTB) directions. The free flow travel time (on both directions) is between 11 and 12 minutes. MTB is the peak direction during the AM peak, while BTM is more congested in the afternoon peak. It is observed from travel time daily profiles (Fig. 4) that the travel times in the morning peak along the BTM direction and the afternoon peak along the MTB direction have similar low levels of congestion. However, the BTM direction exhibited approximately 15% variability in travel times while the MTB direction experienced variability in travel times around 30%. The collected individual travel times are aggregated into 10 minute departure time window. A 10 minute window was verified to provide an adequate sample size in each time window throughout the day while not losing information from data aggregation [17].

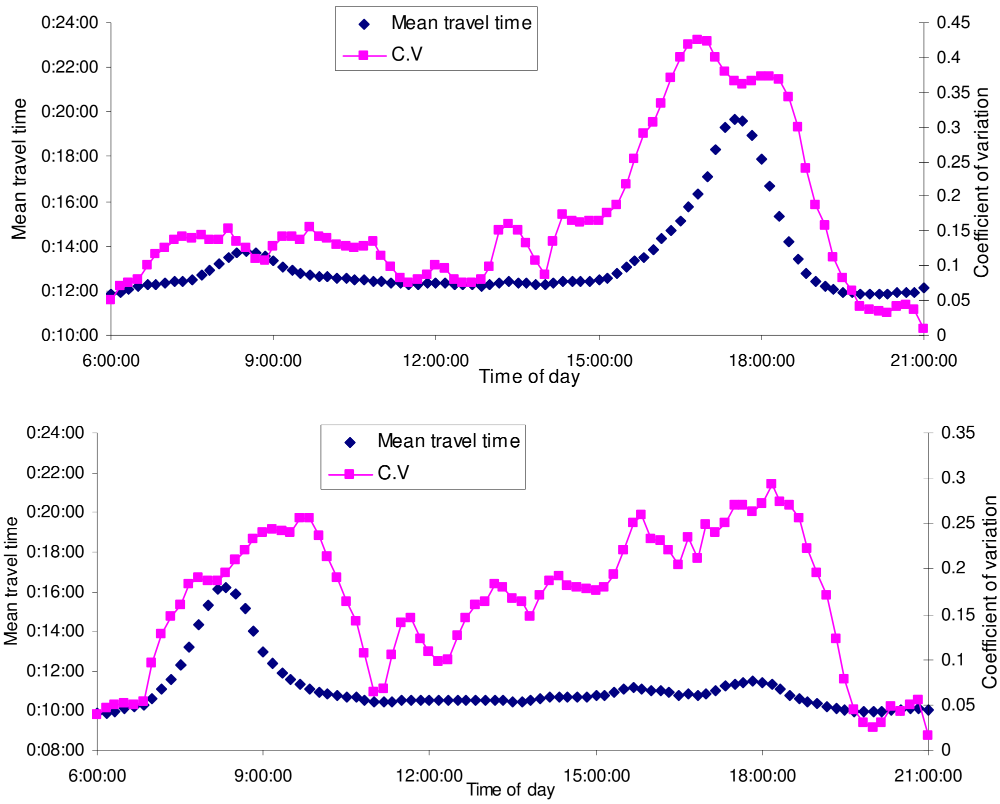

Fig. 4. Mean Travel Time and Travel Time Variability throughout the Day Measured across all Weekdays in 2003 and 2004 for both BTM (Top) and MTB (Bottom) Directions

Travellers make their journey planning decisions mainly according to the weather forecast. Bad weather conditions cause traffic congestion. For long term travel time prediction, the data sources to be used also included weather information. The weather information for 2003 and 2004 were provided by the Bureau of Meteorology, Victoria. The data, selected for recording sites closest to CityLink, comprised three-hourly rainfall, daily minimum and maximum temperature, and three-hourly temperature readings. The linguistics based weather forecast and real time data came in numeric forms, which could be fuzzified as our input layer variables easily (cf. Section 4.2).

4. FUZZY NEURAL NETWORK IMPLEMENTATION

One of the important issues in long term travel time prediction is the selection of a set of relevant input variables. Artificial neural networks (ANNs) are developed to learn the relationship between the input and output variables based on the calibration data, and are supposed to predict for new input data with the generalized relationships learning or inferring from the training data. Irrelevant or insignificant input variables may cause prolonged training time, waste the computational resources or even produce inferior results in some cases [22].

4.1. Input Variable Selection for Long Term Travel Time Prediction

To predict a long term travel time based on ANN, the input variables can be divided into two groups: base variables and weather related variables. The base variables comprise inputs like 'Month of year', 'Day of week', 'Time of day' and indicators for public or school holidays [23]. The weather related variables consist of inputs such as 'Rainfall', 'Precipitation' and 'Maximum daily temperature'.

Based on the experiences gained from previous travel time variability analysis [23], the variables 'Time of day', 'Day of week', 'Public holiday indicator', and 'Rainfall' are clearly relevant variables in long term travel time prediction. Further investigation on 'School holiday', 'Maximum daily temperatures', and 'Month of year' is however required. We grouped the available information into two categories: base variables and tested variables as shown in Table 1. The base variables are those which have significant impacts on travel times in the long term based on experiences and data analysis according to our previous researches. The tested variables will be further investigated to establish their contribution to the performance of the model.

Table 1
Input Variables for Long Term Travel Time Prediction Model

Base variables	Test variable
Time of day Day of week Rain Holiday effect	School holiday Month of year Temperature

4.2. Pre-processing and Fuzzification of Input Variables

Day of week, time of day and month of year: a set of running numbers normalized in the range [0, 1] are assigned to the weekdays from Monday to Friday and month of year, respectively. The time variable is converted to decimal numbers with values ranging from 0 to 1, representing the travel times in 10 minute intervals.

Weather Variables: the membership function for the measured precipitation over a three hour period is built up based on the maximum (20mm/3 hours) and minimum (0) rainfall observed in the two-year data set. In practice, meteorology experts could attribute to the determination of membership functions for weather related variables. Here the rain variable is represented using three membership functions with fuzzy labels light (L), medium (M), and heavy (H) as shown by Fig. 5. The numbers in the parenthesis in Fig. 5 represent the normalized value corresponding to the centre of each membership function. The same approach was applied to the maximum daily temperature variable.

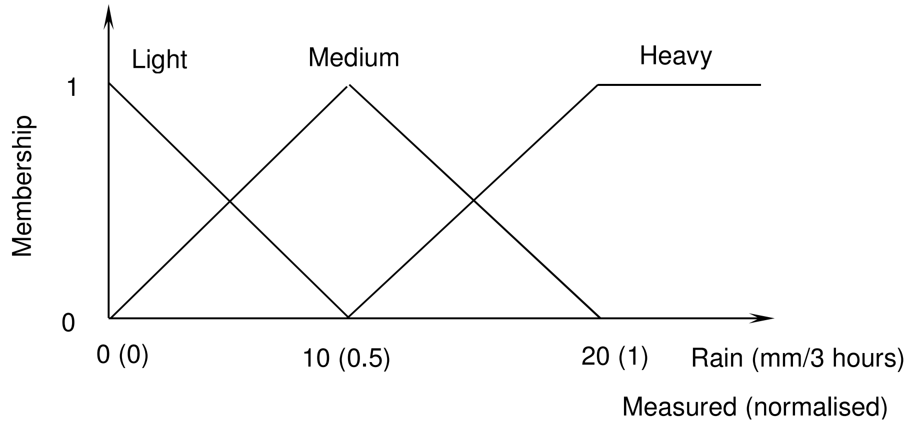

Fig.5. Fuzzification of the Rain Variable

Holiday Effects: the traffic patterns before and after major public holidays are significantly different from the other days owing to flow fluctuations [24]. It is therefore expected that, including a holiday effect variable would improve the travel time prediction before and after holidays, including public holidays and school holidays. Public holidays can be categorized into two groups. One comprises long holiday periods such as Christmas and Easter while the other includes short holidays like Labour Day, Queen's birthday, which are celebrated in Victoria etc. The latter holidays usually fall on a Monday. On this basis, we define four variables related to the holiday effect: before long holiday, after long holiday, before short holiday and after short holiday.

Over the two year period where the travel time data is available (2003 and 2004), there is a relatively small set of short and long holidays. To facilitate model development, assumptions need to be made about the shape of the membership function for the holiday effect variable. The proximity of a weekday to a long holiday is represented by fuzzy numbers (Fig. 6). We assume that the long holiday effect applies up to five days before and after the long holiday. One day before/after the holiday is indicated by 0.9, two days before/after the holiday is 0.7, and so forth. All other days outside the five day boundary have a long holiday membership value of 0. Weekdays which are one day before or after a short holiday are most likely to be affected. They are therefore indicated as 1 for variables of before and after short holiday. As noted above, the two years of data available for model development contains a relatively small set of short and long holidays. The assumption made here about the shape of the membership function could be further tested once data covering more than a two year period are available. On the other hand, school holidays, which are normally a single holiday, were simply indicated as 1 for any weekday which corresponded to a declared school holiday period and 0 otherwise.

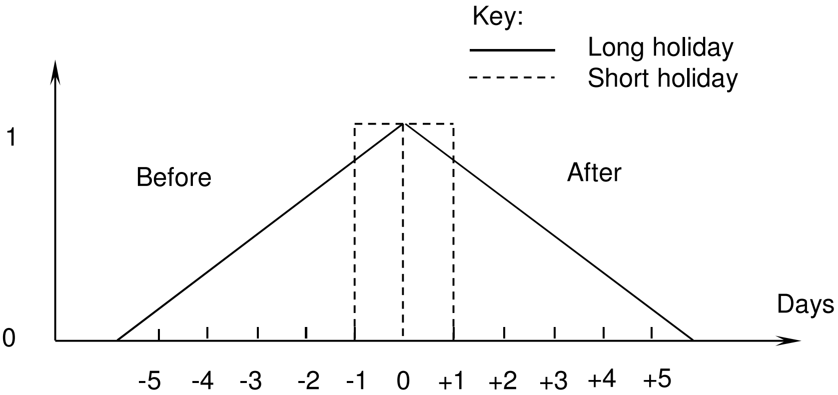

Fig.6. Fuzzification of the Proximity to a Holiday

4.3. Model Performance

A. Evaluation Measurements

During the training process of EFuNN, the network builds associations between the fuzzy input space and the fuzzy output space. Crisp values of the output variable (mean travel time) are obtained after the process of defuzzification, therefore they can be evaluated by conventional error measures. We define the prediction error for data example i as $e_i = \hat{t}_i - t_i$, where $\hat{t}_i$ is the predicted average travel time, and t_i is the actual mean travel time. In this study, $\hat{t}_i$ is the 10-minute average travel time a few days into future, depending on the availability of weather forecasting data. A set of summary measures, shown as Equation. (6-9), are then used:

$$\text{Mean error (ME)} = \frac{\sum_{i=1}^{n} e_i}{n} \quad (6)$$

$$\text{Mean relative error (MRE)} = \frac{1}{\text{n}} \sum_{i=1}^{n} \frac{e_i}{t_i} \quad (7)$$

$$\text{Mean absolute error (MAE)} = \frac{\sum_{i=1}^{n} |e_i|}{n} \quad (8)$$

$$\text{Mean absolute relative error (MARE)} = \frac{1}{\text{n}} \sum_{i=1}^{n} \frac{|e_i|}{t_i} \quad (9)$$

The implementation of the model consists of training the prediction system and the performance evaluation. Evenly distributed training data over the problem space are needed to achieve the highest performance with a neural network. Neural networks are usually trained on the entire space using one test set. However, the uneven distribution of training or testing data points may make the neural network's performance vary from one region to another over the problem space [25]. Furthermore, the parameter estimates in the neural networks are less accurate in low data density regions [22].

B. Base Variables

In this section, we would discuss about the performance between EFuNN and the naive method on simply base variables. We focus on the travel time data in the morning (7:30-9:30 AM) and afternoon (4:30-6:30 PM) peaks in this paper. Separate models were developed for travel times in morning and afternoon peak, respectively. The models were trained on a random sample containing two thirds of the available weekdays in the two year dataset. This corresponds to a training set of 326 days. After the EFuNN has been evolved, it was tested on the remaining one third of the data (comprising 163 weekdays). EFuNNs learn input-output relationships through one pass training and automatically change, and optimize the parameter values when examples are propagated through them. They are therefore completely different from other neural networks, in which either the performance goal or the maximum number of training cycles are used to stop training. Table 2 shows the validation results of the EFuNN models trained on the corresponding morning and afternoon travel times for both directions of travel (MTB and BTM).

As highlighted by the traffic profiles in Fig. 4, during the afternoon peak along the BTM direction, and the morning peak along the MTB direction, large means and high variability were observed. The results in Table 2 illustrate that the MARE values are between 16% and 21% in these cases. The values of MARE shown in Table 2 also indicate that the afternoon peak along the MTB direction is less predictable than the morning peak along the BTM direction. The MARE measures are 11.1% and 5.2%, respectively. Table 2 further compares the performance of the EFuNN with a naive method, which uses the historic average of by day of week and time of day. The results show that the EFuNN outperformed the naive model for predicting the travel times in congested periods. The difference is marginal in the time periods with low variability.

Considering only the base variables, the values of all error measures show that the models provide relatively less accurate results in high variability time periods than in time periods with low variability. Generally, the higher the variability in travel times, the larger the error in forecasts of mean travel time.

Table 2
Long Term Travel Time Prediction Results in the Morning and Afternoon Peaks for EFuNN Model with Basic Input Variables along BTM and MTB Directions

Error measures	BTMAM		BTMPM		MTBAM		MTBPM	
	EFuNN	Naive	EFuNN	Naive	EFuNN	Naive	EFuNN	Naive
ME (sec.)	17	-13	-16	84	7	48	20	57
MRE (%)	2.4	-0.3	1.6	14.2	3.7	9.6	4.4	11
MAE (sec.)	41	43	230	233	128	120	78	108
MARE (%)	5.2	4.4	20.8	23.1	16	17.3	11.1	15.9

C. Conjunction with Tested Variables

EFuNN models with different groups of input variables were developed and evaluated to determine which group of input features yielded superior performance in this section. Each group of input features consists of the base input variables and one of the three test variables (school holiday, month of year and temperature). The prediction models were first trained on a randomly selected data points then tested on the same data to provide a clearest basis for comparison as in the previous analysis. Table 3 shows the model formulations. The prediction results on the same validation data for EFuNN models with basic input variables and individual test variables based on the morning and afternoon peak travel times are reported in Table 4.

Table 3
Model Formulations

	Model							
Time	Morning				Afternoon			
Explanatory variables	1	2	3	4	5	6	7	8
Time of day	✓	✓	✓	✓	✓	✓	✓	✓
Day of week	✓	✓	✓	✓	✓	✓	✓	✓
Rainfall	✓	✓	✓	✓	✓	✓	✓	✓
Holiday effect	✓	✓	✓	✓	✓	✓	✓	✓
School holiday		✓				✓		
Maximum daily temperature			✓				✓	
Month of year				✓				✓

The following conclusions are drawn from Table 4:

1. School holiday effect: The prediction models with school holiday input variable (models 2 and 6) provided same (BTM) or slightly better performance (MTB) than the model using only the base input variables (models 1 and 5) for the travel times in the morning peak. The reverse applies in relation to predicting the travel times in the afternoon peak. These results suggest that in the interest of developing a parsimonious model, the school holiday variable should be included for the EFuNN model developed for the travel times in the morning peak but not for the afternoon peak. The results are consistent with the correlation analysis between the school holiday indicator and the travel times. The correlations between the school holiday and the PM peak travel time are substantially lower than for the AM peak travel time. The partial correlation coefficient between mean travel time in this time period and the school holiday indicator variable is not significant for the BTM direction, and significant but small (0.05) for the MTB direction.

2. Maximum daily temperature effect: According to Table 4, models including the maximum daily temperature variable (models 3 and 7) exhibited larger or unchanged prediction errors over the base models (models 1 and 5). To use the temperature variable in the prediction model would only increase model complexity without a commensurate

improvement in model performance. Therefore, this variable is not included in the long term prediction model.

3. Month of year effect: The prediction models incorporating the month of year variable (models 4 and 8) produced higher prediction errors based on travel times in the afternoon peak, whereas the models did not show any difference in their ability to predict travel times in the morning peak. These results, therefore, do not suggest that seasonality needs to be included in the model.

In summary, the examination of the additional explanatory variables has revealed that the inclusion of maximum daily temperature and month of year would not improve the model performance. The school holiday variable would only impact travel times in the morning peak.

Table 4
Prediction Results for EFuNN Models Developed for Morning and Afternoon Peaks with Base Input Variables and Individual Test Variables for BTM and MTB Directions

	Error measures	Morning				Afternoon			
		Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
BTM	ME (sec.)	17	20	19	16	-16	23	-5	37
	MRE (%)	2.4	2.7	2.7	2.3	1.6	5.3	2.6	6.9
	MAE (sec.)	41	38	42	40	230	241	233	252
	MARE (%)	5.2	5.0	5.4	5.1	20.8	22.4	21.2	24
MTB	ME (sec.)	7	2.3	5	6	20	21	33	22
	MRE (%)	3.7	3.0	3.5	3.6	4.4	4.5	6.3	4.8
	MAE (sec.)	128	127	130	130	78	78	85	79
	MARE (%)	16	15.5	16	16	11.1	11.2	12.3	11.8

4.4. Fuzzy Rules Extracted from EFuNN

As shown in Section 1, a combination of fuzzy neural network could provide rules extracted from the model to obtain knowledge, while learning from historical travel time data due to the transparency of fuzzy neural network. EFuNNs utilize the learning capability of the neural network's parallel structure to extract the fuzzy rules from the training data. The extracted knowledge helps the users to understand how the network arrives at the decisions in terms of the input patterns. In addition, they can be used independently in a fuzzy inference system. Each rule node in an EFuNN represents an association from an area of input space to an area of output space. The number of rule nodes is determined by the parameters related to the knowledge manipulation, including the parameters for rule aggregation and the threshold values T_{1thr} and T_{2thr} for rule extraction. As noted earlier, the general approaches to determining the neural network parameters, such as minimizing an error function, cannot be applied to rule related parameters. Hereby insight is actually obtained by examining both the size and the feasibility of extracted rules.

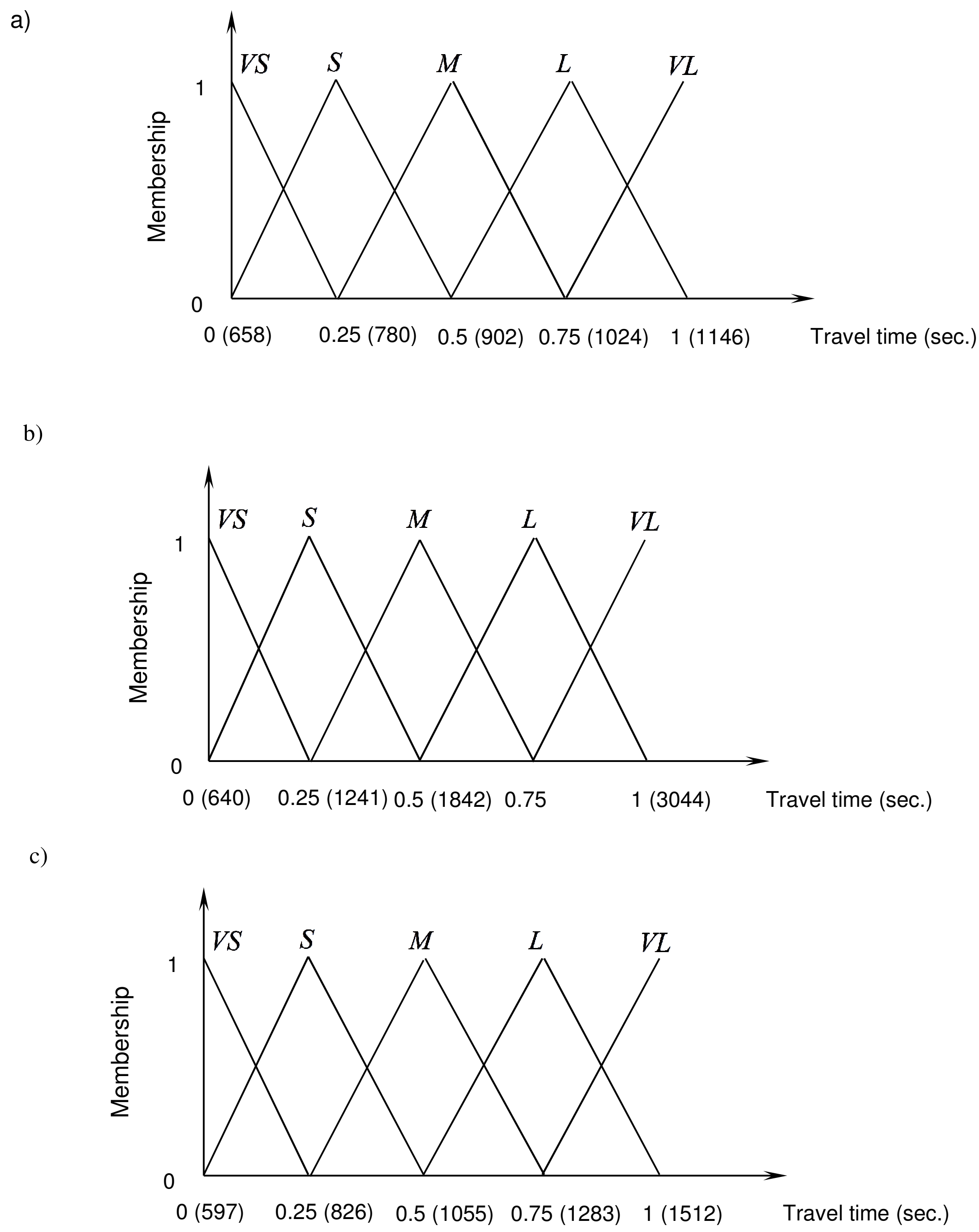

Fig. 7. Fuzzification of the travel time outputted from EFuNN for a) morning Peak travel times in the BTM direction b) afternoon peak travel times in the BTM direction c) morning and afternoon peak travel times in the MTB direction

The membership functions of the input and output vectors in EFuNNs are automatically determined in terms of the minimum and maximum values of each variable. The fuzzy labels for travel times have different membership functions due to the different levels of congestion evident in the morning and afternoon peaks along the two directions. It is possible that the outputs of a given value from different EFuNNs could belong to different membership functions or have different membership degrees, even if they belong to the same membership function. For example, we could assign five fuzzy sets [very small (VS), small (S), medium (M), large (L), very large (VL)] to the variable travel time. A travel time of 1000 seconds could then have membership of 0.2 and 0.8 to fuzzy sets M and L for the EFuNN for the morning peak in the MTB direction, while having membership of 0.4 and 0.6 to fuzzy sets VS and S for a different EFuNN for the afternoon peak in the BTM direction. Hence the interpretation of extracted rules should be based on the corresponding membership functions of the output of different EFuNNs. Fig. 7 shows the membership functions of the travel times for three different EFuNN models. The numbers in the parenthesis are the actual values before normalization.

Using this rule extraction process described above, around 60 rules have been extracted from each of the EFuNNs for travel times in morning and afternoon peaks in both directions ($R_{\max}$= 0.2 and $T_{1thr} = T_{2thr}$= 0.5).

Examples of some of those fuzzy rules are as follows:

1. If the day is a Wednesday AND the time is 8:10-8:20 AM AND rain is very light (1) AND after long holiday (0.818) AND school holiday, THEN mean travel time is small (0.92) (morning peak along BTM).
2. If the day is a Friday and the time is 5:50-6:00 PM AND rain is very slight (0.567), THEN mean travel time is medium (0.694) (afternoon peak along BTM).
3. If the day is a Monday and the time is 8:10-8:20 AM AND school holiday, THEN mean travel time is medium (0.756) (morning peak along MTB).
4. If the day is a Friday AND the time is 4:40-4:50 PM, THEN mean travel time is small (0.552) (afternoon peak along MTB).

5. DISCUSSIONS AND RELATED WORK

A number of studies have considered driver-to-driver variability as a component of travel time uncertainty. [26] estimated the individual travel time using the mean travel time plus a random error, which reflected the individual driver's behaviour. When predicting the confidence level of travel times in future time periods, the driver-to-driver variability is estimated from historical data according to the level of congestion. [26] used only two values of individual variance corresponding to two traffic congestion levels. In contrast, [27] assumed the random errors are stationary and normally distributed and he identified a constant value of variance from historical data. This constant was then used in the construction of a confidence interval for a short term travel time prediction.

In this study, we focus on two approaches to estimating driver-to-driver travel time variability in the context of long term travel time prediction. The first is to predict percentile travel times directly based on the historical percentile travel times. The other approach relies on predicting the mean travel time first, then quantifying the variance associated with that travel time from the relationship between vehicle-to-vehicle travel time variability and mean travel times, as developed in our previous research [28].

Under the first approach, different EFuNN models were developed for 90th, 50th and 10th percentile travel times in the morning and afternoon peaks for both the BTM and MTB directions. The 90th/50th/10th percentile travel times were calculated based on the travel time observations for each 10 min departure time window. During the development of models, which focussed on predicting the mean travel time, the models were trained/tested on data from the same 326/163 workdays. Based on the prediction results in the previous sections, the input variables of EFuNN models in morning peak travel times are time of day, day of week, rain, public holiday effect, and school holiday. The input variables for EFuNN models of afternoon peak travel times include time of day, day of week, rain, and public holiday effect only. The results are summarised in Table 5.

The MARE values in Table 5 reveal that the largest prediction errors are associated with the 90th percentile travel times, while the prediction errors for the 10th percentile travel times were lower. This result indicates that the higher percentile travel times exhibited higher variability; therefore they are more difficult to predict. In contrast, the lower percentiles are somewhat constrained by the legal free flow speed, which represents a best case lower bound travel time.

Table 5

Prediction Results for EFuNN Models Based on Percentile Travel Times in the Morning and Afternoon Peak along BTM and MTB Directions

Percentile travel time	Error measures	BTM		MTB	
		Morning	Afternoon	Morning	Afternoon
90%	ME (sec.)	14	-28	-24	42
	MRE (%)	2.0	1.0	1.8	7.6
	MAE (sec.)	49	266	174	105
	MARE (%)	5.8	22	18.7	14.2
50%	ME (sec.)	14	-13	14	34
	MRE (%)	2.1	1.9	4.4	6.3
	MAE (sec.)	39	229	124	81
	MARE (%)	5.0	20.8	15.5	11.9
10%	ME (sec.)	13	-6	23	18
	MRE (%)	2.0	2.3	4.6	3.7
	MAE (sec.)	34	200	91	56
	MARE (%)	4.6	19.6	12.7	8.7

[28] introduced the notion that vehicle-to-vehicle travel time variability could be approximated by an s-shaped function of mean travel time. [29] further examined the variability in speed-based travel estimation and short-term travel time prediction. If the long term travel time prediction

models are formulated to output mean values based on the available historical data, the percentile travel times can still be obtained by drawing on the relationship. The accuracy of percentile travel times calculated by this approach, when measured by the previously defined error measures, is shown in Table 6. The percentage error ranged 6-22% for the 90th percentile travel times, and 4%-19% for the 10th percentile travel times.

The results in both Tables 5 and 6 reveal that the derived percentile travel times were as accurate as the percentile travel times directly outputted by EFuNN models. The differences in relative error values are at most about 0.5% in the peak periods in both the BTM and MTB directions. This further supports the hypothesis that the vehicle-to-vehicle variability is a function of mean travel time only for a specific road system.

It's noted that, earlier researches in France and Korea by [30,31] as well as [10] have tested ARMA_GARCH model for estimation of variances on travel data sampled from tollway and taxi drivers, where the French study also assessed weather impact on drivers' behaviours. However the reliability of travel time forecast has only been checked recently by [9], where GARCH is applied in their experiments.

Table 6

The Accuracy of Percentile Travel Times Derived from the Predicted Mean Travel Times and Their Relationship with Driver-to-driver Variability

Error measures		BTM		MTB	
		Morning	Afternoon	Morning	Afternoon
90%	ME (sec.)	8	-25	-3	47
	MRE (%)	1.2	1.2	3.8	8.3
	MAE (sec.)	46	269	175	108
	MARE (%)	5.5	22	19	14.7
10%	ME (sec.)	-1	-27	-6	11
	MRE (%)	0.03	0.1	1	2.6
	MAE (sec.)	31	197	85	58
	MARE (%)	4.2	19.1	11.6	8.9

Our results presented in this paper exploited more real-time data, which were collected from a busy tollway equipped with advanced instruments to record all relevant data over two years. The data cover all different types of vehicles under different road and weather conditions by incorporating data obtained from government agency, like the Bureau of Meteorology in Victoria. The training and testing data used in our EFuNN model is more reliable and has integrated all relevant variables meaningful to travel time prediction, no matter it is short term or long term.

6. CONCLUSION

This paper has developed a long term travel time prediction model based on a fuzzy neural network methodology. The methodology combined the learning capability of neural network and fuzzy inference system's capability of embracing vagueness and imprecise concepts. The fusion makes it an ideal tool for long term travel time prediction, in which historical traffic information and weather forecasts are identified as major input variables.

The proposed models were developed and validated on travel time data collected from the CityLink tollway in 2003 and 2004. Because of the significant differences in the traffic conditions for various scenarios (AM and PM peak, by travel direction), the behaviour and prediction results of the proposed model were evaluated and analysed independently for each case. The percentage error of the developed method ranged from 5%-21%.

Therefore the advantages of EFuNN in the travel time prediction have been proved according to the prediction results on the CityLink tollway. The results showed that the fuzzy neural network models have been able to provide reasonable forecasts of mean travel times a few days head. The results also demonstrate the feasibility of predicting long term travel times from the historical profile and weather conditions. The process of input variable selection highlighted that school holidays only had impacts on travel time profiles in the morning peak, while maximum daily temperature and month of year did not improve the model's prediction performance. It should be noted that measured, instead of predicted weather, information was used in the study due to the unavailability of data. However, when linguistic weather forecast information is used, the fuzzification step of variable can be spared, which also introduces some disadvantages of EFuNN. The input data variables could differ from areas to areas and from time to time. In this paper, we took the CityLink tollway as our demonstration. The future work would concentrate on the robustness experiments of EFuNN on different areas.

Driver to driver travel time variability was identified as a source of uncertainty associated with long term travel time prediction. We quantified the uncertainty related to the driver-to-driver travel time variability in two different ways: first by directly learning from historical percentile travel times, and second by drawing on the relationship between mean travel time and the difference in individual travel times based on the predicted mean travel times. The prediction results showed that the two approaches achieved a similar level of accuracy. The second approach can be applied to situations where real time or historical measured individual travel times are not available.

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