
Volume 31C, June 2013
ISSN 0968-090X
TRANSPORTATION RESEARCH
AN INTERNATIONAL JOURNAL
Part C: Emerging Technologies
SPECIAL ISSUE
SPECIAL ISSUE ON ITS FOR LARGER CITIES
Guest Editor: Fritz Busch
Editor-in-Chief: Matthew G. Karlaftis

Transportation Research Part C 31 (2013) 145–157

Contents lists available at SciVerse ScienceDirect

Transportation Research Part C

journal homepage: www.elsevier.com/locate/trc

Urban link travel time estimation based on sparse probe vehicle data

Fangfang Zheng [a,b,*], Henk Van Zuylen [a,1]

[a] Department of Transport and Planning, Faculty of Civil Engineering and GeoSciences, Delft University of Technology, Stevinweg 1, 2628CN Delft, The Netherlands
[b] School of Transportation and Logistics, Southwest Jiaotong Univeristy, No. 111, Erhuanlu Beiyiduan, Chengdu 610031, PR China

ARTICLE INFO

Article history:
Received 22 December 2009
Received in revised form 22 March 2012
Accepted 11 April 2012

Keywords:
Urban link travel time
Probe vehicle data
Artificial Neural Network
Analytical estimation model

ABSTRACT

In the urban signalized network, travel time estimation is a challenging subject especially because urban travel times are intrinsically uncertain due to the fluctuations in traffic demand and supply, traffic signals, stochastic arrivals at the intersections, etc. In this paper, probe vehicles are used as traffic sensors to collect traffic data (speeds, positions and time stamps) in an urban road network. However, due to the low polling frequencies (e.g. 1 min or 5 min), travel times recorded by probe vehicles provide only partial link or route travel times. This paper focuses on the estimation of complete link travel times. Based on the information collected by probe vehicles, a three-layer neural network model is proposed to estimate complete link travel time for individual probe vehicle traversing the link. This model is discussed and compared with an analytical estimation model which was developed by Hellinga et al. (2008). The performance of these two models are evaluated with data derived from VISSIM simulation model. Results suggest that the Artificial Neural Network model outperforms the analytical model.

1. Introduction

Travel time estimation and prediction in urban road networks are challenging subjects because the travel time is intrinsically uncertain. This is due to fluctuations in traffic demand (e.g. due to seasonal effects, population characteristics, traffic information and user responses) and supply (e.g. due to incidents, road works, weather conditions, road geometry), traffic control, stochastic arrivals and departures at signalized intersections, etc. Traditionally, loop detectors are used to collect traffic data (e.g. flow, speed or occupancy) and a lot of models have been developed to estimate or predict travel times based on loop detector data (Petty et al., 1998; Oh et al., 2003; Van Lint and Van Der Zijpp, 2003; Kwon and Petty, 2005; Van Lint et al., 2005; Liu et al., 2006, 2007). However, installing and maintaining loop detectors on an urban network that provide sufficient monitoring information is quite costly. Mobile traffic sensors such as probe vehicles equipped with tracking devices (e.g. GPS or mobile phones) are being used to collect network-wide traffic data. Probe vehicles can collect information such as instantaneous speeds and travel times at any network location without roadside equipments. In this paper, probe vehicles are used as traffic sensors to collect traffic data (speeds, positions and time stamps) in an urban road network. The data is recorded on fixed time intervals, e.g. from 1 s to 1 min.

In recent years, model-based approaches and data-driven approaches have been developed to estimate travel time based on probe vehicle data (PVD). Jula et al. (2008) proposed a mathematical model to estimate travel times along the arcs and arrival times at the nodes of a stochastic and dynamic network in real time. A predictor–corrector form of the Kalman filter was developed to estimate the travel times along that arc for future times. However, the author emphasized more on the mathematical parts instead of considering the real traffic condition in the network. Liu (2009) proposed a model to estimate

* Corresponding author at: School of Transportation and Logistics, Southwest Jiaotong Univeristy, No. 111, Erhuanlu Beiyiduan, Chengdu 610031, PR China. Tel.: +86 18702828126.
E-mail addresses: fzheng@home.swjtu.edu.cn (F. Zheng), H.J.Vanzuylen@tudelft.nl (H.J. Van Zuylen).
[1] Tel.: +31 01527 82761; fax: +31 01527 83179.

0968-090X/$ - see front matter © 2012 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.trc.2012.04.007

arterial travel time by tracing a virtual probe vehicle along an OD route with multiple intersections. High-resolution ‘event-based’ data including every vehicle actuations over loop detector and every signal phase changes is needed to determine three possible maneuvers (acceleration, deceleration and no-speed-change) of the virtual probe. The model works quite well with very low estimation error of 1.8%. Instead of solely utilizing probe vehicle information, Bhaskar et al. (2009) proposed a model to estimate the average travel time on signalized urban networks by integrating the traditional cumulative plots with probe vehicle information. In undersaturated conditions, virtual probe vehicle information is used to correct the cumulative plots and reduce the relative deviations in the cumulative plot with the strong assumption that the travel time of the virtual probe vehicle is free-flow travel time of the link, while in oversaturated conditions real probe vehicle information is needed.

Basically, the traffic data collected by probe vehicles could not provide direct information about flow, density and average speeds that are usually the input for model-based approaches. Therefore, data-driven approaches seem most appropriate for this situation, e.g. regression based (Chan and Tam, 2008), pattern recognition based (Li and McDonald, 2002; Robinson and Polak, 2005) and neural network based models. Neural network based models are more robust than regression models as they utilize the data to build the model structure as well as its parameters. It has been applied in different engineering discipline and has been proven to be a very powerful method of mathematical modeling, especially in modeling nonlinear relationships.

Up to now, most of these models require the information of historical travel times (complete link travel times or route travel times recorded by probe vehicles with very high polling frequencies, e.g. 1 s or less) or speeds to estimate or predict travel times. As a result, most research has been done based on synthetic data. However, in reality the positions of probe vehicles on links are randomly distributed when traffic information is reported to the traffic monitoring center, which means that travel times collected by probe vehicles do not originate from a single complete link but are experienced by probe vehicles from a certain position on one link to a certain position on another link. As for travelers, when making route choices they want to know the complete link or route travel times from their origins to the destinations. It is necessary to allocate the travel times between two consecutive time stamps from probe vehicles into individual links. In this paper, a three-layer Artificial Neural Network (ANN) model is proposed to estimate the complete urban link travel time. For each individual probe vehicle, time stamps, speeds and positions on links at fixed polling moments are input to the neural network model and output is the travel time of this probe vehicle traversing a single complete link. The estimation results are compared with those from an analytical model developed by Hellinga et al. (2008), which considers the stopping probability and congestion probability when assigning the travel times to individual links. In Section 2, the detailed description about ANN model is given. In Section 3, the performance of the proposed model is evaluated using the data from a simulated urban network. The results are compared with those from Hellinga's method. In Section 4, some sensitivity analysis of the input information on performance of the ANN model is presented. In the final section, some conclusions and future research are presented.

2. Methodology

2.1. Link travel time allocation

Travel times collected by probe vehicles do not originate from a single complete link but are experienced by probe vehicles from a certain position on one link to a certain position on another link. These can be categorized into three types as illustrated in Fig. 1a–c.

P_0, P_1, P_2, P_3, P_4 are positions on the corresponding links and t_0, t_1, t_2, t_3, t_4 are time stamps. $t_{1,decomposed}$, $t_{2,decomposed}$, $t_{3,decomposed}$, $t_{4,decomposed}$ represent the reallocated link travel times based on the travel times collected by probe vehicles. The complete link travel time here is defined as the time difference between the time instant when the vehicle passes the upstream stop line and the time instant when the vehicle passes the downstream stop line.

Type 1: The reported positions are on the same link (e.g. link 2) as shown in Fig. 1a, the complete travel time of link 2 is composed of three parts:

$$T_{L2} = t_{2,decomposed} + t_3 - t_2 + t_{3,decomposed} \tag{1a}$$

For this case, the link is long or the traffic condition on the target link is likely to be congested or vehicles need to wait for the red time since the probe vehicle experiences long travel time (at least longer than the sampling interval) on this link.

Type 2: The first and second reported positions are on adjacent links shown in Fig. 1b, then the travel time of link 2 is estimated as:

$$T_{L2} = t_{2,decomposed} + t_{3,decomposed} \tag{1b}$$

Type 3: At least one full link is existing between two consecutive reported positions illustrated in Fig. 1c, the travel time of link 2 is:

$$T_{L2} = t_{2,decomposed} \tag{1c}$$

For this case, the traffic condition on the target link is likely to be free flow or undersaturated since the probe vehicle experiences short travel time.

Now the question is how to reallocate travel times into individual links only based on probe vehicle data. In the following, an Artificial Neural Network model and an analytical model are discussed.

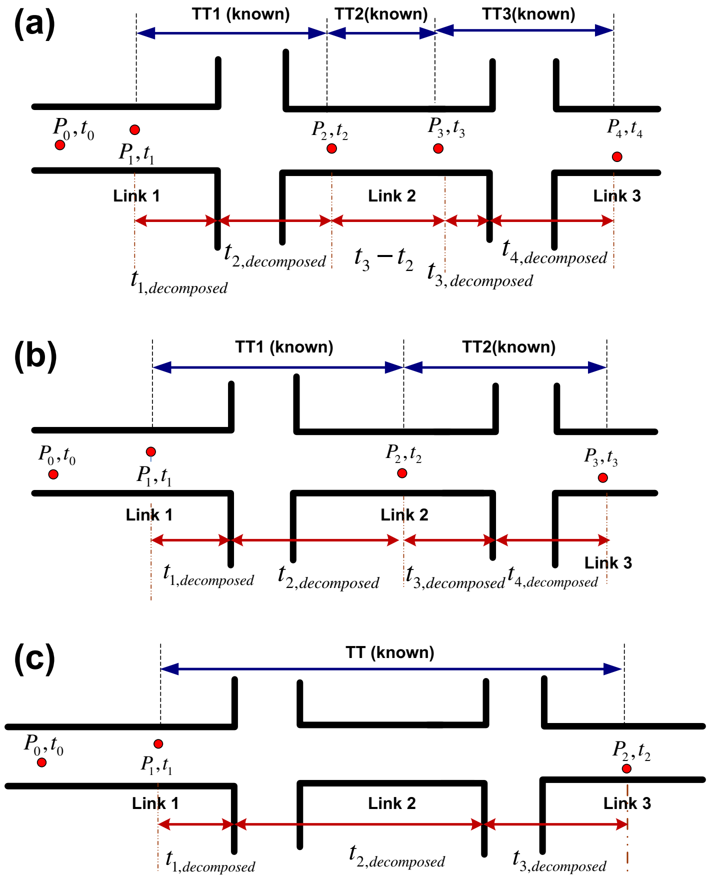

Fig. 1. Sketch of assignment of travel times between recorded positions to the link in the middle.

2.2. Artificial Neural Network model for travel time estimation

Basically, the traffic data collected by probe vehicles include positions, time stamps and speeds on the route. Therefore, positions, time stamps and speeds can be used as the input data in the Artificial Neural Network (ANN) model. Traffic flow and signal timings are considered optionally since on one hand, they are not always available on the urban road network and on the other hand, we are trying to develop a model to estimate travel time as accurate as possible with least information and make the model more generic. As discussed in Hellinga et al. (2008), the traffic condition the probe vehicle experiences during the recent sampling interval is considered not substantially different from that on the route traversed by the same probe vehicle during the previous sampling interval. In our ANN model, the probe vehicle information on previous sampling interval is incorporated with the information on the recent sampling interval. In Section 3, an application of the model in terms of three types described in Section 2.1 is discussed. Fig. 2 shows the structure of the ANN model. The mathematical description of the model is as follows:

2.2.1. Input layer

$$X(i) = \begin{bmatrix} x_1(i) \\ \vdots \\ x_N(i) \end{bmatrix} = \begin{bmatrix} p(i) \\ s(i) \\ t(i) \\ v(i) \end{bmatrix} \tag{2}$$

where $p(i)$ is the position vector of probe vehicle i on the upstream link, target link and downstream link; $s(i)$ is the link number vector indicating on which links the probe vehicle positions are; $t(i)$ is the time stamp vector which indicates the time instances when the probe vehicle sends the information; $v(i)$ is the speed vector.

$$p(i) = \begin{bmatrix} p_1(i) \\ \vdots \\ p_n(i) \end{bmatrix}, \quad s(i) = \begin{bmatrix} s_1(i) \\ \vdots \\ s_n(i) \end{bmatrix}, \quad t(i) = \begin{bmatrix} t_1(i) \\ \vdots \\ t_n(i) \end{bmatrix}, \quad v(i) = \begin{bmatrix} v_1(i) \\ \vdots \\ v_n(i) \end{bmatrix}$$

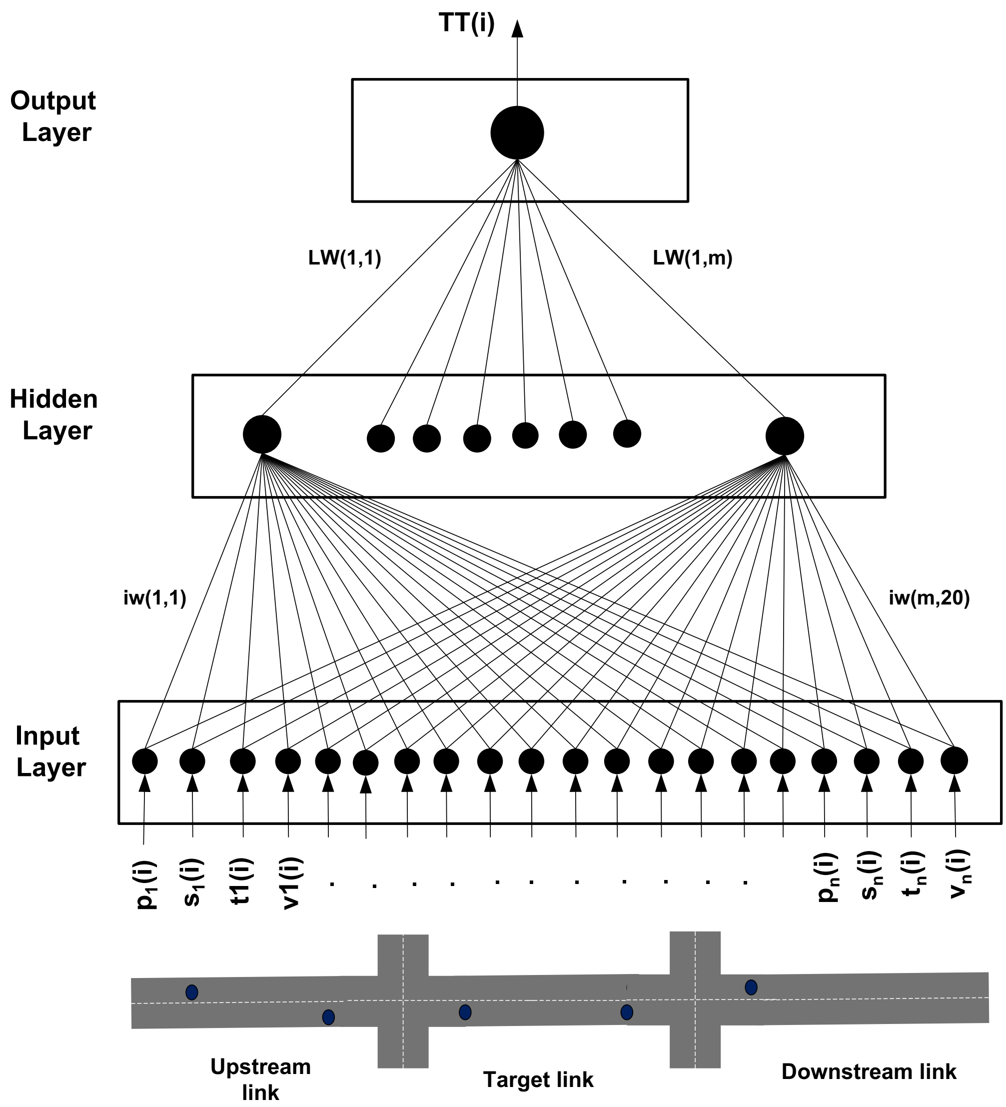

Fig. 2. Topology of an Artificial Neural Network for link travel time estimation.

The number of input neurons in our model can be determined as:

$$N = n * m \tag{3}$$

where n is the number of information points taken into consideration for each probe vehicle; m is the categories of information, here m is chosen to be 4 (positions, link IDs, time stamps and speeds).

For the case in Fig. 1a, the information on the previous sampling interval is also taken into account, so the input neurons are $5 * 4$ (5 positions + 5 link IDs + 5 time stamps + 5 speeds) for each probe vehicle. For the case in Fig. 1b, $4 * 4$ input neurons are used and $3 * 4$ input neurons are needed for the case in Fig. 1c.

2.2.2. Hidden layer

$$H(i) = \begin{bmatrix} h_1(i) \\ \vdots \\ h_m(i) \end{bmatrix} = \begin{bmatrix} \varphi\left(\sum_{j=1}^{N} \omega_{j,1} x_j(i) + b_1\right) \\ \vdots \\ \varphi\left(\sum_{j=1}^{N} \omega_{j,m} x_j(i) + b_m\right) \end{bmatrix} \tag{4}$$

where $h_m(i)$ denotes the value of the mth hidden neuron, $\omega_{j,m}$ denotes the weight connecting the jth input neuron and the mth hidden neuron, h_m denotes a bias with a fixed value for the mth hidden neuron; φ is the transfer function. Common forms of the transfer function are *logistic sigmoid* and *hyperbolic tangent* functions. In practice, the latter is found to give rise to faster convergence. Thus, we choose $\varphi(y) = \frac{1-\exp(-2y)}{1+\exp(-2y)}$.

2.2.3. Output layer

$$Y(i) = TT(i) = \varphi\left(\sum_{k=1}^{m}\omega_k h_k(i) + b\right) \tag{5}$$

where $Y(i)$ and $TT(i)$ denote the estimated travel time of probe vehicle i on the link under consideration; ω_k denotes the weight connecting the kth hidden neuron and the output neuron; b is the bias for the output; φ is the transfer function and a linear function is commonly used for the output units.

2.3. Hellinga's model

Different from the Artificial Neural Network, Hellinga proposed an analytical model to decompose recorded partial link or route travel time into individual links considering the stopping probability and congestion probability. On the following, a brief introduction of this method is given. More detailed information about this method is given in Hellinga's original paper (Hellinga et al., 2008).

According to the definition proposed by Hellinga, link travel times in the urban road network can be decomposed into three parts:

(1) Free flow travel time.
(2) Stopping time caused by traffic control devices (deceleration and acceleration are included).
(3) Delay due to traffic congestion.

Therefore, the travel time between two consecutive time stamps of a probe vehicle can be expressed as:

$$t_{m,i+1} - t_{m,i} = \sum_{j=0}^{J(m,i)}\{t_f(l_{m,i,j}) + t_s(l_{m,i,j}) + t_c(l_{m,i,j})\} \tag{6}$$

where $t_{m,i}$, $t_{m,i+1}$ are consecutive time-stamps of probe vehicle m on link i and link $i + 1$; $t_f(l_{m,i,j})$ is the free flow travel time on link j; $t_s(l_{m,i,j})$ is the stopping time on link j and $t_c(l_{m,i,j})$ is the congestion time on link j. (We used the same notation as Hellinga did, so some confusion may arise due to the indices that have different meaning in Hellinga's article and in our previous section.)

The free flow travel time on a link is calculated as the link length divided by the free flow speed:

$$t_f(l(n_i, n_j)) = \frac{|l(n_i, n_j)|}{v_f(n_i, n_j)} \tag{7}$$

where $|l(n_i, n_j)|$ is the length of the complete link or partial link between the nodes n_i and n_j, $v_f(n_i, n_j)$ is the free flow speed for the complete or partial link. However, in reality, free flow speeds vary with driving behavior, speed limit, weather conditions, etc. It is difficult to estimate free flow speeds. Instead, the maximum allowed speed is used to calculate the free flow travel time. In order to see how Hellinga's method performs with different free flow speeds, a sensitivity analysis of the free flow speed is discussed in Section 3.

Hellinga calculates the congestion time and stopping time based on the probability function as:

$$t_c(l_{m,i,J}) = \int_0^{w_{\max}} \sigma_{m,i,J}\tau_c \frac{\sum_{j=0}^{J(m,i)} P_w(m,i,w)P_s(l_{m,i,J},w)}{Q_s(m,i)}dw \tag{8}$$

$$t_s(l_{m,i,J}) = \int_0^{w_{\max}} \tau_s \frac{P_w(m,i,w)P_s(l_{m,i,J},w)}{Q_s(m,i)}dw \tag{9}$$

where w is the degree of congestion which is the ratio of the congestion time on the route to the sum of the congestion time and the free flow travel time on the route; τ_c is the total congestion time; τ_s is the total stopping time; $J(m, i)$ is the position of vehicle m on the last (partial) link; $P_w(m, i, w)$ is the congestion probability which is used to capture the likelihood of a certain degree of congestion experienced by a probe vehicle m when traversing a given link. It is defined as:

$$P_w(m,i,w) = \min\left(1, \frac{T_c(m, I_p(i)) + T_c(m,i)}{t_{m,I_p(i)+1} - T_{m,I_p(i)} + t_{m,i+1} - t_{m,i}}\frac{1}{w}\right) \tag{10}$$

where $T_c(m, i)$ is the maximum delay the probe vehicle m experiences due to congestion; $P_s(l_{m,i,J}, w)$ is the stopping probability, which assumes that a probe vehicle stops at most once on the route. It is defined as:

$$P_s(l_{m,i,j}, p, w) = \begin{cases} H_s(l_{m,i,0}, w) & \text{if } J(k,i) = 0 \\ H_s(l_{m,i,J,w})\Pi_{j\neq J}(1 - H_s(l_{m,i,j}, w)) & \text{otherwise} \end{cases} \tag{11}$$

where $H_s(l_{m,i,J}, w)$ is the probability of stopping on a link. Hellinga gives explicit functions for the calculation of $H_s(l_{m,i,J}, w)$. It is worth mentioning that there are two parameters c_1 and c_2 in the stopping probability function that need to be calibrated. In Section 3, we give a sensitivity analysis regarding these two parameters.

3. Model application

3.1. Test urban road network

As shown in Fig. 3, an urban road called 'Kruithuisweg' in Delft city in the Netherlands was modeled using the Vissim simulation model. Kruithuisweg is a typical urban road with signalized intersections lying between two freeways, A4 and A13. In order to mimic the real traffic situation on this road, traffic was assigned using Dynamic Traffic Assignment (DTA) based the OD matrix. All the traffic signal controllers at the intersections are demand actuated. The free flow speed is set to be 100 km/h, which is the speed limit on the real situation. The blue dots are the data collection points which record the information of vehicles every second. The red arrow indicated in the figure is the target link for travel time estimation.

Besides data sets from the simulated network, a real data set was collected by a car with a GPS device driving back and forth on the road 'Kruithuisweg' 7 times. All the GPS positions, time stamps, speeds were recorded every 0.3 s.

3.2. Data preparation

3.2.1. Re-sampling process

The network was simulated for a period of 65 min for each simulation run. Data from the first 5 min of simulation were considered to be the warm-up period and were not used in the analysis. Every second, positions, time stamps and speeds of vehicles were recorded by the data collection point. However, in real world, the sampling interval is much longer than 1 s. Instead, the sampling interval of 30 s or 60 s is more often used in reality. Hence, a 'Re-sampling' procedure with 60 s interval was taken to extract the data from the original simulation data set. One thing we should keep in mind is that the position of the probe vehicle can be anywhere on the link when sampling, which means if we just take one position on the link as the initial sampling position, the estimation results will be biased. Fig. 4 explains the 'Re-sampling' strategy. E.g., if the initial sampling moment is i, when applying 60 s sampling strategy, the next moment is $i + 60$, and then $i + 120$, $i + 180$, etc. We can get different moment combinations to estimate the travel time of link 2.

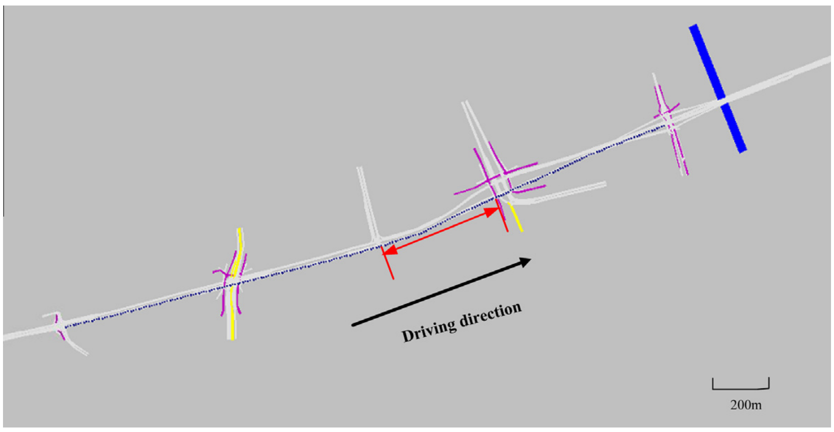

Fig. 3. Vissim model of Kruithuisweg road in Delft, The Netherlands.

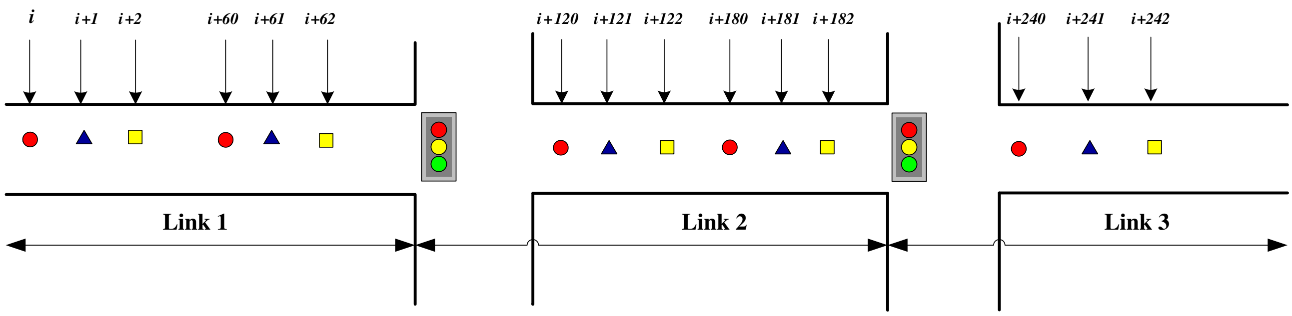

Fig. 4. Different moments (positions) recorded by probe vehicles on different links.

Combination 1: i, $i + 60$, $i + 120$, $i + 180$, $i + 240$, ...

Combination 2: $i + 1$, $i + 61$, $i + 121$, $i + 181$, $i + 241$, ...
...

Therefore, the expectation value of the travel time of a probe vehicle k traversing link 2 can be calculated as:

$$TT_{k,L2} = \frac{1}{n}\sum_{i=1}^{n} TT_{k,i} \tag{12}$$

where n is the number of different initial sampling moments, $TT_{k,i}$ is the estimated link 2 travel time of probe vehicle k with the initial sampling moment i. The true link travel time of a probe vehicle traversing the target link is recorded by data collection points located at the beginning of the link and the end of the link.

The re-sampling process was also applied to the real data collected on this road, which gives rise to another evaluation data set.

3.2.2. Data for training and evaluation

After the 'Re-sampling' process, the extracted data were used for training the neural network and estimating the link travel time. Total 70 random seeds were simulated and probe vehicle data from 30 random seeds, in which 20 random seeds are in the undersaturated condition and 10 random seeds are in the highly oversaturated condition, were used for the training process. The other 40 random seeds were used for the performance evaluation. Four scenarios were chosen for evaluation. The subdivision of data sets for training and evaluation is indicated in Table 1.

- *Scenario 1:* Original demand (undersaturated condition).
- *Scenario 2:* 20% demand increase.
- *Scenario 3:* 50% demand increase.
- *Scenario 4:* 100% demand increase (highly oversaturated condition).

The same 're-sampling' process was also applied to the real GPS data set as recorded by the GPS device. A new set of GPS data with 60 s sampling interval was derived by extracting GPS data from the original data set. This new data set is therefore used for validation purpose.

3.3. Neural network training

A training process is needed before the ANN model can be applied to estimate link travel times. Three procedures including training, validation and testing were conducted in the whole training process. The total training data set was divided into three subsets which are 18 random seeds for training, 6 random seeds for validation and 6 random seeds for testing. During the training process, different hidden neurons, e.g. 10, 15, 20, 25, were chosen. The testing results show that the performance in terms of Mean Square Error (MSE) for the case of 10 and 15 neurons is not as good as that of 20 or 25 neurons. Therefore, 20 hidden neurons were used to build the network.

Levenberg–Marquardt algorithm (Ranganathan, 2004) was chosen so that the over fitting phenomenon could be avoided. Besides, the Levenberg–Marquardt algorithm can provide fast convergence even for large networks that contain a few hundred weights. The trained ANN model is applied to estimate link travel times both in undersaturated conditions and oversaturated conditions.

3.4. Evaluation

In order to evaluate how the ANN model and Hellinga's model perform, two performance indicators are used to quantify the performance, the Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE):

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(t_{PVD,i} - t_{true,i})^2} \tag{13}$$

Table 1
Simulated data sets for training and evaluation.

	Training			Evaluation		
	Training	Validation	Testing	Scenario 1	Scenario 2	Scenario 3
Number of random seeds						
Undersaturation	12	4	4	10	10	10
Oversaturation	6	2	2			

$$\mathrm{MAPE} = 100 * \frac{1}{n}\sum_{i=1}^{n}\left|\frac{t_{PVD,i} - t_{true,i}}{t_{true,i}}\right| \quad (14)$$

where $t_{PVD,i}$ is the estimated travel time of the ith probe vehicle; $t_{true,i}$ is the true link travel time of the ith probe vehicle recorded by the data collection points.

3.5. Sensitivity analysis in Hellinga's model

In Hellinga's model, link travel time is composed of three parts including free flow travel time, congestion time and stopping time. In order to estimate free flow travel times, free flow speeds need to be determined. Besides, in the stopping likelihood function as proposed by Hellinga, two model parameters denoted by c_1 and c_2 were used to reflect the stopping likelihood pattern of the link. In this section, the sensitivity of the performance (in terms of RMSE and MAPE) of this model in both low traffic demand conditions and high traffic demand conditions are investigated. Fig. 5 gives an illustration of how different combinations of c_1 and c_2 influence the performance of the Hellinga's model in terms of RMSE and MAPE. The free flow speed was set to be the speed limit (100 km/h) for this case. The best combination of c_1 and c_2 was then chosen and the next step is to analyze the sensitivity of the performance to the free flow speed, for which a range of speeds from 50 km/h to 150 km/h was used. The best combination of c_1, c_2 and the free flow speed for each scenario is given in Table 2. The selected parameter values are used in Hellinga's model to estimate complete link travel times.

3.6. Results based on simulation data

Fig. 6 provides the comparison between the estimated link travel times based on the ANN model and Hellinga's model and true link travel times. Fig. 6a, c, e, and g indicates the correlation between the estimated link travel times based on the ANN model and the true link travel times with different traffic demand. When estimating link travel times in different traffic conditions, the same ANN model with the same weights is applied. Fig. 6b, d, f, and h shows the correlation between the estimated link travel times based on Hellinga's model and the true link travel times under different traffic conditions. Each point represents individual travel time for each probe vehicle. A linear regression is applied to compare the estimated links travel times with the true (simulated) link travel times. When traffic demand increases from original free flow condition to high demand condition, the ANN model performs very well. The estimated link travel times based on ANN exhibit no

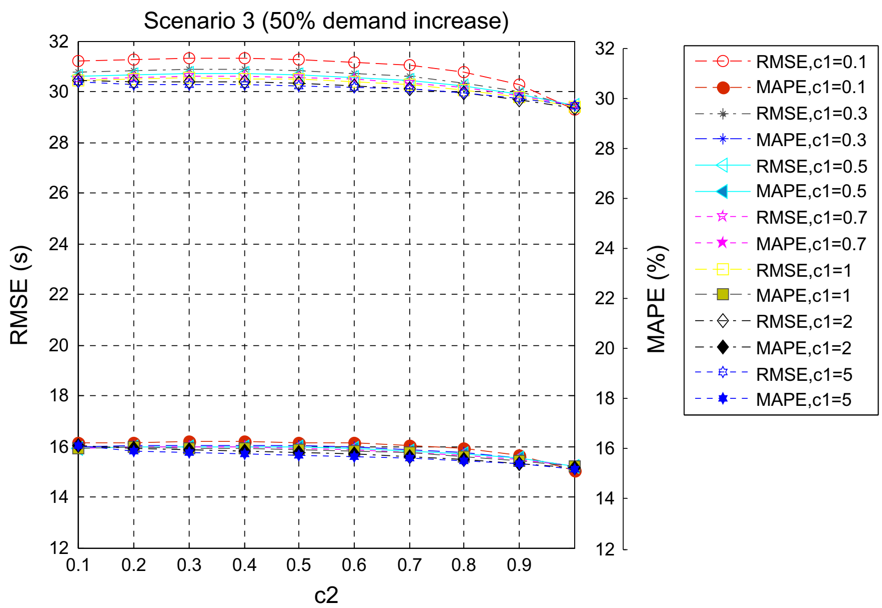

Fig. 5. Performance of Hellinga's model with different combinations of c_1 and c_2 in scenario 1.

Table 2
Parameter values in Hellinga's model under different traffic conditions.

Parameters	Scenario 1	Scenario 2	Scenario 3	Scenario 4
c_1	5	5	0.1	0.1
c_2	1	1	1	1
Free flow speed (km/h)	80	80	100	110

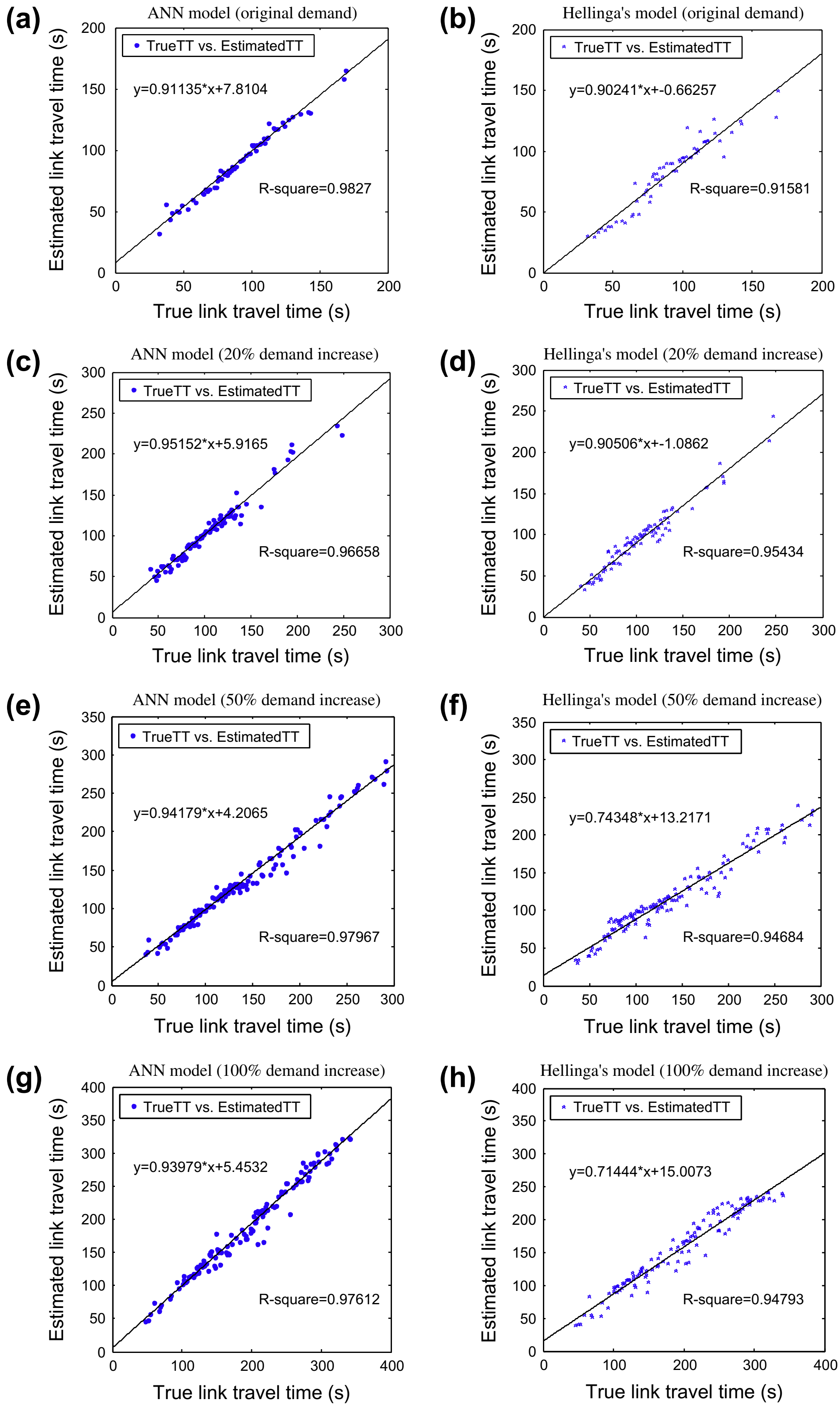

Fig. 6. Correlation between estimated link travel times and true link travel times with 60 s sampling interval.

Table 3
Performance measurements of ANN and Hellinga's model with different traffic demand.

	Scenario 1		Scenario 2		Scenario 3		Scenario 4	
	ANN	Hellinga	ANN	Hellinga	ANN	Hellinga	ANN	Hellinga
RMSE (s)	4.53	12.98	151	13.69	9.97	29.44	13.48	48.55
MAPE (%)	3.97	12.20	5.96	10.96	4.98	15.18	5.08	20.03
Average Travel time (s)	91.35		105.73		137.80		192.51	

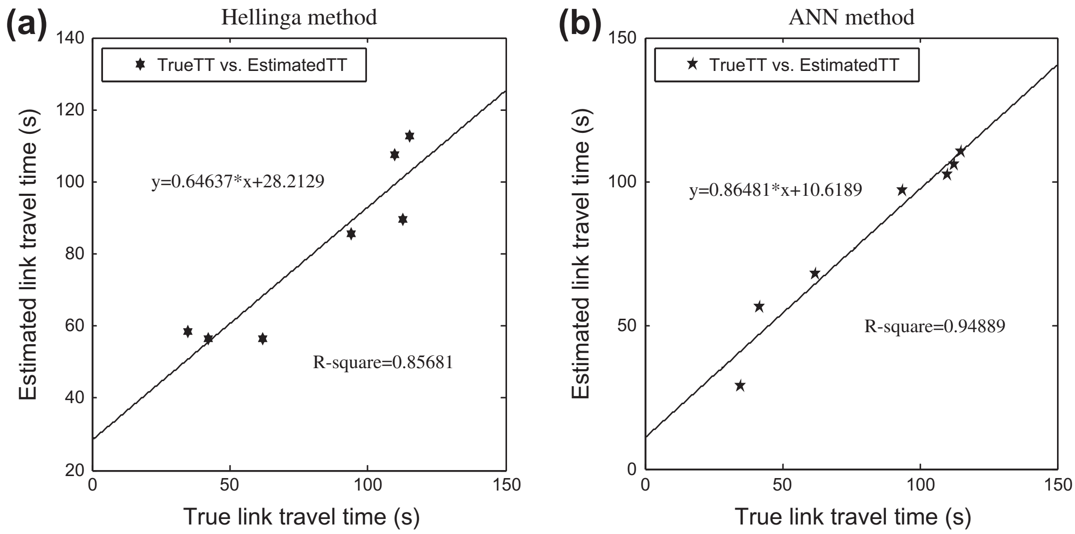

Fig. 7. Correlation between estimated link travel times and true link travel times based on real GPS.

apparent bias and have very high correlation with the true link travel times ($R^2 > 96\%$ as shown in Fig. 6a, c, e, and g). As for Hellinga's method illustrated in Fig. 6b, d, f, and h, the estimated link travel times deviate from the true link travel times as the demand increases with fixed values for c_1 and c_2, especially when demand increases by 50% and 100%. The performance of the two estimation methods in terms of RMSE and MAPE is indicated in Table 3. As for ANN model, both RMSE and MAPE increase marginally as traffic demand increases. The increase of MAPE is less than 2%. As for Hellinga's model, the MAPE increases from 10% to 20% when traffic demand increase from undersaturated conditions (original demand and 20% demand increase) to oversaturated conditions (50% demand increase and 100% demand increase).

3.7. Results based on real GPS data

The trained ANN model was also applied to estimate travel times based on the real GPS data. A car with a GPS device was driving back and forth on the same road 'Kruithuisweg' 7 times and all the GPS positions were recorded every 0.3 s. In the sampling procedure, 60 s sampling interval was applied to extract GPS data from the original data set. The estimation result is shown in Fig. 7. Each point represents the travel time for each trip. From the regression formula in the figure, it can be seen that the trained ANN model performs reasonably well. The RMSE and MAPE are about 7.8 s and 10.9%, respectively. While for the Hellinga's model, the estimation accuracy is lower with RMSE and MAPE of 14.2 s and 20.6%, respectively. Though one could argue that the real data set is too small to give a statistically sound result, it shows the possibility to apply the ANN model to the real GPS data.

4. Sensitivity analysis of input information in ANN model

As discussed in previous sections, the input data for ANN model include positions, link IDs, time stamps and speeds. One of the remaining questions is whether all the input information plays a role in the estimation results of ANN model. Two categories of input data, which are positions and speeds, are analyzed and discussed in the following subsections. It needs to be noted that link IDs and time stamps are always kept as input data. On the following, ANN models with different input information were developed. The model performance in terms of Absolute Percentage Error is analyzed and discussed.

4.1. Model 1: absolute position information

The positions of probe vehicles in the proposed model are relative positions on the link where the vehicles are registered. Therefore, link IDs are additionally needed to distinguish on which links probe vehicles are traversing. One alternative way is the absolute position, which combines the percentage position with the link ID. For instance, if we set a reference point as the start of the route, the position on the route can be determined as the distance from the current point to the reference point.

4.2. Model 2: without position information

The position information of probe vehicles on different links is used as one category of input data in the proposed model in Section 2. The ANN model with link numbers without position information was trained as model 2.

4.3. Model 3: without speed information

In many traffic models, speed information is considered as an important piece of information for traffic state estimation or travel time estimation. In the ANN model, speeds are also used as the input data as discussed in Section 2. Nevertheless, whether the speed information really helps improve the performance of the ANN model remains unknown. Hence, the ANN model without speed information was trained as model 3.

4.4. Model 4: decrease of input data points

As discussed in Hellinga's model, the traffic condition a probe vehicle on a certain link experiences in the most recent polling interval is not substantially different from the condition on the same link in the current polling interval. Therefore, the information on the previous polling moment is considered in the re-calculation of travel times in his model. The ANN model developed in Section 2 also takes the information from the previous polling moment into account. Whether this information is redundant or has significant influence on the model performance is unknown. An alternative model without the information from the previous polling moment was developed as model 4.

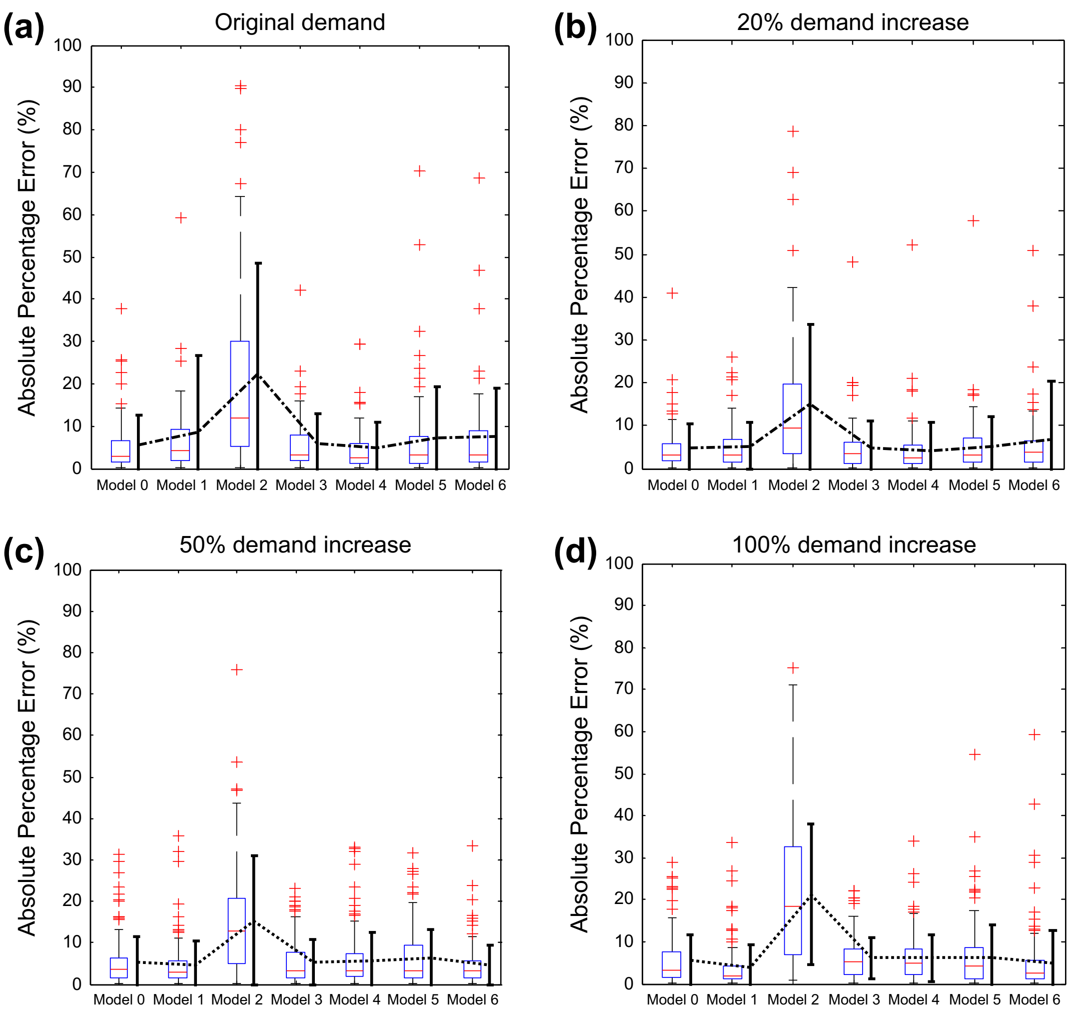

Fig. 8. Influence of different input information on the ANN model performance in terms of Absolute Percentage Error.

4.5. Model 5: decrease of input data points with relative position information and no speed information

This model is the combination of models 3 and 4. The input information includes the time stamps, relative positions and link IDs. The information on the previous polling moment is not used as the input data.

4.6. Model 6: decrease of input data points with absolute position information and no speed information

This model is the combination of models 1, 3 and 4, in which the time stamps, absolute positions are used as the input information while the information from the previous polling moment is not considered.

In order to be able to visualize both the median and spread of the Absolute Percentage Error (APE) in different models, the results are represented in box-plots as shown in Fig. 8. The horizontal axis represents different ANN models, in which 'Model 0' is the ANN model proposed in Section 2 with time stamps, positions, link IDs and speeds as the input information. The vertical axis represents the Absolute Percentage Error for each model. The horizontal lines in the boxes refer to the median value of APE, while the upper and lower boundaries of the boxes indicate respectively the upper quartile (75 percentile) and the lower quartile (25 percentile). The black lines on top and below the boxes show the maximum and minimal values considered, respectively. The extreme values are indicated as '+'. On the right side of each box is the error bar of the MAPE with one standard deviation. It is obvious that both the median value of APE and MAPE from model 2 (without position information) are much higher compared with those of the other models. The spread of APE is even more pronounced. This implies that the position information has a significant influence on the performance of the proposed model, whereas incorporating the speed information and the information from the previous polling moment improve the performance only marginally. The performance of the proposed model is not sensitive to different position references (relative position or absolute position).

5. Discussion and conclusions

Link travel time estimation based on the travel times collected by probe vehicles is one important application of PVD. Up to now, there is not much research about travel time allocation using PVD. In this paper, a three-layer Artificial Neural Network model is proposed to estimate complete link travel times. The input information in the ANN model includes individual probe vehicle's positions, link IDs, time stamps and speeds. The estimation results are compared with those from Hellinga's model. As discussed in Section 3, the ANN model performs quite well under different traffic conditions. On average, the MAPE is less than 6%. As for Hellinga's model, the performance decreases significantly when the traffic demand is increasing. The MAPE increases from 12% to 20%. In Hellinga's model, the link travel time is composed of free flow travel time, stopping time and congestion time. When congestion occurs, stopping time and congestion time are the main components of the estimated link travel time, which also suggests that stopping probability and congestion probability should be properly calibrated, especially when dealing with signalized intersections. The delay time can be caused by either traffic control or congestion. One thing worth mentioning is that the number of parameters in the ANN model is much higher than those in Hellinga's model as discussed in Section 3. The better performance of the ANN model is probably also due to the higher number of parameters. The conclusion might be that Hellinga used a too simple model to give a valid estimation of the link travel time.

From the sensitivity analysis of the input information in Section 4, it was found that the position is an important factor influencing the accuracy of the ANN model. When no position information is applied, the performance of the ANN model deteriorates significantly as shown in Fig. 8. One plausible reason for this phenomenon is that the position provides implicit information about intersections, which are considered to be critical in estimating link travel times on the urban road network. It could be concluded that the position of a probe vehicle on a link, e.g., close to the intersection, in the middle of the link or downstream of an intersection, is a very important piece of information for link travel time estimation in our proposed model. The measured speed is not a critical factor influencing the performance of the ANN model as discussed in Section 4. The accuracy of the ANN model improves marginally when speed information is applied. As we know, speed information is commonly used to indicate the traffic state on the freeway. However, speed is not such a good indicator on an urban road network. Speeds are volatile and can change largely within one time step.

The proposed ANN model in the paper deals with link travel time estimation. In future, it is recommended to validate this model based on a larger real data set. Further, it is also recommended to apply this model to estimate the route travel time based on the PVD. Finally, further research could be done to combine an analytical model with the ANN model to give better estimation of travel times on the urban road network.

Acknowledgements

This work has been made possible by financial support from TRANSUMO (TRANsition towards SUstainable MObility) and the Chinese National Science Commission.

References

Bhaskar, A., Chung, E., Dumont, A.G., 2009. Travel time estimation on urban networks with mid-link sources and sinks. In: TRB 88th Annual Meeting, Washington, DC.

Chan, K.S., Tam, M.L., 2008. Using spatial travel time covariance relationships for real-time estimation of arterial travel times. In: 87th Annul meeting of Transportation Research Board, Washington, DC, USA.

Hellinga, B., Izadpanah, P., Takada, H., Fu, L.P., 2008. Decomposing travel times measured by probe-based traffic monitoring systems to individual road segments. Transportation Research Part C: Emerging Technologies 16, 768–782.

Jula, H., Dessouky, M., Ioannou, P.A., 2008. Real-time estimation of travel times along the arcs and arrival times at the nodes of dynamic stochastic networks. IEEE Transactions on Intelligent Transportation Systems 9, 97–110.

Kwon, J., Petty K., 2005. A travel time prediction algorithm scalable to freeway networks with many nodes with arbitrary travel routes. In: TRB 84th Annual Meeting, Washington, DC.

Li, Y., McDonald, M., 2002. Link travel time estimation using single GPS equipped probe vehicle. In: The IEEE 5th International Conference on Intelligent Transportation Systems, Singapore.

Liu, H., 2009. A virtual vehicle probe model for time-dependent travel time estimation on signalized arterials. Transportation Research Part C: Emerging Technologies 17, 11–26.

Liu, H., Van Lint, H., Van Zuylen, H.J., 2007. Neural-network-based traffic flow model for urban arterial travel time prediction. In: TRB 86th Annual Meeting, Washington, DC.

Liu, H., Van Zuylen, H.J., Van Lint, J.W.C., Salomons, M., 2006. Urban arterial travel time prediction with state-space neural networks and Kalman filters. Transportation Research Record: Journal of the Transportation Research Board 1968, 99–108.

Oh, J.S., Jayakrishnan, R., Recker, W., 2003. Section travel time estimation from point detection data. In: 82nd Annual Meeting of Transportation Research Board, Washington, DC, USA.

Petty, K.F., Bickel, P., Ostland, M., Rice, J., Schoenberg, F., Jiang, J., Ritov, Y.A., 1998. Accurate estimation of travel times from single-loop detectors. Transportation Research Part A: Policy and Practice 32, 1–17.

Ranganathan, A., 2004. The Kevenberg–MArquardt Algorithm.

Robinson, S., Polak, J.W., 2005. Modeling urban link travel time with inductive loop detector data by using the k–NN method. Transportation Research Record: Journal of the Transportation Research Board 1935, 47–56.

Van Lint, J.W.C., Hoogendoorn, S.P., Van Zuylen, H.J., 2005. Accurate travel time prediction with state-space neural networks under missing data. Transportation Research Part C: Emerging Technologies 13, 347–369.

Van Lint, J.W.C., Van Der Zijpp, J., 2003. Improving a travel time estimation algorithm by using dual loop detectors. Transportation Research Record: Journal of the Transportation Research Board 1855, 41–48.