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Highway travel time estimation using multiple data sources

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Jure Pirc[1] ✉, Goran Turk[2], Marijan Žura[2]
[1]*Q-Free Traffic Design, Kamniška 50, 1000 Ljubljana, Slovenia*
[2]*Faculty of Civil and Geodetic Engineering, University of Ljubljana, Jamova 2, 1000 Ljubljana, Slovenia*
✉ *E-mail: jure.pirc@q-free.com*

Abstract: Travel time is considered the most useful travel related information as it is the best indicator of the level of service on the road stretch and is completely understandable to all users. Various technologies for measuring traffic flow parameters provide the optimal background for the implementation of data fusion schemes to gain the maximum accuracy from the combination of the available data. The objective of the data fusion is to gain knowledge of predicted departure based travel time from the two outdated accurate measurements. In this paper a new and simple algorithm is proposed for short-term highway travel time prediction by fusing direct travel time measurements estimated by vehicle reidentification, indirect travel time estimated by the extrapolation of spot speed measurements and additional qualitative data in terms of the level of service. The proposed algorithm has been in operation on the A1 highway in Slovenia for more than two years and has shown robust behaviour in the real world environment. The algorithm is capable of providing short-term travel time prediction in real time with a 9 % better accuracy than the presently used travel time prediction algorithms.

1 Introduction

1.1 Travel time

Travel time is a key input to today's modern traffic management and control systems [1] as it is the best indicator of the level of service (LOS) on a road stretch [2], and is completely understandable to all users. Travel time is the worthiest information from the user's point of view [3]. It is also useful to the road operators as it is a basic input for assessing the operational management of a highway, and is a good indicator of the LOS and effectiveness of traffic systems [4].

There are two main methodologies for estimating the travel time on a road link: direct measurement and indirect estimation [5]. The first one depends on measuring the time a chosen vehicle needs for covering the distance from point A to point B. By using direct measurements, a representative sample of the measurements is required since the outliers can ruin the reliability of travel time estimation. The outliers in this instance are vehicles, whose shortened or extended travel times are not related to traffic conditions, but are the result of individual behaviour of each vehicle. Various AVI based methods for measuring travel times between consecutive locations have emerged in the recent years [6]: license plate matching [7], Bluetooth signature reidentification [8, 9], reidentification of toll tags [10], travel time measurements in closed toll highways by using traditional tickets [11] and so on. As the measurement is available only after the vehicle has completed the journey, this time lag represents an outstanding shortcoming of real time information systems, especially when congestion builds up or dissolves.

An alternative is the indirect travel time estimation from the measured traffic flow parameters, such as speed and flow from the spot measurements and their extrapolation to the target section. In this method each subsection of the longer section is assigned to one spot measurement site, and the assumption is made that this point detector is representative for the entire subsection. This assumption is acceptable only during the free flow traffic conditions, but it can completely ruin the estimation in case of evolving traffic conditions. The travel time for a longer section is estimated by summing up the travel times estimated on the subsections in the latest time interval. The main benefit of using the indirect travel time estimation is therefore in the temporal immediacy of the information.

On the one hand, the directly measured travel time provides accurate travel time measurements with a time delay, while on the other hand, the indirect estimation is characterised by a limited spatial coverage, although has the benefit of temporal immediacy. The situation represents an optimal environment for data fusion, combining the characteristics of individual measurements in combination with greater precision.

1.2 Time lag of direct measurements and spatial limitations of spot speed estimation

The reason for combining data from different sources is therefore to ensure a more efficient, more reliable and more accurate result than the primary source of information that is combined. By fusing various data sources, each of them may contribute specific advantages. Data fusion can lead to an improved operational efficiency of the system, and to the extended spatial and temporal coverage.

The drawback of accurate direct travel time measurements is the time lag that exists between the measured and the true travel time, the final objective of the estimation that is not known at the moment. The time lag between measured and true travel time is equal to the time needed for traversing the section. The time lag is attributable to time difference between the cars from which the travel time is estimated and the cars receiving the travel time information [12]. As can be seen from Fig. 1, $t–\Delta$ represents the departure time of the vehicles used for disseminating the measured travel time to the vehicles departing at a current time t. The difference Δ between $t–\Delta$ and t is the time lag in information dissemination. This time lag is not evident in the case of the free flowing traffic, but can have a negative effect in case of dramatic changes in traffic conditions.

On the other hand, the current travel time estimated from the extrapolation of the spot speed measurements reflects the very last events on the highway, while the measured travel time is available only when the vehicle finishes its journey. In congestion situations with frequent stop-and-go traffic, the measured spatial mean speed from point detectors can be very different from the real mean speed of traffic flow on the concerned subsection, as detectors only

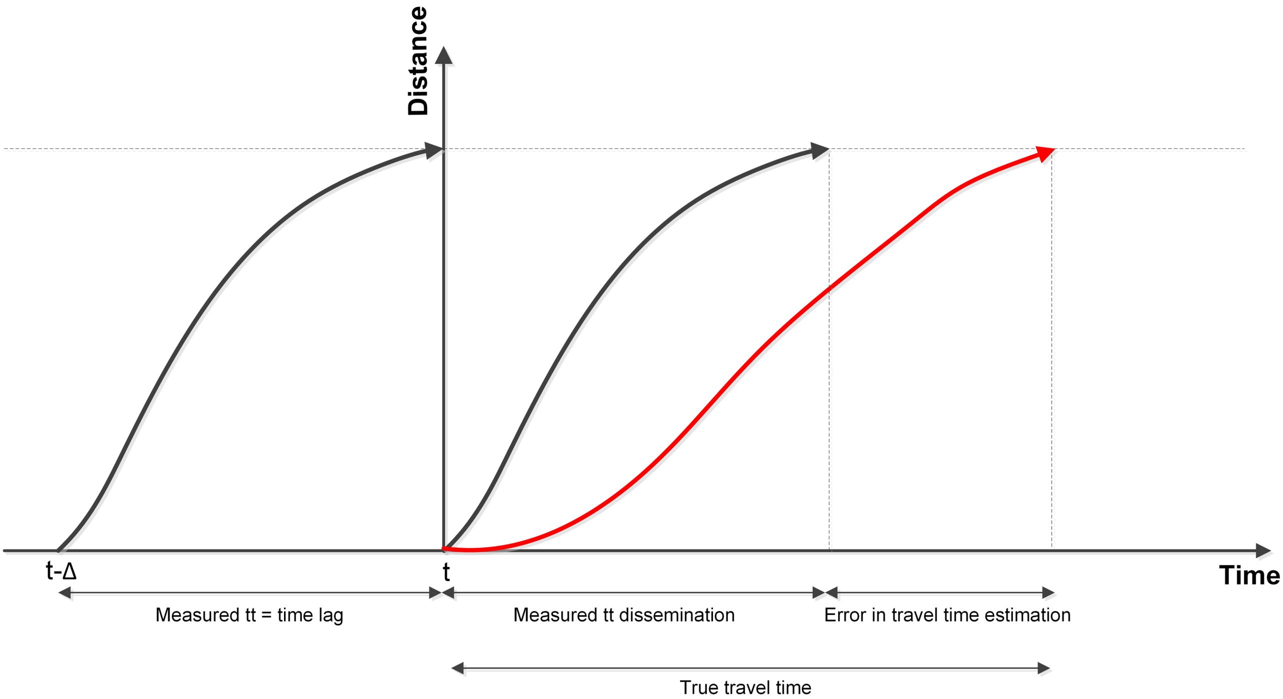

Fig. 1 *Time lag problem: error in travel time estimation based on measured travel times*

measure the speed of the vehicles on one location. As a result of this flaw, travel time estimations using this algorithm in congested situations can be largely under or overestimated.

The information that is available at the time instance t are the measured arrival based travel time for the previous time interval gathered from the direct travel time measurements and the indirectly estimated travel time extrapolated from the point speed measurements both for the time intervals t_{i-1}, t_i. The challenge of the short-term travel time prediction is how to predict the expected departure based travel time for the next time intervals t_i, t_{i+1} on the basis of the arrival based measured travel time and estimated current travel time (both from the previous time intervals t_{i-1}, t_i).

1.3 Findings from the literature

Various algorithms and methodologies have been developed to estimate travel time data from traffic measurements. Turner *et al.* [13] give a comprehensive overview of these estimation methods. Studies of various data fusion methodologies are found in the literature [13, 14]. They can be conceptually divided into parametric models (linear regression, auto regression (ARIMA), vector regression, Kalman filter), non-parametric models (neural networks, Bayesian model, Dempster–Shafer theory, fuzzy logic, *k*-nearest neighbours algorithm) and hybrid models combining various before mentioned models. Detailed description of various methods and algorithms for travel time data fusion can be found in [5].

Although travel time data fusion has been tackled from various perspectives, a preferred fusion method is still not established since individual studies cannot be accurately compared due to lack of a common measure of effectiveness. Consequently, only a few researchers have made an attempt to compared their proposed technique with alternative techniques. One of the few comprehensive evaluations of data fusion techniques for traffic speed estimation known to the authors was made by Bachmann *et al.* [15]. In their study various multi-sensor data fusion based estimation techniques were investigated: linear regression, Kalman filter, ordered weighted averaging, fuzzy logic and artificial neural networks. They found that each of the data fusion techniques investigated perform reasonably well, and in almost all cases decreases the estimation error. In a practical sense, many of these techniques perform similarly, and there is certainly not a single method that substantially outperforms all others in all cases. This is an important conclusion, since many algorithms are quite complex, and their complexity is questionable since they do not result in an essential added value. As some of the methods are much simpler to understand, implement, and compute than others, it might be difficult to justify the implementation of a complex algorithm, if it does not outperform its competition substantially [15].

The objective of the proposed data fusion algorithm is to provide the driver entering the highway with accurate information on the travel time for the trip he is going to undertake. Since none of the existing studies takes into account qualitative measures used to relate the quality of traffic service in terms of performance measures such as speed, flow and density this paper proposes a new data fusion method that also includes information about the LOS as an additional input variable. If judged by the results of its application on A1 highway in Slovenia during two years testing period, this simple travel time data fusion algorithm outperforms most commonly used travel time estimation algorithms.

2 Data fusion methodology

2.1 Data fusion

The main purpose of the proposed algorithm is to provide the value of travel time as input to a travel time information system. Since the system should provide the driver with a departure-based travel time information, some kind of forecast must be made [16]. The nature of the algorithm requires the ability of real-time learning of new incident situations based on predefined structure of the model, thereby gradually improving the effectiveness of the algorithm by self-learning.

The algorithm for combining the directly measured and indirectly estimated travel times was chosen based on the purpose of the data fusion, sensor configuration and predicted input data behaviour. The data architecture was defined by taking into account the desired robust behaviour of the algorithm. The proposed data fusion algorithm is based on the multiple linear regression, that turns out to be the optimal solution in terms of the complexity and computational effort needed [17]. Multiple linear regression attempts to model the relationship between explanatory variables (directly measured travel time, travel time estimated from spot speed measurements, LOS) and a response variable (departure-based travel time) by fitting a linear equation to observed data [18]. Every value of the independent variable is associated with a corresponding value of the dependent variable.

In contrast to the existing studies that take into account only the quantitative measurements of traffic flow, the proposed algorithm

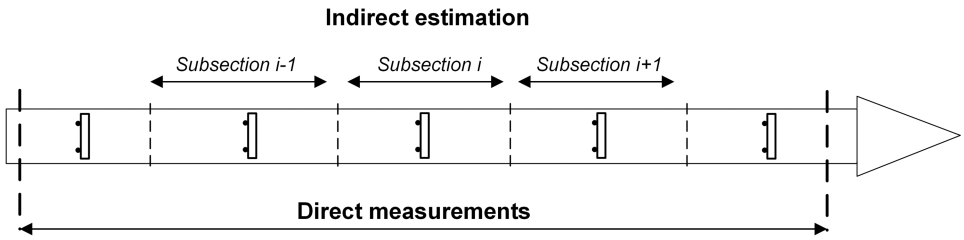

Fig. 2 *Spatial alignment of direct measurements and indirect estimation*

was upgraded with additional input data in terms of the LOS. The method estimates the representative value of travel time based not only on the input data from personal cars, but also taking into account the LOS as a good indicator of the traffic conditions on the highway. By combining three data sources, a short-term travel time prediction is achieved.

2.2 Original data to be fused

The detailed description how the original data to be fused is obtained is out of the scope of the paper, therefore only a short description is provided. The herein proposed algorithm fuses one linear measurement and two point estimations. The linear measurement is obtained by an algorithm using robust statistics to eliminate the outliers, further on described in [19]. The first point estimation is based on personal cars measured speed obtained from spot measurements and extrapolated to the belonging subsection. To ensure the robustness and a quick response a special algorithm has been developed that is able to smooth random speed fluctuations while providing a quick response to abrupt changes in traffic flow. The method is able to determine whether a speed variation represents a random fluctuation due to individual driver's behaviour and should therefore be smoothed or is a consequence of a change in traffic conditions as a result of a shock wave and should therefore be kept as it is in order to provide prompt response of the algorithm. The travel time on the section is then obtained by summing up the travel time values from each individual subsection.

The second point estimation is based on the information about the LOS. LOS is a qualitative measure used to relate the quality of traffic service. It is used to characterise highways by categorising traffic flow and assigning quality levels of traffic based on performance measure like speed, density and so on. LOSs are obtained from the ATMS system, by measuring speed and calculating density of all vehicle classes at 13 locations along the observed highway. Specific speed and density thresholds (Table 1) are then used to determine LOS 0 to 4, with 0 being the best and 4 being the worst [20].

2.3 Spatial and temporal alignment

When fusing the data on travel times obtained from the direct measurements and from indirect estimation, the data from sources with different spatial coverage and different sampling time intervals is combined. Therefore their spatial and temporal alignment should be made before fusing the two sources.

In our case, the section defined by direct measurements coincides with subsections that are assigned to the spot speed measurement sites. This means that the subsections assigned to spot speed measurements form the same section as the direct measurement section. This ensures the spatial alignment of the two measurements, as shown in Fig. 2: spatial alignment.

Beside the spatial alignment, the temporal alignment of the measurements should be made as well. To ensure representative sample of direct travel time measurements, a longer sampling time interval is needed as compared to data obtained from spot speed measurements where shorter sampling time interval is needed to detect fluctuations in traffic flow. The temporal alignment is therefore made based on a shorter sampling time interval, in our case of spot speed measurements, while the data from direct measurements remain constant until the next updating. In our case the direct travel time measurements sampling time interval $\Delta T = 5$ min, while the spot speed measurements are updated every $\Delta t = 1$ min (Table 2).

2.4 Data fusion architecture

The centralised data fusion architecture was used, where the fusion unit is located at a central processor that collects all raw data from various sensors as shown in Fig. 3. All processing and decisions are made at this node, and appropriate instructions or task assignments are given out to the respective sensors.

For each sampling time interval (1 min) and for each subsection (13 subsections in our case) defined by the spot measurement equipment, the travel time obtained by the speed extrapolation (TT) and the information about the LOS are provided beside the measured travel time (tt) for the whole section (Table 3).

During the evaluation phase, two different data fusion architecture schemes were compared in terms of how accurately they are able to predict the departure-based travel time:

- Proposed algorithm $tt + TT_i + \mathrm{LOS}_i$, fusing travel time TT_i and level of service LOS_i from spot measurements and directly measured tt.
- Existing algorithm $tt + TT_i$, fusing travel time TT_i from spot measurements and directly measured tt.

2.5 Learning phase of the algorithm

To ensure an optimal performance of the algorithm for data fusion, an initial learning period of the algorithm is needed. This is done with sample data and can be regarded as a kind of algorithm adaptation or calibration. The input data for the algorithm learning can be real measurements or simulated data (microsimulation). The latter data allow learning of various traffic situations not yet observed in real examples on the concerned highway section.

Microsimulation was also used as a comparison. The learning of the algorithm based on the simulated data was done using VISSIM microscopic simulation program for traffic flow modelling. The model has been calibrated through multiple field measurements at the Technical University of Karlsruhe, Germany. Periodical field measurements and their resulting updates of model parameters ensure that changes in driver behaviour and vehicle improvements are accounted for. The system has been validated by

Table 1 LOS estimation in Slovenian ATMS

Speed level	Speed, km/h	Density level	Density, veh./km		G0	G1	G2	G3	
V0	0–30	G0	0–5	V0	LOS 0	LOS 4	LOS 4	LOS 4	
V1	31–50	G1	6–40	V1	LOS 0	LOS 3	LOS 3	LOS 4	
V2	51–60	G2	41–75	V2	LOS 0	LOS 0	LOS 2	LOS 3	
V3	61–75	G3	>75	V3	LOS 0	LOS 0	LOS 2	LOS 2	
V4	>75				V4	LOS 0	LOS 0	LOS 2	LOS 2

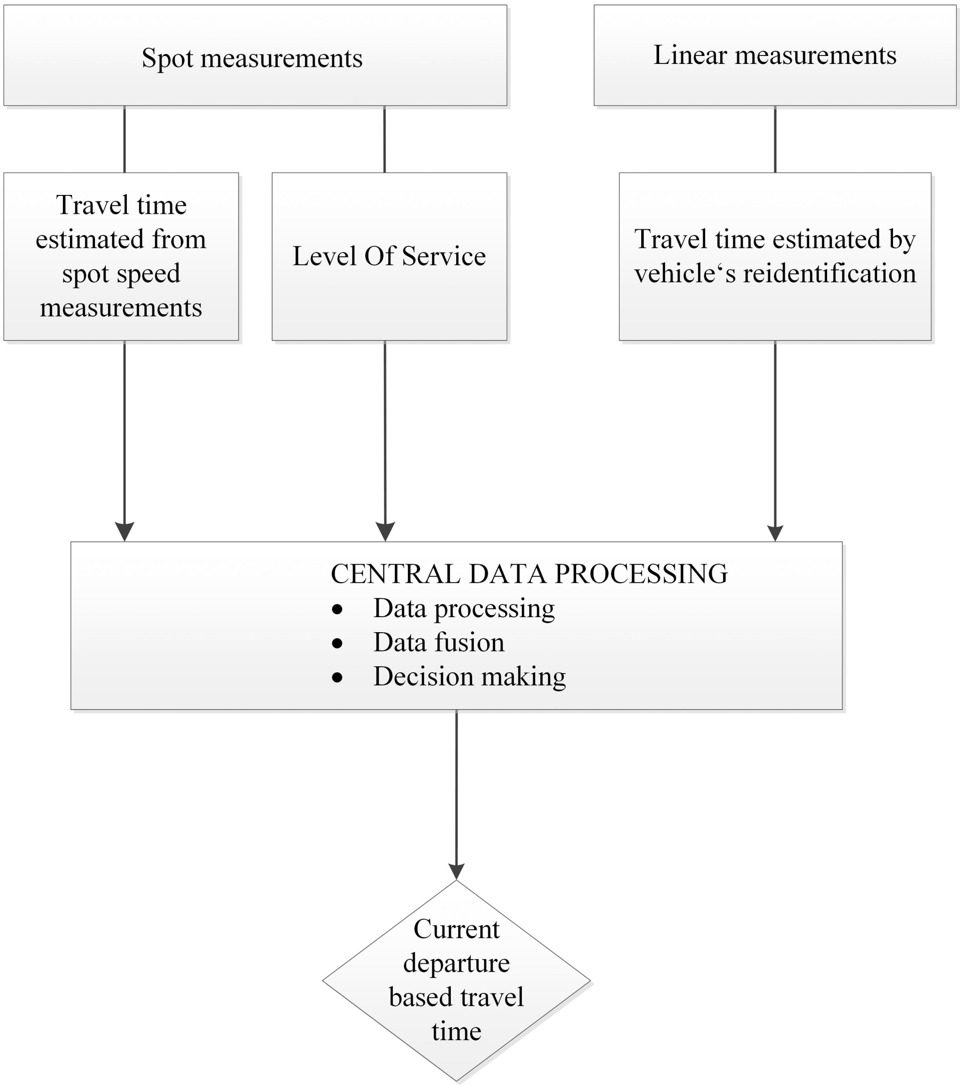

Fig. 3 *Data fusion algorithm*

comparing modelled and measured travel times on the concerned highway section. Input data like speed distribution, vehicle type and type of the driver are based on field observations.

With microsimulation tool various traffic situations were modelled including different traffic flows, different capacities and various parameters such as the type of vehicles and drivers, distribution of speed, speed limits and so on. By using a microsimulation tool different scenarios were tested: traffic accidents, lane closures, tunnel closure and so on, all of them along various locations along the highway section concerned. During the learning period different incident situations along the highway section were simulated to ensure alternation of the independent

Table 2 Temporal alignment of direct measurements and indirect estimation [5]

			Travel time data estimation Space					Spatial and temporal aligned data to be fused
time			point	subsection i	subsection $i+1$	· · ·	subsection $i+n$	
			linear		section (i,j)			
	ΔT	Δt	point	$TT_{i(t)}$	$TT_{i+1(t)}$	· · ·	$TT_{i+n(t)}$	$TT_{i(t)}+TT_{i+1(t)}+\cdots+TT_{i+n(t)}$
			linear		$tt_{AB(T)}$		$tt_{AB(T)}$	
		Δt	point	$TT_{i(t+1)}$	$TT_{i+1(t+1)}$	· · ·	$TT_{i+n(t+1)}$	$TT_{i(t+1)}+TT_{i+1(t+1)}+\cdots+TT_{i+n(t+1)}$
			linear		$tt_{AB(T)}$		$tt_{AB(T)}$	
		Δt	point	$TT_{i(t+2)}$	$TT_{i+1(t+2)}$	· · ·	$TT_{i+n(t+2)}$	$TT_{i(t+2)}+TT_{i+1(t+2)}+\cdots+TT_{i+n(t+2)}$
			linear		$tt_{AB(T)}$			$tt_{AB(T)}$
		Δt	point	$TT_{i(t+3)}$	$TT_{i+1(t+3)}$	· · ·	$TT_{i+n(t+3)}$	$TT_{i(t+3)}+TT_{i+1(t+3)}+\cdots+TT_{i+n(t+3)}$
			linear		$tt_{AB(T)}$			$tt_{AB(T)}$
		Δt	point	$TT_{i(t+4)}$	$TT_{i+1(t+4)}$	· · ·	$TT_{i+n(t+4)}$	$TT_{i(t+4)}+TT_{i+1(t+4)}+\cdots+TT_{i+n(t+4)}$
			linear		$tt_{AB(T)}$		$tt_{AB(T)}$	
			point	$TT_{i(t+5)}$	$TT_{i+1(t+5)}$	· · ·	$TT_{i+n(t+5)}$	$TT_{i(t+5)}+TT_{i+1(t+5)}+\cdots+TT_{i+n(t+5)}$
			linear		$tt_{AB(T+1)}$			$tt_{AB(T+1)}$

Where *TT* is travel time estimated based on the extrapolation of spot speed measurements and *tt* is travel time from the direct measurements.

Table 3 Input data for travel time data fusion algorithm combining travel time estimates based on speed extrapolation (*TT*) and direct measurements (measured *tt*) and an example of prolonged travel times on seventh subsection (grey). All times are in seconds, LOS is the information about the LOS

Subsection	1		2		6		7		8		12		13		Measured *tt*	*Departure TT*
Time	*TT*	LOS	*TT*	LOS	*TT*	LOS	*TT*	LOS	*TT*	LOS	*TT*	LOS	*TT*	LOS		
3.12.2013 6:15	19	0	53	0	56	0	36	0	67	0	47	0	31	0	796	1003
3.12.2013 6:16	19	0	53	0	56	0	36	0	67	0	47	0	32	0	796	1003
3.12.2013:6:17	19	0	55	0	56	0	36	0	67	0	48	0	32	0	796	1003
3.12.2013 6:18	19	0	54	0	56	0	41	1	67	0	48	0	32	0	796	1003
3.12.2013 6:19	19	0	53	0	56	0	54	2	67	0	47	0	32	0	796	1003
3.12.2013 6:20	19	0	54	0	56	0	76	2	67	0	47	0	32	0	807	1235
3.12.2013 6:21	19	0	53	0	56	0	117	3	67	0	47	0	31	0	807	1235
3.12.2013 6:22	19	0	53	0	56	0	162	3	67	0	47	0	32	0	807	1235
3.12.2013 6:23	19	0	53	0	56	0	160	4	67	0	47	0	32	0	807	1235
3.12.2013 6:24	19	0	53	0	56	0	163	4	68	0	47	0	31	0	807	1235
3.12.2013 6:25	19	0	53	0	56	0	169	4	67	0	47	0	29	0	881	1236
3.12.2013 6:26	19	0	53	0	56	0	205	4	67	0	47	0	30	0	881	1236
3.12.2013 6:27	19	0	53	0	56	0	220	4	68	0	47	0	30	0	861	1236
3.12.2013 6:28	19	0	53	0	56	0	246	4	69	0	47	0	30	0	881	1236
3.12.2013 6:29	19	0	53	0	56	0	259	4	67	0	47	0	31	0	881	1236

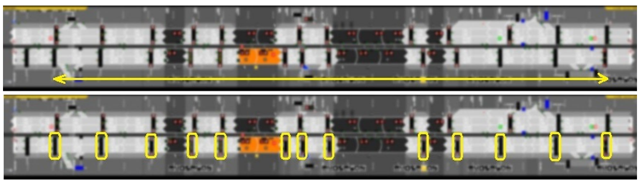

Fig. 4 *Test site providing direct travel time measurements (above) and indirect travel time estimation by spot speed measurements (below)*

variable and therefore the value of the regression coefficient, which had to be different from zero.

The learning of the algorithm needs travel time measured from direct measurements, travel time estimated by spot speed extrapolations, information about the LOS and true departure-based travel time. Obtaining the true departure-based travel time in the off-line manner is not a problem as departure based travel time and measured travel time are the same values with a time lag between observations equal to the travel time. True departure based travel time is therefore available in the off-line context.

The primary task of the algorithm learning is to model the relationship between explanatory variables and a response variable by fitting a linear equation to observed data by using regression coefficients (CoefTT_i, Coef$\text{LOS}_i$and Coef*tt*). During the learning period the algorithm obtains a knowledge based on experience while searching for the rules in the training data, which subsequently provide an optimal response in cases which do not participate in the learning process. The data fusion algorithm combines the travel times obtained by direct measurements (*tt*), by the spot speed extrapolation (TT_i), and the information about the LOS (LOS_i), both for each subsection i defined by spot measurements. The output of the algorithm is the current departure-based travel time (1) representing the estimated travel time which the driver entering the highway will need to traverse the targeting section

$$TT_{\text{estimated}} = \sum_{i=1}^{13} \text{Coef}TT_i * TT_i + \sum_{i=1}^{13} \text{CoefLOS}_i * \text{LOS}_i + \text{Coef}tt * tt \quad (1)$$

3 Research results and algorithm evaluation

3.1 Test site

In each study, it is desirable to support the theoretical findings with the data from the field. The proposed algorithm was put into practice through the travel time estimation system implemented on the A1 highway between Vransko and Blagovica being one of the busiest highway sections in the Republic of Slovenia (EU), as a part of the V. Pan-European corridor stretching from Barcelona (Spain) to Kiev (Ukraine). On this 22 km long highway stretch, the traffic is managed by an ATMS consisting of 24 variable message signs, 50 microwave detectors, 32 video detection cameras, 35 pan-tilt-zoom video surveillance cameras, 5 road weather stations, a license plate matching system and a Bluetooth signature reidentification system.

The system provides an ideal platform for experimentation, allowing for transparent and replicable testing of scientific theories, computational tools and new technologies. The test site with its challenging route and installed surveillance equipment provides a large amount of data for both free flow conditions and different incident situations resulting in congestion episodes (accidents, severe weather situations, road closures, traffic diversions etc.). The database of the events is constantly growing, and all the improvements can be tested in the real-time environment (Fig. 4).

Table 4 Determination coefficient

Linear regression	*R*	R_{adjusted}
using the information about the LOS	0.852	0.851
without the information about the LOS	0.809	0.809

3.2 Performance of the regression analysis

The main difference between the proposed and the existing algorithms is that the proposed algorithm uses additional qualitative information about the traffic flow in terms of the LOS. To determine the general performance of the algorithm two statistical measures were used, the determination coefficient and standard deviation of the regression model. The determination coefficient is the key estimate of the successfulness of regression analysis. It is interpreted as the proportion of the variance of the dependent variable that is predicted by the independent variable. R^2, is a number that indicates how well data fit a statistical model (Table 4). The higher the absolute value of *R*, the higher is the proportion of the variance of the dependent variable that is predictable by the independent variable.

The standard deviation of the regression model measures the dispersion of points around the regression line (Table 5). The lower the number, the lower is the dispersion of the points around the regression line, the better is regression.

At the last stage a statistical hypothesis testing is done trying to verify whether the variables X_i (*tt*, TT_i, LOS_i) and *Y* (departure based *TT*) are statistically significantly linearly dependent. The test

Table 5 Standard deviation of the regression model

Linear regression	σ_ε
using the information about the LOS	82.6
without the information about the LOS	93.7

defines if the specific parameters in the model (especially LOS_i) are a meaningful addition to the proposed algorithm.

Performing the statistical F test we can argue at the significance level lower than 0.05 the linear model with 27 parameters (13 subsections each defining travel time TT_i and level of service LOS_i and one measured travel time tt) significantly describes the variation within the data.

The size of the effect independent variables have on the dependent variable is tested by the T test. The null hypothesis here says that the inclusion of the term b_iX_i in the regression equation does not further explain the variability of the data. Table 6 shows that in all cases where the information about the LOS is present, the null hypothesis can be rejected at the significance level lower than 5%. Therefore the addition of the LOS statistically significantly explains the variability of the data. The smaller the P value, the lower is the risk to reject the null hypothesis and the greater is the influence of each parameter. Individual variables significantly explain the variation between the data except in certain cases, namely variable TT on subsections 8 and 13, which can be attributed to the random selection of scenarios that were tested.

As seen from the statistical measures, using the information about the LOS helps estimating the departure-based travel time in a better way.

Table 6 *P*-value determination

Subsection	Variable	*P*-value
1	*TT*	0.021663
	LOS	3.78×10^{-8}
2	*TT*	0.0240362
	LOS	4.56×10^{-22}
3	*TT*	2.88×10^{-14}
	LOS	2.67×10^{-20}
4	*TT*	8.61×10^{-6}
	LOS	2.16×10^{-22}
5	*TT*	0.0000259
	LOS	1.95×10^{-60}
6	*TT*	0.0472315
	LOS	1.33×10^{-6}
7	*TT*	3.48×10^{-12}
	LOS	6.52×10^{-6}
8	*TT*	0.431882
	LOS	1.05×10^{-95}
9	*TT*	0.00001014
	LOS	9.59×10^{-7}
10	*TT*	0.0007858
	LOS	2.82×10^{-22}
11	*TT*	0.00005364
	LOS	0.0006727
12	*TT*	0.0513988
	LOS	2.30×10^{-11}
13	*TT*	0.398209
	LOS	0.061025

3.3 Research results

During the two year's evaluation period an extensive comparison of the proposed algorithm with the existing algorithms was made. From the ATMS database, the list of all the events and incidents was extracted. Here only one example is presented in detail.

Fig. 5 *Congestion in front of the tunnel due to heavy vehicle breakdown in tunnel Trojane*

3.3.1 Lane reduction due to the heavy vehicle breakdown: On 3 December 2013 at 6:14 am the breakdown of a heavy vehicle occurred. As the event happened in the morning peak period, the result was a queue and prolonged travel times (Fig. 5).

Comparing the coefficient of correlation for different data fusion architectures (Fig. 6 top left), a strong positive correlation can be seen in relation to the departure-based travel time. From the coefficient of correlation point of view, the proposed algorithm performed best with a value of 0.94. As expected, the lowest value is achieved by direct travel time measurement as the vehicle has to finish the journey before the information is available. Comparing the root mean squared error (RMSE) gives similar results (Fig. 6 top right). By using the proposed algorithm the error made compared with the directly measured travel times is reduced for 47%, and compared with the existing algorithms not using the information about the LOS, the error is reduced for 6%.

If the learning of the algorithm is made only by the data based on simulations (Fig. 6 bottom left), the coefficient of correlation (0.94) is lower than if the learning set contains only the data from real situations (0.96). The same is with the RMSE (Fig. 6 bottom right) where learning the algorithm based on real events reduced the error by 28% compared with learning based only on simulations.

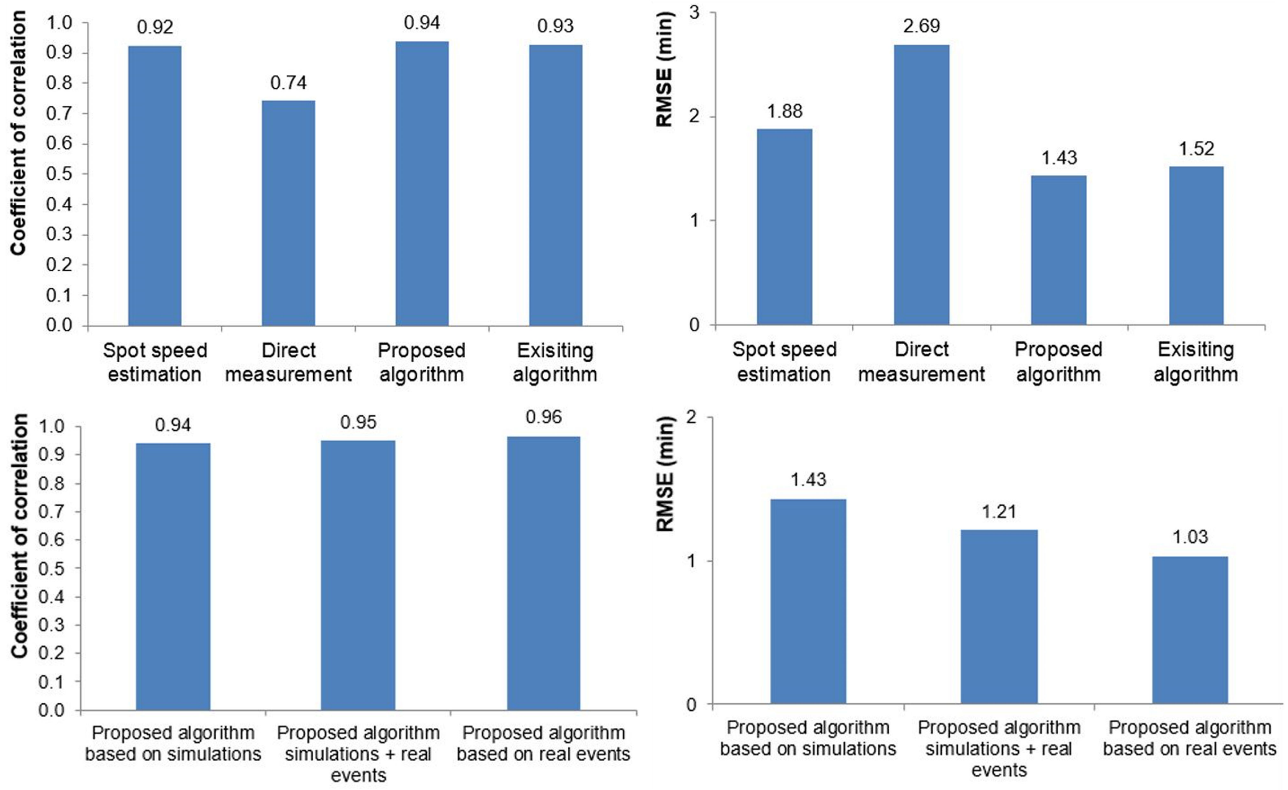

Fig. 6 *Comparing coefficient of correlation and RMSE error for different data fusion architectures (above) and for different learning sets (below) for a concrete example of prolonged travel times due to a lane reduction*

Coefficient of correlation and RMSE do not give a complete picture about the performance of the algorithm. An important aspect is also the response of the algorithm to prolonged travel times when the queue builds up, and to reduced travel times after the congestion dissolves. Comparison between the direct travel time measurement and the departure-based travel time (Fig. 7) exhibits the time lag of the direct measurements, since the vehicle has to finish the journey before the information becomes available for dissemination. Informing the drivers based on measured travel times can therefore deliver information that is absolutely mistaken. On the other hand, travel time estimated from the spot speed measurements reduces the information delay if compared with directly measured travel time. As the traffic conditions are not equal along the entire subsection, the trip travel time estimated by spot speed measurements also differ from the departure-based travel time.

When showing travel times estimated by the proposed algorithm to the same graph (Fig. 7 bottom), a much better fit to the departure-based travel time can be observed. As seen from Fig. 7 bottom, the vehicles entering the section at 6:20 needed around 21 min to traverse the section. The proposed algorithm estimated the prolonged travel times just 3 min later, at 6:23, when the speed drop was observed at the first spot measurement site just a few hundred metres before the incident took place. Algorithm based on the directly measured travel times did react to the prolonged travel times 20 min later, at 6:40.

3.3.2 Findings based on the analysis of various incidents: Comparison between the performances of different data fusion architectures for various events that happened in the evaluation period shows that including the qualitative information about the LOS significantly improves the estimation of the departure-based travel time.

Comparing the RMSE for different data estimation algorithms versus the departure-based travel time (Fig. 8 top right), by using the proposed algorithm the error made compared with the directly measured travel times is reduced for 43%, and compared with the existing algorithms not using the information about LOS, the error is reduced for 9%.

As seen from the results, the proposed algorithm outperforms existing algorithms. In addition, the spot speed estimation of travel time performs much better than the direct measurement. This means that indirect estimation with temporal immediacy, although with limited spatial coverage, gives better results than accurately measured, but delayed travel time.

If the learning of the algorithm is made only based on the data from simulations (Fig. 8 below left), the coefficient of correlation (0.79) is lower than if the learning set contains only the data from real situations (0.84). The same is with the RMSE (Fig. 8 bottom right), where learning the algorithm based on real events reduced the error by 8% compared with learning based only on simulations. This means that the algorithm is capable of self-learning based on the historical data, which will in the future significantly improve its performance.

4 Conclusion

This paper presents a new and simple algorithm for short-term highway travel time prediction. It is obtained by fusing direct travel time measurements, indirect travel time estimation and additional qualitative data in terms of the LOS for the driver entering a highway section concerned.

As none of the existing studies takes into account the qualitative measurements of traffic flow, the proposed algorithm was upgraded with additional input data in terms of the LOS. For combining the data from multiple sources, the multiple linear regression was chosen. It was observed that additional qualitative data helps the algorithm to learn complex relationships between the variables. The method estimates the representative value of travel time based only on the input data from personal cars, while taking into account also the LOS estimated based on all vehicles data. By combining data sources, a good short-term travel time prediction is achieved, as the input for the travel time information system.

The results of the two-year's evaluation period on the A1 highway in Slovenia showed that including the qualitative information about the LOS significantly improves the estimation of the departure-based travel time. Comparison between the performances of different data fusion architectures for various events that happened in the evaluation period shows that the

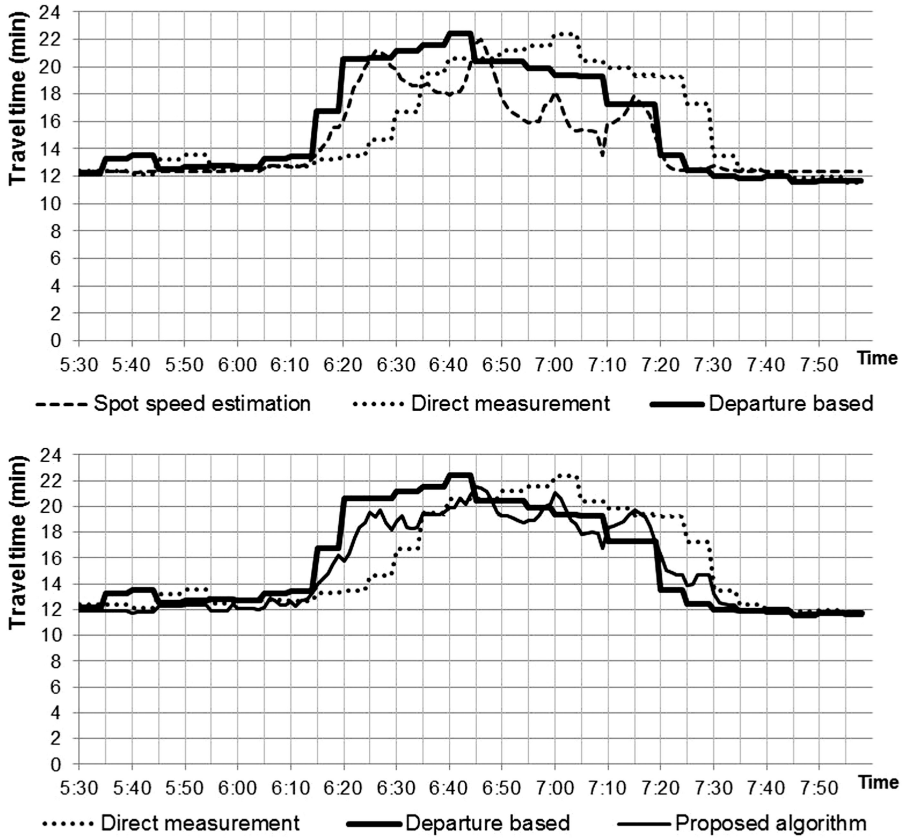

Fig. 7 *Comparing directly measured and estimated travel time with departure based travel time with evident time lag of the measured travel time (above) and reduced time lag when using proposed algorithm for travel time estimation by fusing different data sources (below)*

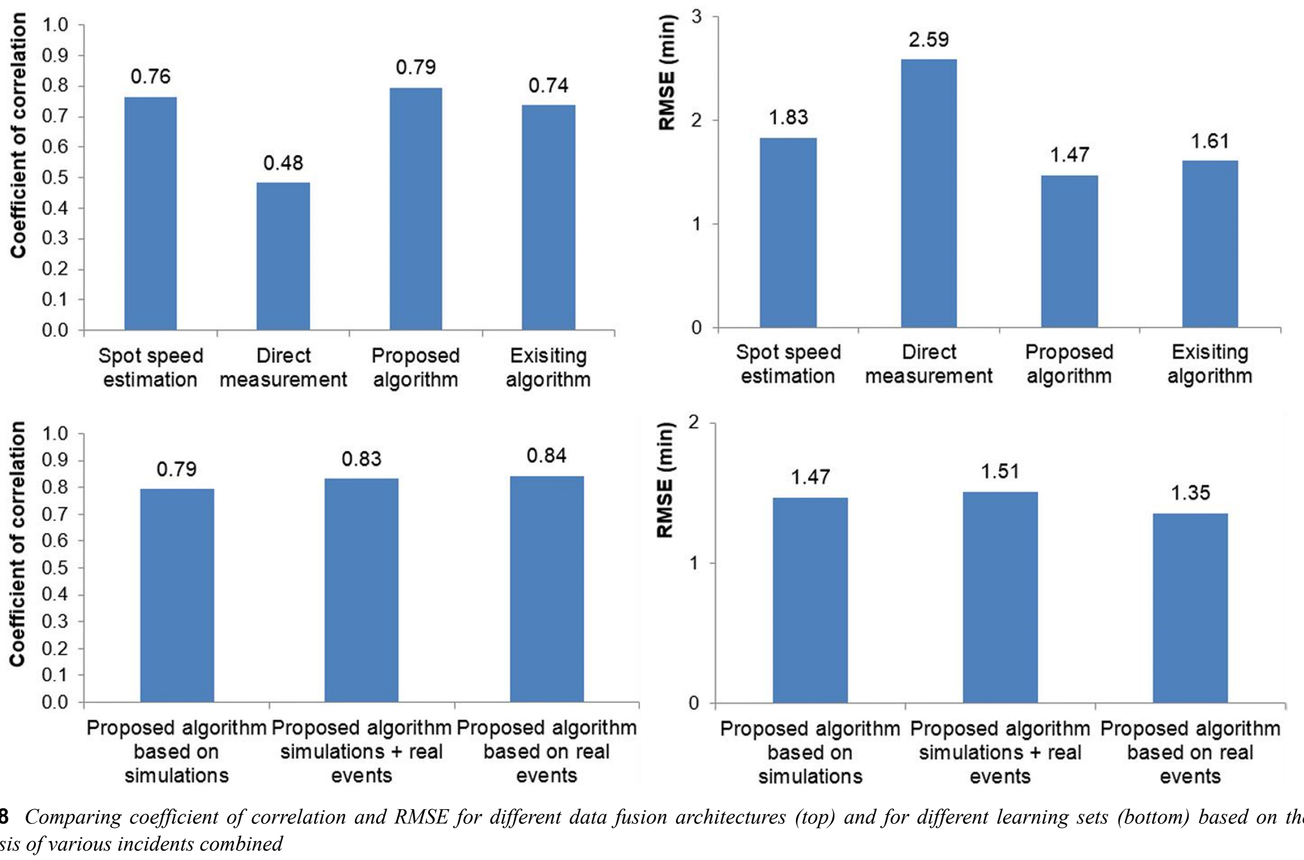

Fig. 8 *Comparing coefficient of correlation and RMSE for different data fusion architectures (top) and for different learning sets (bottom) based on the analysis of various incidents combined*

algorithm can predict travel times 9% more accurate than the existing travel time algorithms. RMSE for all incident situations in the evaluation period was less than 1 min and 30 s, which means that the proposed algorithm is capable of providing the travel time forecast with the error of less than 90 s. As seen from the results, the proposed algorithm outperforms the raw data and existing algorithms.

The algorithm is capable of self-learning based on the historical data, which will in the future significantly improve its performance. The proposed algorithm has shown a high accuracy and low computational effort and can be easily put into practice with all different, already existing measurement technologies on the highways.

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6 References

[1] Markovič, H., Bašić, B.D., Gold, H., *et al.*: 'GPS data based non-parametric regression for predicting travel times in urban traffic networks', *Promet – Traffic Transp.*, 2010, **22**, (1), pp. 1–13

[2] El Faouzi, N.-E., Billot, R., Bouzedba, S.: 'Motorway travel time prediction based on toll data and weather effect integration', *IET Intell. Transp. Syst.*, 2010, **4**, (4), pp. 338–345

[3] Margulici, J.D., Ban, X.: 'Benchmarking travel time estimates', *IET Intell. Transp. Syst.*, 2008, **2**, (3), pp. 228–237

[4] Berta, T., Török, A.: 'Travel time reduction due to infrastructure development in Hungary', *Promet – Traffic Transp.*, 2010, **22**, (1), pp. 23–27

[5] Soriguera, F., Robusté, F.: 'Highway travel time accurate measurement and short-term prediction using multiple data sources', *Transportmetrica*, 2009, **7**, (1), pp. 1–25

[6] Cambridge Systematics Inc.: 'Travel time data collection'. White paper, Florida Department of Transportation, District IV, 2012, p. 52

[7] Yasin, A.M., Karim, M.R.: 'Travel time measurement in real-time using automatic number plate recognition for Malaysian environment', *J. Eastern Asia Soc. Transp. Studies*, 2009, **8**, p. 14

[8] Malinovskiy, Y., Wu, J.Y., Lee, U.K.: 'Field experiments on Bluetooth based travel time data collection'. Proc. of the 89th Annual Meeting of the Transportation Research Board, Washington, DC, USA, 2010, p. 17

[9] Pucket, D.D., Vickich, M.J.: *'Bluetooth-based travel time speed measuring systems development'. Final report*, Department of Transportation, Research and Innovative Technology Administration, Washington, DC, USA, 2010, p. 56

[10] Schneider, M., Linauer, M., Hainitz, N., *et al.*: 'Traveller information service based on real-time toll data in Austria', *IET Intell. Transp. Syst.*, 2009, **3**, (2), pp. 124–137

[11] Soriguera, F., Rosas, D., Robusté, F.: 'Travel time measurement in closed toll highways', *Transp. Res. B*, 2010, **44**, (10), pp. 1242–1267

[12] Lim, S., Lee, C.: 'Data fusion algorithm for travel time prediction improvement'. Proc. of the 17th ITS World Congress, Busan, S. Korea, 2010, p. 16

[13] Turner, S.M., Eisele, W.L., Benz, R.J., *et al.*: *'Travel time data collection handbook'. Research report FHWA-PL-98-035*, Federal Highway Administration, Washington, DC, USA, 2008, p. 341

[14] Fei, X., Lu, C.C., Liu, K.: 'A Bayesian dynamic linear model approach for real-time short-term freeway travel time prediction', *Transp. Res. C*, 2011, **19**, pp. 1306–1318

[15] Bachmann, C., Roorda, M.J., Abdulhai, B., *et al.*: 'Fusing a Bluetooth traffic monitoring system with loop detector data for improved freeway traffic speed estimation', *J. Intell. Transp. Syst.*, 2013, **17**, (2), pp. 152–164

[16] Kehagias, D., Salamanis, A., Tzovaras, D.: 'Speed pattern recognition technique for short-term traffic forecasting based on traffic dynamics', *IET Intell. Transp. Syst.*, 2015, **9**, (6), pp. 646–653

[17] Xu, W.: 'Vehicle travel time prediction based on multiple kernel regression', *J. Netw.*, 2014, **9**, (7), pp. 1921–1926

[18] Andrews, D.F.: 'A robust method for multiple linear regression', *Technometrics*, 1974, **16**, (4), pp. 523–531

[19] Pirc, J., Turk, G., Žura, M.: 'Using the robust statistics for travel time estimation on highways', *IET Intell. Transp. Syst.*, 2015, **9**, (4), pp. 442–452

[20] Pirc, J.: 'Evaluation of traffic model as a part of the traffic management system on highways'. Master thesis, Faculty of Civil and Geodetic Engineering, Ljubljana, Slovenia, 2008