21st EURO Working Group on Transportation Meeting, EWGT 2018, 17-19 September 2018, Braunschweig, Germany

Assessing traffic-related environmental impacts based on different traffic monitoring applications

João Teixeira[a], Eloísa Macedo[a,*], Paulo Fernandes[a], Jorge M. Bandeira[a], Nagui Rouphail[b], Margarida C. Coelho[a]

[a]*University of Aveiro, Department of Mechanical Engineering, Centre for Mechanical Technology and Automation, Campus Universitário de Santiago, 3810-193, Aveiro, Portugal*

[b]*NC State University, Department of Civil, Construction and Environmental Engineering, 208 Man Hall, Raleigh NC 27695-7908, North Carolina, United States of America*

Abstract

The objective of this study is to propose a methodological approach to assess the capability of different traffic monitoring applications to estimate emissions generated by road traffic. Global Navigation Satellite Systems and traffic data were collected from different roadways in Portugal and Spain. Emissions were estimated through the Vehicle Specific Power concept, and then, data mining tools were explored to reveal patterns hidden on large amount of data (154 000 sec). Finally, the best relationships between traffic variables and emissions are evaluated. Results show a prediction for CO_2 emissions of 99% and 98% to NO_X.

Peer-review under responsibility of the scientific committee of the 21st EURO Working Group on Transportation Meeting.

Keywords: Traffic-related environmental impacts; Emissions; VSP

1. Introduction and Objectives

Development in technologies (such as mobile traffic sensors or Global Positioning System (GPS)-equipped devices) has opened up new opportunities for location-based services. According to Kalamaras et al. (2018) these include traffic measurements and sophisticated models for accurate short-term traffic predictions which has resulted in lower infrastructure costs in comparison with fixed location sensors. Nonetheless, mining traffic data can be a challenging task furthermore for traffic flow improving or traffic performance prediction. Through linear regressions and sequential minimal optimization regression techniques, it has been possible to analyse the historical traffic big data to extract and find abnormal traffic patterns, and thus improving traffic management systems (Alam et al. (2017)).

The advent and development of FCD (floating car data) systems in accordance with Siddique et al. (2017) and Bandeira et al. (2013), such as Google traffic or TOMTOM, allows mapping and identifying hotspot congestion locations on different road types. Stevens et al. (2017) state that a definition of a criterion to describe traffic congestion on a road segment involves the balancing of competing objectives. The congestion causes can be determined by surveying speed, travel time or traffic flow data (Lu et al, 2015). Through surveying speed analysis, the

* Eloísa Macedo. Tel: +351 234 370 200
E-mail address: macedo@ua.pt

2352-1465
Peer-review under responsibility of the scientific committee of the 21st EURO Working Group on Transportation Meeting.

implementation of speed management techniques can also be helpful to the reduction of emissions and the minimization of the trade-off between the minimization of CO_2 and other pollutants (Bandeira et al, 2016).

Bisoffi et al. (2017) refer that despite currently available techniques use continuous probe data collected from Global Navigation Satellite Systems (GNSS) installed in vehicles or smartphones, the detection of congestion and its causes along a segment is not trivial. Moreover, mobile traffic sensors can provide wider coverage than fixed location sensors, as demonstrated in a study carried out by Herrera (2009). Bandeira et al. (2018) developed a platform based on empirical GPS data and microscopic simulation models of traffic, emissions and noise. The authors highlighted the need to consider real-time activity patterns in a way that will be possible to implement sustainable traffic management measures. Also Rao et al. (2012) showed that micro-level congestion can be triggered by factors as too many people want to move at the same time, while macro level congestion depends of land use patterns or car ownerships trends.

Recently, Teixeira et al. (2017) developed a fluidity formula based on surveying speed and travel time to determine a criterion that could identify and describe vehicle dynamic patterns along an urban arterial. However, the proposed model was only tested in a single case study, so there is a lack of evidence of its scalability to other scenarios. With these concerns in mind, the purpose of the present research is to extend the methodology developed in Teixeira et al. (2017) for wider application in several real-world arterials using variables dependent on driver behaviour. This paper intends to address this issue by developing a simple and generic formula that can predict traffic emissions through traffic variables. The main contribution of this research is the possibility to include the developed models in sensors that will require low processing capacity, making the production and implementation economically viable.

In the literature, it is known that vehicle operating variables are quite related to pollutant emissions. One of the objectives of the present work is to compare values of speed, acceleration and traffic volume with levels of CO_2 and NO_x emissions. Therefore, in this paper it is proposed a conceptual system in which data related to vehicle operating variables serve as input, and information regarding CO_2 and NO_x emission values is the output. In a first phase, different scenarios on data acquisition strategies were simulated, namely, wi-fi sensors, speed radar each 100 meters along a road, and FCD for different time intervals. Then, after obtaining the best traffic/vehicle monitoring application, expressions for deriving estimates for CO_2 and NO_x emissions were developed. Concretely, the objectives are: i) to test the applicability of different traffic monitoring applications; ii) to correlate traffic and emissions variables; iii) to create a generic equation capable of describing CO_2 and NO_x emissions in both urban and national roads.

2. Methodology

2.1. Field Campaigns

Vehicle activity along with traffic flow measurements were collected in five corridors in Aveiro (Portugal), one in Guimarães (Portugal) and one in Badajoz (Spain). These areas were selected to account for variability in real-world rural and urban corridors, namely: number of lanes, traffic controls (roundabouts, traffic signals), speed limits. Table 1 shows some of the routes' characteristics. Data was collected at the candidate locations between 2016 and 2017. For vehicle dynamic characterization, a light duty vehicle equipped with a GNSS was used to collect second-by-second data (as travel time, instantaneous speed and acceleration). The probe vehicle always moved according to the driver's perception of the traffic flow. Video cameras were installed in strategic points of the studied locations to record segment-specific traffic volume. Prior to on-road dynamic tests, the minimum sample size (number of travel time runs) on each location was investigated such that the minimum required within a reasonable confidence interval based on the density of traffic lights, intersections, etc., was satisfied (Dowling et al, 2004). Total data collected included 571 GPS travel runs, which corresponded to a road coverage of 431km over 107h.

Table 1. Routes characteristics.

Route ID	Type of road	Length (m)	N. of lanes	N. of trips	Travel distance (km)	Road capacity
a)	arterial	2,200	1/2	12	26	3600
b)	urban	1,400	2	32	45	2610
c)	urban	102	2	136	13	1800
d)	arterial	950	1/2	80	76	2880

e)	urban	850	1	92	78	2240
f)	arterial	850	2	80	68	3420
g)	arterial	900	2	139	125	3600

2.2. Emission estimation

The probe vehicle was used to collect dynamic data as vehicle speed and acceleration. Emissions were estimated second-by-second with these data and through Vehicle Specific Power (VSP) methodology. It includes the impact of different levels of accelerations and speed changes on emission calculations according to Frey et al. (2006) and Coelho et al. (2009). VSP is a function of speed, acceleration-deceleration and slope, and it can be expressed by Equation 1. These parameters are computed second-by-second:

$$VSP = v[1.1a + 9.81(\mathrm{atan}(\sin(g))) + 0.123] + 0.000302v^3 \quad (1)$$

where *VSP* is the vehicle specific power (kW/ton); *v* is the instantaneous speed (m/s); *a* is the instantaneous acceleration (m/s^2) and *g* is defined as the instantaneous vertical rise/horizontal distance (± %).

According to US EPA (2002), each VSP can be categorized in 14 engine modes, which in turn is associated to an emission rate for CO_2 and NO_X. Modes 1 and 2 represent deceleration episodes or traveling downhill, whereas mode 3 represents idling or low speed situation. Modes 4 to 14 describe combinations of increasing and positive accelerations or hill climbing.

2.3. Extracting meaningful information framework

The general framework can be seen in the Figure 1.

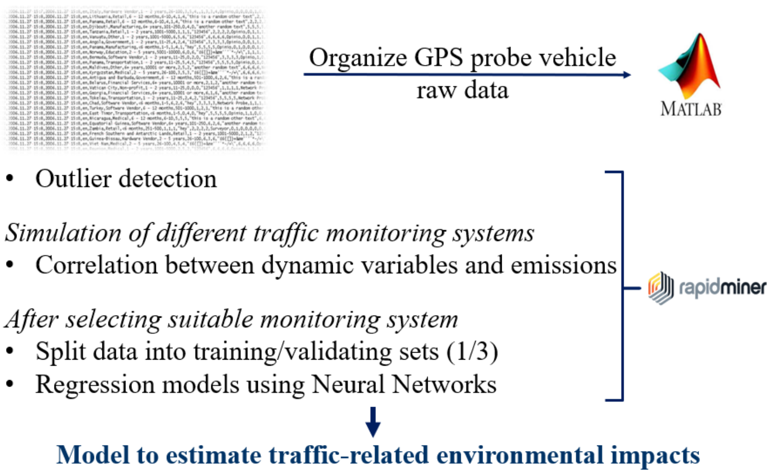

Figure 1. General framework overview.

2.4. Testing applicability of different traffic monitoring scenarios

One of the aims of the present study is to test the applicability of different traffic monitoring applications with the purpose of selecting the best way to collect data that will serve as input in the generic model we will present in Section 2.5. The examined traffic monitoring applications are depicted in Figure 2.

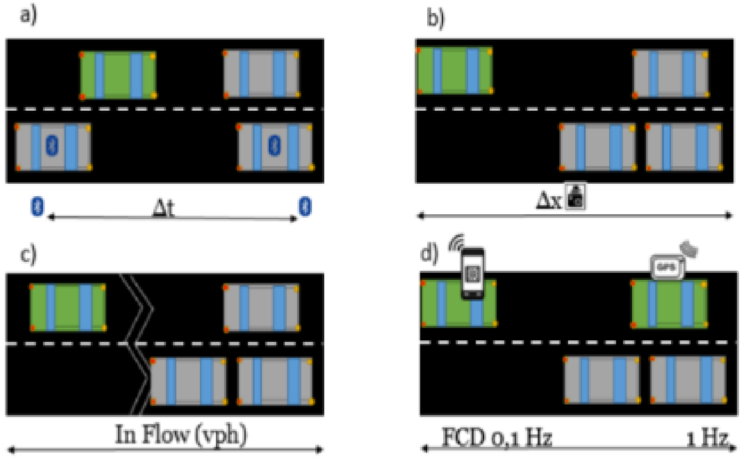

Figure 2. Data acquisition methods.

In particular, various data acquisition methods were simulated (Table2). This table presents the coefficient of determination (R^2) between the dynamic variables (mean speed or mean acceleration) for each data acquisition method (as Bluetooth or Wi-Fi sensors represented in figure 1a)) with emissions variables (CO_2 and NO_X) and traffic volume.

Table 2. Coefficient of determination (%) between dynamic variables and emissions/traffic volume.

Data acquisition methods	Variables	Coefficient of determination R^2 (%)		
		Traffic volume	CO_2 emissions	NO_X emissions
Wi-Fi sensors (road segment analysis)	mean speed	37	0.8	0.3
	mean acceleration	2	3	5
	traffic volume	-	2	1
Floating car data second-by-second	Instantaneous speed	13	8	5
	Instantaneous acceleration	0	**58**	**63**
	traffic volume	-	1	1
Floating car data each 5 second interval	mean speed	13	**11**	**9**
	mean acceleration	0	**61**	**60**
	travel distance	13	0	7
	traffic volume	-	2	2
Floating car data each 10 second interval	mean speed	14	**20**	**16**
	mean acceleration	0	**57**	**53**
	travel distance	11	1	4
	traffic volume	-	4	4
Radar in each 100 meters using instantaneous information	Instantaneous speed	13	4	3
	Instantaneous acceleration	0	**61**	**69**
	traffic volume	-	1	0
Speed Radar in the end of the intersections using instantaneous information	Instantaneous speed	29	4	2
	Instantaneous acceleration	2	**71**	**71**
	traffic volume	-	2	2

From Table 2 it can be observed that route travel time using WI-FI sensors can explain 37% of the variability and flow changes. When collecting data in intervals of 1, 5 or 10 seconds, instantaneous or mean acceleration are the suitable variables to predict CO_2 and NO_X emissions. It is possible to see a better equilibrium in the 5 seconds interval. It is not possible to predict traffic volume based on sub-segments of GNSS data collected in regular time. Speed radar, particularly in the end of the segments, presents the best relationship, however it presents more difficulties to predict in all the segment emissions with the same precisions of floating car data. Acceleration showed to be suitable to describe CO_2 and NO_X emissions in all scenarios. Regarding traffic volume, only a segment analysis enables a prediction of traffic volume. The two best hypotheses to do the data collection to feed the proposed system, would be in 5 seconds intervals or speed radar in the end of the segments, due to the high correlation values as a systematic relation for the two pollutants in order to obtain a general expression as it is exemplified in Section 3.

After comparing the two best hypotheses, the 5 second interval methodology was chosen over the radar in the end of the segment for two main reasons:

- It describes the emissions with more reliability in the entire road segment;
- In a strategic way of implementing the developed system, it will be less expensive the use of FCD equipment already installed in the vehicles, than installing speed radars over all segments in a city.

2.5. System design

Considering the foregoing discussion and having in mind that using limited floating car data at each 5 second interval may be an efficient way to collect traffic-related data to be further used to estimate associated emissions, the main steps of the proposed system to predict CO_2 and NO_X emissions can be outlined as follows (Figure 3):

1. Extract vehicle dynamics information in 5-second intervals, meaning that only information of few vehicles will be needed, reducing thus, the amount of data to store.
2. Compute travel distance in each 5-second interval (e.g. mean speed of the five instantaneous speeds gathered in the interval).
3. Send the information to the server (both dynamic and static);
4. Treat dynamic information to get relevant variables. The information is available in a 3-way matrix:
    1. Data related to the driver location such as latitude or travelled distance;
    2. Static information based on vehicles' position such as weather, speed limits or road capacity, and dynamic information such as instantaneous speed and acceleration-deceleration;
    3. CO_2, NO_X prediction levels.
5. Results are sent to the user interface.

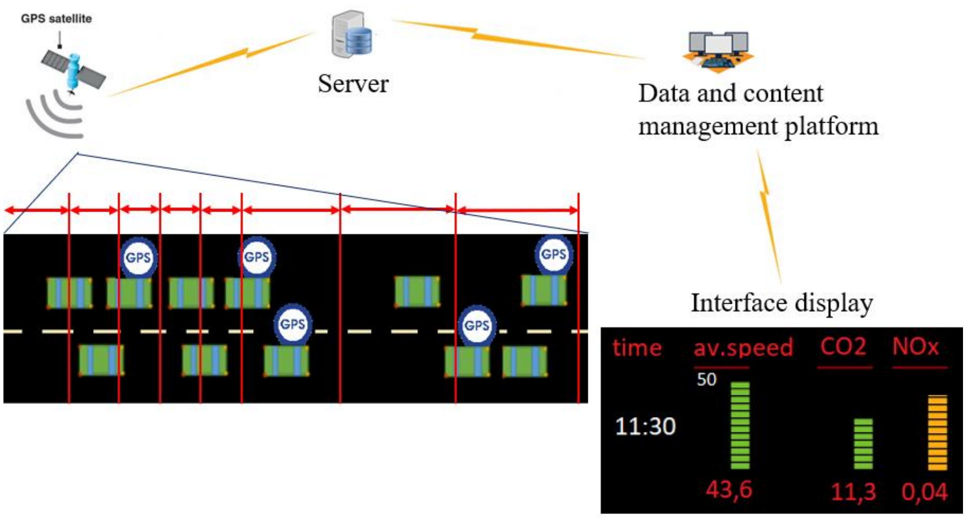

Figure 3. Demonstration of the proposed system.

3. Results

In what follows, the results of our work will be presented and discussed.

3.1. Estimating Emissions: Generic Model SEI

To construct a general model to estimate the level of traffic-related emissions, a regression model was developed using neural networks with a single hidden layer in a process conducted in the Rapid Miner software (Kotu et al, 2014). First, the input data was pre-processed to deal with possible outliers and then, divided into training and evaluation subsets, with a ratio of 70% for training (to identify the variables) and the remaining 30% for evaluation (output results).

The developed linear regression for predicting the traffic-related CO_2 emissions (e_{CO2}) for a single vehicle involves maximum speed, $MaxSpeed$, average speed, $AvSpeed$, and average acceleration, $AvAcc$, for each 5-second interval as predictor variables. The obtained model is given by:

$$e_{CO2} = 0.139MaxSpeed + 0.26AvSpeed.AvAcc + 1.417. \qquad (2)$$

The above regression gives us a prediction of CO_2 emissions (g/s) taking into account few variables of data collected at each 5 seconds (R^2 = 87%).

Moreover, the results suggest a direct connection between CO_2 and NO_X emissions (e_{NOx}) (both in g/s). In particular, we were able to derive the following linear relationship (R^2 = 86%):

$$e_{NOx} = 0.003e_{CO2} \ .$$

These results allow one to estimate CO_2 and NO_X emissions in an easy and inexpensive way. Furthermore, we empirically derived a general model in the form of an index that is able to provide estimates of pollutant emissions, which we had called Segment Emission Index (SEI). For this purpose, we used the variables of the expression (2) and introduced another one as follows:

$$SEI = \frac{MaxSpeed}{\bar{d}_0} + 50\frac{AvSpeed.AvAcc}{\bar{d}_0^{\ 2}}, \qquad (3)$$

where $\bar{d}_0$ is the average travelled distance under free-flow speed. The objective of this expression is that it returns an index which corresponds to a specific level of CO2 and NOX emissions for a single vehicle (in the present study, for a passenger car).

The following section is devoted to presenting the clear relationship between SEI values and pollutant emission levels.

3.2. SEI model results

In what follows, the relationships between SEI values and CO_2 and NO_X emissions per vehicle on specific links are presented. Figure 4a (b) exhibits the relation between CO2 (NO_X) emissions and SEI values applied to each 5-second data. To perform a regression analysis, the goodness-of-fit measures used here were the coefficient of determination, R-square and adjusted R-square, and the standard error of the regression. As it can be observed in Table 3, the findings suggest the model fits well the data in all studied locations. In particular, it can be verified that SEI can explain around 99% of the average CO_2 emissions per vehicle, while it can explain 98% of the NO_X emissions. This means that the there exists strong linear relationship with SEI values. The standard error of the regression is the precision that the regression coefficient is measured and the results show coefficients are clearly large when compared to the error, and thus, they are statistically significant with *p*-value under 0.05.

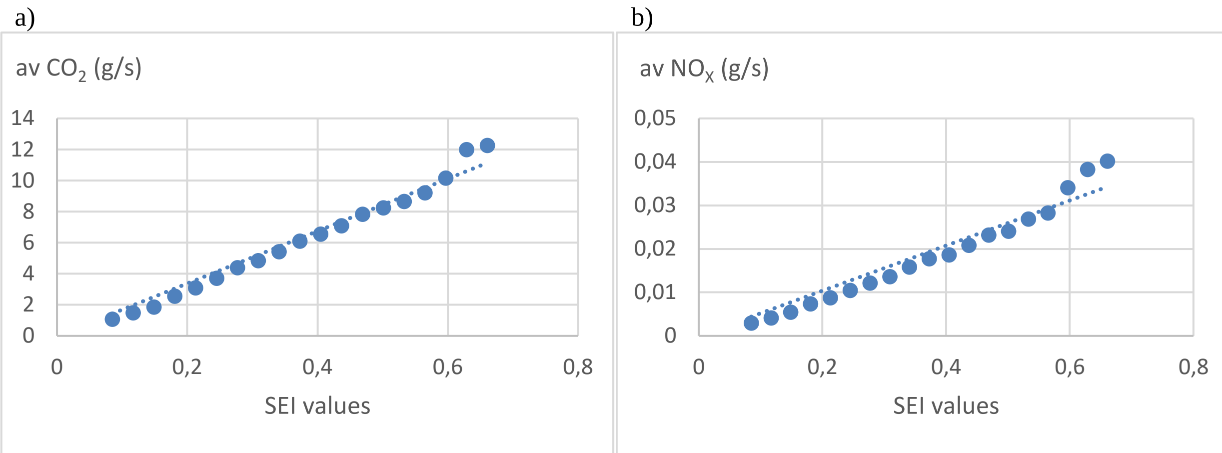

Figure 4 Relation between SEI values and average CO_2 (a) and NOx (b) emissions per vehicle in each 5-second interval.

Table 3. Regression statistics and coefficients for SEI as predictor variable for explaining pollutant emissions.

	CO_2	NO_X
R-square	99	98
Adjusted R-square	94	93
Standard Error	0.553	0.003
Coefficient	16.8587	0.0519
Standard error	0.3081	0.0015
t Statistic	54.7143	34.0732
p-value	1.8099E-21	8.4170E-18

Equation (3) returns an index which corresponds to an emission level. In particular, the SEI values were approximated in ranges of 0.032 values. For each of these intervals, a mean of the emissions related to each value was computed. Figure 4 shows the relation of estimation of these values with the average emissions for each 5 seconds given by VSP. Because volume was calculated per segment, to a number of vehicles per hour, there was a wide range of SEI values, making impossible to make a direct correlation. SEI values increase proportionately with emissions. Although SEI can predict the average emission rate per a 5-second interval, at this moment it is not possible to know exactly which emissions are due to the presence of traffic or not.

4. Conclusions

In this paper, a conceptual system for providing vehicle CO_2 and NO_x emission values was suggested. For that purpose, various vehicle monitoring applications were simulated and analysed. Among the different monitoring applications, the method of disseminating the data in 5-second intervals (although this requires second-by-second information to the server for each 5 seconds to be computed) showed to be the most suitable tool for this case. This method was also the most appealing because of the lack of need of investing in more infrastructures to obtain higher resolution data. Then, expressions for deriving estimates for CO_2 and NO_x emissions levels were developed. In particular, the Segment Emission Index (SEI) model was proposed, which is a single expression that allows one to conclude about estimates of such emissions with high-level of accuracy.

The analysis allows to conclude the predictions using the proposed SEI approach can be useful for predicting traffic-related emissions. The proposed models showed to be consistent with emission model estimates based on instantaneous speed and acceleration. The approach enabled the prediction of CO_2 emissions with a coefficient of determination around 99% and of NO_X emissions around 98% (with p-value<0.05).

The results are very promising since the models can be incorporated in sensors, which in turn lead to massive memory savings, because the input information to predict traffic-related externalities only requires storing data in 5-

second of time resolution. It also reduces the information needed to predict traffic-related impacts with respect to data collected only for a small set of vehicles along the segment. In essence, there is great potential benefit of using SEI for traffic management with environmental concerns. The advantages of using SEI is that no infrastructure in vehicles or along the road is needed, it returns timely and accurate information, and it is easily deployable in traffic network. However, there are also some limitations such as estimated emissions from VSP were considered as benchmark, which we can overcome in the future using a portable emissions measurement system (PEMS).

Acknowledgements

The authors acknowledge the projects: Strategic Project UID-EMS-00481-2013 and CENTRO-01-0145-FEDER-022083 (FCT Portuguese Science and Technology Foundation), and Projects: CISMOB (PGI01611, funded by Interreg Europe Programme), @CRUiSE (PTDC/EMS-TRA/0383/2014, funded within the Project 9471 - Reforçar a Investigação, o Desenvolvimento Tecnológico e a Inovação and supported by the European Community Fund FEDER) and MobiWise (P2020 SAICTPAC/0011/2015, co-funded by COMPETE2020, Portugal2020 - Operational Program for Competitiveness and Internationalization, European Union's ERDF (European Regional Development Fund), and FCT). Special thanks go to Caetano Auto, S.A. for providing vehicles for the data collection and also to Pavlos Tafidis for his cooperation in the data collection.

References

Alam, I., Ahmed, M. F., Alam, M., Ulisse,. J., Farid, M., Shatabda, S., Rossetti, J., (2017). Pattern mining from historical traffic big data. In IEEE Region 10 Symposium (TENSYMP). pp. 1-5.

Bandeira, J., Almeida, T., Khattak, A., Rouphail, N., Coelho, M. (2013). Generating emissions information for route selection: Experimental monitoring and routes characterization. Journal of Intelligent Transportation Systems. 17(1). 3-17.

Bandeira, J., Carvalho, D., Khattak, A., Rouphail, N., Fontes,T., Fernandes, P., Pereira, S., Coelho, M., (2016). Empirical assessment of route choice impact on emissions over different congestion scenarios. International Journal of Sustainable Transportation, 10(3), 271-283.

Bandeira, J., Guarnaccia, C., Fernandes, P., Coelho, M.,(2018). Advanced Impact Integration Platform for Cooperative Road Use. International Journal of Intelligent Transportation Systems Research. 16(1). 1-15.

Bisoffi, A., Biral, F., Da Lio, M., Zaccarian, L., (2017). Longitudinal Jerk Estimation of Driver Intentions for Advanced Driver Assistance Systems. IEEE/ASME Transactions on Mechatronics. 22(4). 1531-1541.

Coelho, M., Frey, H., Rouphail, N., Zhai, H., Pelkmans, L., (2009). Assessing methods for comparing emissions from gasoline and diesel light-duty vehicles on microscale measurements. Transportation Research Part D 14. 91 - 99.

Dowling, R., Skabardonis, A., Alexiadis, V., (2004). Traffic analysis toolbox volume III: guidelines for applying traffic microsimulation modeling software (No. FHWA-HRT-04-040).

Frey, H., Rouphail, N., Zhai, H., (2006). Speed and Facility-Specific Emission Estimates for On-Road LightDuty Vehicles based on Real-World Speed Profiles. Transportation Research Record 1987. 128 - 137.

Herrera, J. (2009). Assessment of GPS-enabled smartphone data and its use in traffic state estimation for highways (PhD Thesis, U. California).

Kalamaras. I.. Zamichos. A.. Salamanis. A.. Drosou. A.. Kehagias. D. Margaritis. G., Tzovaras. D. (2018). An Interactive Visual Analytics Platform for Smart Intelligent Transportation Systems Management. IEEE Transactions on Int. Transportation Systems. 19(2). 487-496.

Kotu, V., Deshpande, B., (2014). Predictive analytics and data mining: concepts and practice with rapidminer. Morgan Kaufmann.

Lu, Y., Shladover, E., Jawad, I., Jagannathan. R., Phillips, T., (2015). Novel Algorithm for Variable Speed Limits and Advisories for a Freeway Corridor with Multiple Bottlenecks. Transportation Research Record: Journal of the Transportation Research Board (2489), 86-96.

Siddique, C., Ban, J., (2017). Traffic State Estimation Based on Vehicle Trajectory Segmentation (No. 17-06072). Presented at the 96th Annual Meeting of the Transportation Research Board. Washington DC.

Stevens, R., Barkley, A., Miller, S., (2017). Impact of Site-Specific Data on the Accuracy of Volume Delay Functions (No. 17-05161). Presented at the 96th Annual Meeting of the Transportation Research Board. Washington DC.

Rao, A., Rao, K., (2012). Measuring Urban Traffic Congestion-A Review. International J. for Traffic & Transport Engineering. 2(4):286-305.

Teixeira, J., Fernandes, P., Bandeira. J., Coelho. M., (2017). Information Management for Smart and Sustainable Mobility (No. 17-03507). Presented at the 96th Annual Meeting of the Transportation Research Board. Washington DC.

US EPA. Methodology for developing modal emission rates for EPA's multi-scale motor vehicle & equipment emission system. Publication Prepared by North Carolina State University for US Environmental Protection Agency. EPA420. Ann Arbor. MI. 2002.