15th ITS European Congress, Lisbon, Portugal, 22-24 May-2023

Paper ID #

Integrative Emissions and Health-Based Scoring Algorithm Development for Driving Style Optimization

Engin Özatay*, Orhan B. Alankuş[1]

Abstract

The impact of road transport on local air quality and its share of total greenhouse gases is considerable. Although there are efforts toward the development and commercialization of green and electric vehicles, it is necessary also to optimize the emissions of the existing fleet. As part of the MODALES project, a mobile application has been developed to guide the driver for optimum emission driving style including tyre and brake particle emissions. As part of the application, an innovative score calculation system has been developed taking into account tyre and brake emissions, using a weighted aggregate emission value. Parametric weights have been selected in line with air quality and cost of health.

Keywords:

Scoring Algorithm, Aggregate emission optimization

Introduction

The impact of road traffic on local air quality is a major policy concern. In 2019, about 27% of the total green house gases (GHG) came from the transport sector and 72% of the contribution was from road transport [1]. The European Green Deal (COM(2019) 640 final) sets out the aim to achieve a carbon neutral EU by 2050. This requires the decarbonisation of all sectors. In its proposal for the Climate Law (COM(2020) 80 final), the European Commission proposed to increase the intermediate GHG emission reduction target for 2030 to 55%, accepted by the European Council at the end of 2020.In September 2020, the Commission published 'Sustainable and Smart Mobility Strategy' (COM(2020) 789 final), laying out its vision to ensure that the EU transport system can achieve a green transformation. However, improving underlying vehicle and fuel technologies, traffic management and enforcement did not give the expected results. Although it is appreciated that zero tailpipe emission technologies may solve the problem in the long term, fleet renewal takes time and current road traffic is clearly dominated by internal combustion fleets with a share of more than 95%. Recent studies[2],[3] have also shown the adverse effects of particles in human health for which brake and tyre wear particles have also an important role in addition to that of exhaust-induced particles. In this study, the related exhaust emissions which create more problems for air quality and human health together with the PM emissions from brake and tyre wear are taken into account to guide the driver for a more emission optimization driving style. An innovative and flexible scoring algorithm has been prepared for this purpose and instantaneous scores can be calculated and displayed to the driver to improve the driving style.

Literature Survey

Regulation (EU) 2017/1151 describes in appendix 7a the methodology to determine the driving

[1] Istanbul Okan University, Turkey, orhan.alankus@okan.edu.tr

dynamics. In the annex two parameters were considered mainly. v.a (Velocity multiplied by acceleration) and RPA (Relative Positive Acceleration). Dynamic parameters like acceleration, $v \cdot a_{pos}$ or RPA are required to be determined with a speed signal of accuracy of 0,1 % for all speed values above 3 km/h and a sampling frequency of 1 Hz.

Kurtykaa and Pielechaa[4] used mainly RPA and v.a under different driving cycles urban, rural and highway and showed different emission results for each cycle even with the same RPA and v.a values. Zeyu Zang et al[5] used speed and acceleration but as a function of VSP (Vehicle Specific Power). Although Ying Yao et al [6], mainly estimates fuel consumption, for driving style determination they don't use just velocity and acceleration but also acceleration and deceleration time percentage and cruising time percentage. Bodisco and Raze[7] refer to the TRL manual and define driving styles for Euro6 using the kinematic parameters explained in the TRL manual.

Analysis of Emissions:

Satlawa et al[8], using mainly v.a and RPA, comes up with the following results;

For the urban part, (less than 60 km/hr) no significant influence of the driver's driving style on instantaneous THC emissions was observed. On the other hand, CO2 and NOx emissions significantly increase with the increase of driving dynamics.

For the rural and motorway parts (over 60 km/h) the instantaneous emission values depended very much on the dynamics of the driving style. CO emissions have increased very rapidly after exceeding the allowed dynamic parameter (v.apos). At the cold engine, THC emissions were very high (around 100 times). Dynamic tests were defined with v.apos values of 15,8; 24 and 29,6 for urban, rural and motorway respectively and with RPA values of 0,2292; 01071, 0,0616.

Zhai et al,[9] have used VSP (Vehicle Specific Power) windows and related parameters to check the emissions behavior on CO2, CO, NOx and PN. The parameters were engine speed, engine torque, engine load in %, air-fuel ratio, vehicle speed and acceleration, altitude, road grade and road type, catalyst temperature, ambient temperature and time of the day. The paper focuses on documenting the variability in emissions under similar vehicle powers, thus, capturing the effects of other variables clearly. Vehicle emissions are strongly associated with engine speed, torque, and load, as well as air-fuel ratio. The process of high engine speed, torque, and load produces high emissions. The CO2, CO and PN emissions during lean-burn are significantly lower than the emissions during the stoichiometric mix and rich burn, while the NOx emissions during rich burn are the lowest. Emissions are also strongly associated with vehicle speed and acceleration. The process of high speed and aggressive acceleration produces high emissions, while the process of braking produces low emissions.

KPI and Scoring

One way to evaluate a driving style is to calculate a numerical score, in real-time, possibly with several dimensions. It has been shown above that v.a and RPA are parameters suggested also in regulation EU 2017/1151 and recent literature shows coherent results with these parameters and emissions. However, converting these results to scoring requires a rigorous methodology. Below a short introduction of the literature for scoring is presented.

Most scoring systems are related to “aggressive driving scoring" as a means of insurance policies.

Abdelrahman et al[10] have developed a methodology for scoring for aggressive driving related to car insurance companies.

Chen et al[11] has developed a methodology for scoring and evaluation related to driving behavior for eco-driving. Although this approach is for eco-driving principles can easily be applied for optimized emission driving. In this study fuel consumption per 100 km is obtained through tests. Nine driving events have been identified which are most relevant to fuel consumption like sharp acceleration, deceleration, long-time deceleration, long time-idling, low speed, high-speed cruising, moderate start, frequent start-stop and moderate braking.

Scoring is calculated with a linear equation as follows,

$$SCORE\,a = 40 + (1 - (FPH - 6)/(14 - 6)) \times 60, \qquad FPH \in [6, 14],$$

14 is the maximum fuel consumption and 6 is the minimum. Minimum score is 40 occurring when the maximum fuel consumption is achieved.

Then the authors have used multiple linear regression model to develop a driver evaluation model. Principal Component Analysis has been used and first three principle components have been calculated. Taking three principal components as arguments and vehicle fuel consumption as depend variable, multiple linear regression was used to establish driver's eco-driving behaviour evaluation model.

Lopez et al[12] has used different algorithms to develop scoring namely genetic, fuzzy inference, driving safety index, random forest regression, Bayesian Ridge regression, support vector regression and multi-layer perceptron regressor and found out than the genetic algorithm gives the best results.

Castignani et al[13] uses fuzzy logic control for event detection and also uses weather and day/night info to change the weight of acceleration, braking and steering events as shown in the below figures. The scoring function and weights of each event is given in line with the severity effect of each event.

Wang et al,[1analyzed driver aggressiveness. To increase the number of data they used SUMO to randomly create around 22000 driving styles. For classification of the results, they compared random forest (RF), logistic regression (LR), decision tree (DT), Naïve Bayes Model (NB) methodologies. RF gave the best result. The proportion of bad drivers in N number of drivers was used as a methodology of scoring. This methodology can be applied for insurance policies but for driving style scoring to optimize emissions a numeric relational system is to be used.

Proposed Methodology for Optimum Emission Driving (OED) Style Scoring

The literature survey analysis shows basically two different approaches for scoring. The first approach is to carry out event detection and also scoring in a combined manner by using AI methodologies such as random forest and the second methodology is to perform event detection first and calculate the scoring as a second step through a methodology like "Principal Component Analysis". Principal component analysis is usually used when a large number of parameters are involved. In our case only two parameters will be used with deceleration values. Maximum number of parameters will be four. Therefore, scoring could be merged with the event detection process.

The literature shows that using $v.a_{\_95\ perct}$. and RPA to determine the driving dynamic events and also deceleration and deceleration frequency for brake and tyre emissions give a good guide to characterizing the driving style. v.a and RPA can be calculated also for decelerations with the same as a weight a positive value considering the severity of tyre and brake emissions on human health. RPA gives info about the frequency of accelerations whereas v.a gives info about the value of the acceleration. Kurtyka et.al show also the correlation of v.a and RPA with emissions as has been done by Satlawa et.al.

Literature survey shows that an aggressive driving style so high acceleration and deceleration values affect brake and tyre emissions considerably. Therefore, if in RPA and v.a calculations also negative accelerations are taken into account, a trend for brake and tyre emissions will also be determined. In general, aggressive driving tends to worsen all the emissions including brake/tyre emissions. However, frequent deceleration is also not a good way of driving for emissions therefore it should be detected and should be also used in scoring with a relevant weight

The following stages can be used for scoring,

1- Calculation of RPA and $v.a_{-95\ \mathrm{percentile}}$ both for positive and negative accelerations

2- Event identification and scoring through AI methodology like Random Forest methodology or genetic programming

Methodology used

Previous studies have proposed various systems for recognizing and classifying driving behaviours [15, 16, 17]. Among them, smartphones were often used to collect data for driving behaviour analysis. Compared to other data collection devices such as cameras, telematics boxes, smartphones have several advantages: Firstly, smartphone-based solutions are scalable, upgradeable, and cheap. Secondly, smartphones can perform on-line assessment and provide instantaneous driver feedback. Lastly, due to the short replacement and development cycles, smartphones can offer a shortcut to new technologies. Driving behaviour classification using smartphone sensing has been widely investigated [18,19].

In this study, the process is focused on collecting smart phone sensor data including GPS and accelerometer and detecting driving events namely acceleration, deceleration, cornering and speeding. The acceleration event is a driving event where the driver speeds up for a certain amount of time and exceeding predefined limit. Similarly, deceleration is an event when the driver slows down either by pressing braking or just coasting with the effect of road topology which can be a straight level road or an inclined road. Cornering is another event when the driver turns the steering wheel and the event is sensed by lateral acceleration values collected from accelerometer sensor.

The events are detected with the following flow diagram. The original sensor data is collected and filtered. Then based on accelerometer values the calibration parameters are determined such that the z direction of the calibrated value points to the centre of the world, the x direction points to the longitudinal direction of the vehicle and the y direction points to the lateral movement of the vehicle.

Figure 1- Flow diagram for event detection

Having determined the calibration parameters, the accelerometer signals are fused with GPS data which has latitude, longitude, speed and direction information. Then by analysing the sensor data in real time based on excitation of the signals event occurring regions are determined. Then the process continues with feature extraction, feature selection steps. Those steps forms the input for random forest algorithm which finally categorizes the event as acceleration, deceleration, cornering and speeding driving behaviours.

Feature Extraction Methodology

The feature extraction process is further detailed with the below figure which shows a flow diagram of the proposed methodology, which is divided into four modules.

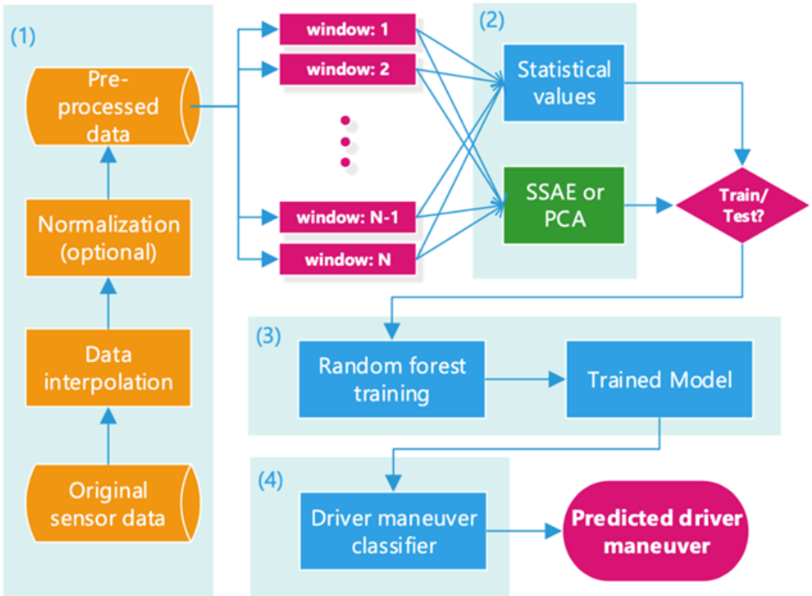

Figure 2- Flow diagram for training and feature extraction

Random forest (RF) is a tree-based algorithm, which builds a specified number of classification trees without pruning. The nodes are split on a random drawing of m features from the entire feature set M. A bootstrapped random sample from the training set is used to build each tree. Since it is a collection of many decision trees. Decision trees are prone to over-fitting individually. This leads to high variance and in turn causes errors in prediction. A collection of decision trees will solve the problem of higher variance. Every decision tree is trained on a random subset of data. The errors caused by each decision tree is random and when they are averaged what remains is the actual prediction that was desired.

Training and Testing Sets

There is one final step of data preparation: splitting data into training and testing sets. During training, we let the model 'see' the answers, in this case the actual driving events, so it can learn how to predict the event from the features. We expect there to be some relationship between all the features and the target value, and the model's job is to learn this relationship during training. Then, when it comes time to evaluate the model, we ask it to make predictions on a testing set where it only has access to the features not the answers, because we do have the actual answers for the test set, we can compare these predictions to the true value to judge how accurate the model is. Generally, when training a model, we randomly split the data into training and testing sets to get a representation of all data points I am setting the random state to 21 which means the results will be the same each time I run the split for reproducible results.

We can look at the shape of all the data to make sure we did everything correctly. We expect the training features number of columns to match the testing feature number of columns and the number of rows to match for the respective training and testing features and the labels.

As a summary the steps followed are,

- One-hot encoded categorical variables
- Split data into features and labels
- Converted to arrays
- Split data into training and testing sets

Post Trip Scoring System

A post trip scoring system will give the driver a realistic feedback about his/her driving profile as to optimize the total emissions. The score calculated must be related to the total emissions including the particles emitted from the brakes and tires. The above explained scoring algorithm has been used to calculate the score at the of the journey to give a feedback to the driver for the overall driving behaviour.

Parametrized Multi-objective Training Set Preparation for aggregate emission

As a part of the MODALES project, road tests have been conducted by VTT with 6 passenger cars and a standard PEMS device measuring the emission gases CO, CO2, NO, NO2, NOx, PN and also fuel consumption. For each vehicle there are around 30 sets of trip data reaching to more than 180 sets of data. This data is sufficient for sound training, however the training tables must be prepared for aggregate emissions, including all the different types exhaust gases and particles. Different exhaust gases and particles have different impact on human health. As a first stage a parametrised multi-objective aggregation for the emissions and particles is to be prepared. Determination of the parameters have been carried out by using the “Air Quality Index “[20,21] and health costs related to the exhaust gases and particles effect on human health. [22] Considering also the fuel consumption causing carbon emissions accelerating global warming, the following weights for the parametrization of different emissions have been determined to be used for the training sets.

Table 1- Weighted parameters for aggregate emission

Fuel consumption	NOx	PM10	PM2.5
0,50	0,09	0,14	0,27

On the training data sets VTT tables are reorganized by multiplying the fuel consumption and emissions with the above weights to find one multi-objective aggregate emission indicator. However, the tables are to be redesigned once again by adding PM values coming from brake and tyre wear. The formulae for PM values calculations are elaborated at the MODALES project(www.modales-project.eu) as a part of work-package 3 and depicted below,

For the brake wear (m),

$$m = \rho V_w = \varphi K \frac{F_N \rho L}{3} = \frac{K\rho\varphi M}{6Nk}(v_1^2 - v_2^2) \quad \begin{cases} \varphi=1 & T_{pad} < 200°C \\ \varphi=1.8 & 200°C \leq T_{pad} \leq 250°C \\ \varphi=5.6 & T_{pad} > 250°C \end{cases}$$

Where,

N is the number of brake assembly of each vehicle; k is friction coefficient; M is mass of vehicle; v1 is velocity when the vehicle begins to brake; v2 is velocity when the vehicle stop to brake; ρ is density of brake pad or brake disc; φ is coefficient regarding brake pad temperature

Tyre Wear formula is given at 5.5 of deliverable 3.2 as follows,

$m_T = \varphi k_1 (w)^{k_2} BD$ w=(P(t))/ϕNBL

Where,

m_T is the mass loss; φ is the transverse reduction coefficient due to the tyre pattern; w is the frictional power per unit contact area; k1 and k2 are two constants that characterize the wear behaviour of the rubber compound at a given temperature and on a given abrasive surface; B is contact width between tyre and ground and D is the driven distance of vehicle; N is the number of tyre of the vehicle; L is the contact length between tyre and ground; P(t) is the energy consumption.

The P(t) can be obtained from the equation below according to the literature

$P(t) = \frac{1}{3600\eta_d} v(t) \left\{ \frac{\rho}{25.92} C_D C_h A_f v(t)^2 + \frac{g\,M\,C_r}{1000} [c_1 v(t) + c_2] + g\,M\,G(t) + (1+\lambda)\,M \frac{dv}{dt} \right\}$ Where,

C_h is altitude; g is gravity; ρ is air density; G(t) is slope; M is vehicle weight; A_f is vehicle frontal area; C_D is aerodynamic drag coefficient; C_r is rolling resistance factor; c_1 and c_2 are rolling parameters; η_d is driveline efficiency; λ is Rotl masses. (usually 0.8 for passenger cars)

After the calculations to obtain tyre and brake particle mass, new columns for total PM10 and PM2.5 is necessary. Literature shows that for Tyres PM10 and PM2.5 distribution is almost equal whereas for brakes 40% for PM10 and 60% for PM2.5 will be more adequate.

Threshold and multiplication values for score calculation

Training is used to fine-tune the threshold values derived from the literature [3] for each speed range and also to determine the penalty values related to duration and extensions of acceleration over the threshold values. The threshold values determined for passenger cars are given below,

Table 1- Threshold values

Thres. (g)	Velocity (kph)												
	0	10	20	30	40	50	60	70	80	90	100	110	120
Acceleration	0.30	0.30	0.25	0.25	0.25	0.20	0.20	0.20	0.20	0.15	0.15	0.15	0.15
Deceleration	-0.50	-0.50	-0.50	-0.25	-0.25	-0.25	-0.25	-0.20	-0.20	-0.20	-0.20	-0.20	-0.20
Left Turn	0.35	0.35	0.35	0.35	0.30	0.30	0.30	0.25	0.25	0.25	0.20	0.20	0.20
Right Turn	-0.35	-0.35	-0.35	-0.35	-0.30	-0.30	-0.30	-0.25	-0.25	-0.25	-0.20	-0.20	-0.20

An example for the acceleration profile is shown below to explain the penalty factor in relation to the acceleration duration and value,

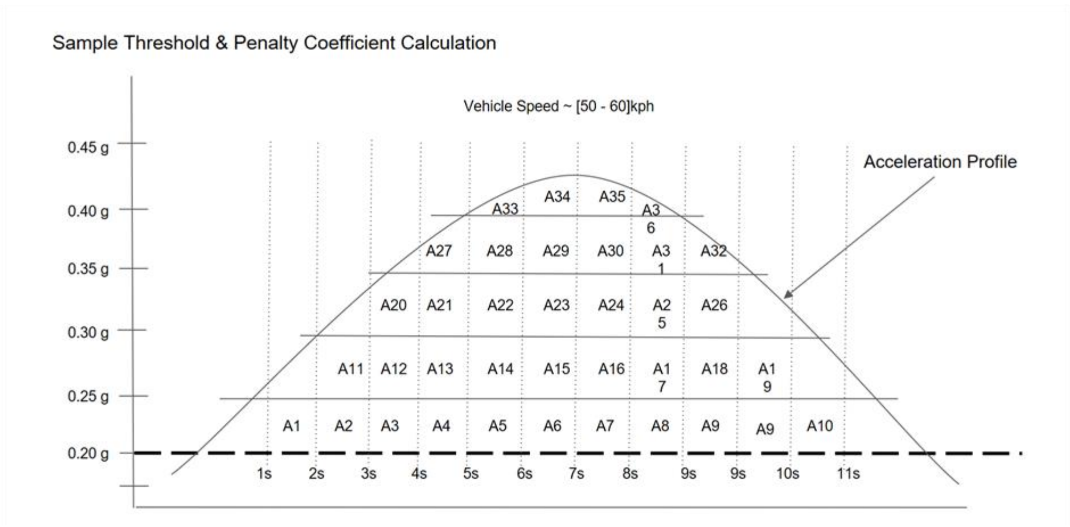

Figure 3: example for a acceleration profile

Penalty factors are assigned separately for each speed range in line with the results of training.

For each interval above threshold level, the penalty factor increases. For the example of Fig.3, for areas between A1-A10 (for acceleration range between 0.2g -0.25g) penalty factor is 3, for a areas between A11-A19 (Acceleration range 0.25g-0.3g) is 5 and so on.

The formula for the score and the related penalty factor calculation is shown below,

SCORE = 100-(Penalty Factor/total acceleration time)*100

Penalty Factor = (A1+A2+...+A10) * 3 + (A11+A12+...+A19) * 5 + (A20+A21+...+A26) * 7 + (A27+A28+...+A32) * 9 + (A33+A34+A35+A36) * 11

Results and Conclusion:

Described methodology gave good results and shows a good relation between the scoring and the aggregate emission and fuel consumption values. The below figures show clearly the relation between the score and the fuel consumption and emissions.

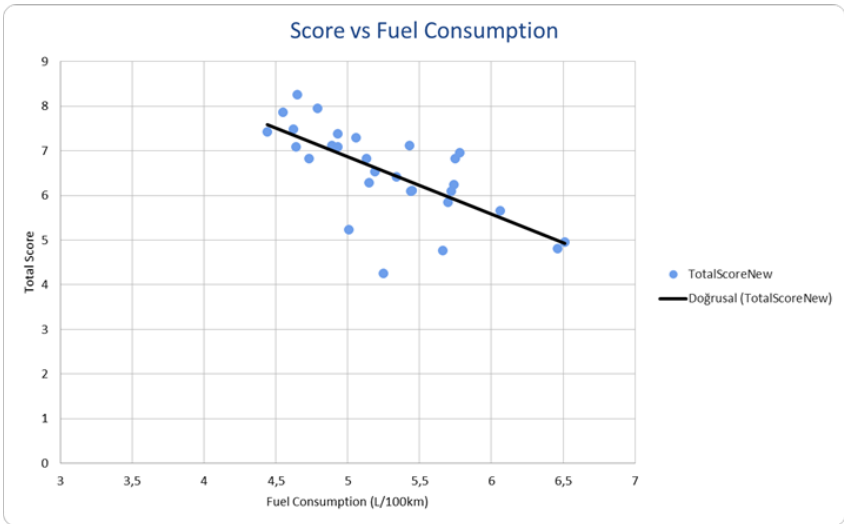

Figure 4: Fuel consumption score correlation

The extensive road tests will provide more data for the results.

Acknowledgement

The research reported in this paper was supported by the EU-funded project MODALES (grant agreement No 815189).

References

1. https://www.eea.europa.eu/ims/greenhouse-gas-emissions-from-transport

2. Hakkarainen et.al., (2020)"Toxicological evaluation of exhaust emissions from light-duty vehicles using different fuel alternatives in sub-freezing conditions", Particle and Fibre Toxicology

3. Choma et.al., (2021)"Health benefits of decreases in on-road transportation emissions in the United States from 2008 to 2017", PNAS 2021 Vol. 118 No. 51

4. Karolina Kurtykaa, Jacek Pielechaa,(2019) " The evaluation of exhaust emission in RDE tests including dynamic driving conditions " (13th International Scientific Conference on Sustainable, Modern and Safe Transport (TRANSCOM 2019)

5. Zeyu Zhang, Guohua Song, Jiaoyang Chen, Zhiqiang Zhai and Lei Yu(2020)"Development of a Simplified Model of Speed-Specific Vehicle-Specific Power Distribution Based on Vehicle Weight for Fuel Consumption Estimates", Transportation Research Record 2020, Vol. 2674(12) 52–67

6. Ying Yao,Xiaohua Zhao,Chang Liu,Jian Rong,Yunlong Zhang,Zhenning Dong and Yuelong Su (2020), "Vehicle Fuel Consumption Prediction Method Based on Driving Behavior Data Collected from Smartphones", HindawinJournal of Advanced Transportation,Volume 2020

7. Timothy Bodisco and Ali Zare,(2019) "Practicalities and Driving Dynamics of a Real Driving Emissions (RDE) Euro 6 Regulation Homologation Test", Energies 2019, 12, 2306; doi:10.3390/en12122306

8. Mateusz Satlawa , Piotr Pajdowski, Dariusz Pietras(2020) "The Impact of the Driver's Driving Style on the EXHAUST Emissions of a Passenger Car during a Real Road Cycle", SAE International,Published Sept 15,2020

9. Zhiqiang Zhai , Ran Tu , Junshi Xu, An Wang and Marianne Hatzopoulou,(2020) "Capturing the Variability in Instantaneous Vehicle Emissions Based on Field Test Data", Atmosphere 2020, 11, 765; doi:10.3390/atmos11070765

10. Abdalla Abdelrahman, Hossam S. Hassanein , Najah Abu-Ali,(2018) "Data-driven Robust Scoring Approach for Driver Profiling Applications", GLOBECOM 2018 - 2018 IEEE Global Communications Conference

11. Chen Chen, Xiaohua Zhao, Jian Rong and XiaomingLiu ,Ying Yao,Yunlong Zhang,(2018) "Driver's Eco-Driving Behavior Evaluation Modeling Based on Driving Events" , Journal of Advanced Tranportation, January 2018

12. Jesús R. López, Luis C. González ,Johan Wahlström, Manuel Montes y Gómez, Leonardo Trujillo, and Graciela Ramírez-Alonso,(2018) "A Genetic Programming Approach for Driving Score Calculation in the Context of Intelligent Transportation Systems", IEEE SENSORS JOURNAL, VOL. 18, NO. 17, SEPTEMBER 1, 2018

13. German Castignani, Thierry Derrmann, Raphaël Frank, and Thomas Engel,(2015) "Driver Behavior Profiling Using Smartphones:A Low-Cost Platform for Driver Monitoring", IEEE Intelligent transportation systems magazine, Spring 2015

14. Wenfu Wang, Yao Yang, An Chen, Zhijie Pan,(2019) "A Scoring Method for Driving Safety Credit Using Trajectory Data", 2019 IEEE DOI 10.1109/SmartWorld-UIC-ATC-SCALCOM-IOP-SCI.2019.00135

15. Arief Koesdwiady, Safaa M Bedawi, Chaojie Ou, and Fakhri Karray (2017)" End-to-end deep learning for driver distraction recognition. In International Conference Image Analysis and Recognitio", pages 11–18. Springer, 2017.

16. Yuan Liao, Shengbo Eben Li, Wenjun Wang, Ying Wang, Guofa Li, and Bo Cheng (2016) "Detection of driver cognitive distraction: A comparison study of stop-controlled intersection and speed-limited highway." IEEE Transactions on Intelligent Transportation Systems, 17(6):1628–1637, 2016.

17. Y. Ma, Z. Zhang, S. Chen, Y. Yu, and K. Tang(2019)"A comparative study of aggressive driving behavior recognition algorithms based on vehicle motion data" IEEE Access, 7:8028–8038, 2019.

18. J. Xie, A. R. Hilal, and D. Kulic(2018) "Driver distraction recognition based on smartphone sensor data" In 2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC), pages 801–806, Oct 2018.

19. Jie Xie, Allaa R Hilal, and Dana Kulic(2018) "Driving maneuver classification: A comparison of feature extraction methods" IEEE Sensors Journal, 18(12):4777–4784, 2018.

20. DIRECTIVE 2008/50/EC OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 21 May 2008 on ambient air quality and cleaner air for Europe

21. https://www.eea.europa.eu/themes/air/air-quality-index

22. Ye Liu , Haibo Chen , Ying Li b, Jianbing Gao , Kaushali Dave , Junyan Chen , Tiezhu Li , Ran Tu,(2022), "Monetary values of exhaust and non-exhaust emissions emitted from conventional and electric vehicles", Journal of Cleaner Production,Volume 331, 10 January 2022, 12996