Adapting driver behaviour for lower emissions

MODALES D2.1: Variability of driving behaviours and Low-emission driving requirements

WORK PACKAGE	**WP2: Knowledge of low-emission factors**
TASK 2.1	Variability of driving behaviours
TASK 2.4	Low emission driving requirements
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Glossary of terms

Term	Description
China-STARWINGS	The STARWINGS project simulated traffic flow using information on drivers' behaviours coupled with real-time traffic information for Beijing.
CMEM	CMEM was initially developed in the late 1990's with sponsorship from the National Cooperative Highway Research Program (NCHRP) and the U.S. Environmental Protection Agency (EPA) to fulfil the need for microscopic emissions modelling.
DaCoTa	EU FP7 project (2010-2012, www.dacota-project.eu) which gathered and analysed data from 30 European countries on a wide range of road safety topics. The aim was to share the benefits of this leading-edge research and the decision-making tools with the international Road Safety Community in an effort to reduce casualties worldwide through data and knowledge-based policy-making.
ecoDriver	EU FP7 project (2011-2016) which addressed the need to consider the human element when encouraging "green" driving, as driver behaviour is a critical element in energy efficiency. The focus of the project was on technology working with the driver. The project delivered effective feedback to drivers on green driving by optimising the driver-powertrain-environment feedback loop.
EuroFOT	EU FP7 project: "European Large-Scale Field Operational Test on Active Safety Systems" (2008-2012). euroFOT identified and coordinated an in-the-field testing of new Intelligent Vehicle Systems with the potential for improving the quality of European road traffic. This permitted assessing their effectiveness on actual roads, while determining how they perform towards the intended objectives.
MODALES	This EU Horizon 2020 project: "Modify Drivers' behaviour to Adapt for Lower Emissions" (2019-2022, http://modales-project.eu)
MOVES	EPA's Motor Vehicle Emission Simulator is an emission modelling system that estimates emissions for mobile sources at the national, county, and project level for criteria air pollutants, greenhouse gases, and air toxics.
NAEI	The NAEI estimates annual pollutant emissions from 1970 to the most current publication year for the majority of pollutants. The data were collected and analysed from a wide range of sources – from national energy statistics through to data collected from individual industrial plants.
PHEM	PHEM (Passenger Car and Heavy Duty Emission Model) is an instantaneous vehicle emission model developed by the TU Graz since 1999. PHEM is based on an extensive European set of vehicle measurements and covers passenger cars, light duty vehicles and heavy duty vehicles from city buses up to 40 ton semi-trailers.
PRIMES-TREMOVE	PRIMES-TREMOVE projects the evolution of demand for passengers and freight transport by transport mode and transport mean, based on economic, utility and technology choices of transportation consumers, and projects the derived fuel consumption and emissions of pollutants.
RETEMM	The "RETEMM: Real-world Traffic Emissions Measurement and Modelling" project was funded by the UK EPSRC to research real-world regulated and unregulated emissions affected by driver behaviour for vehicles driven in a range of urban traffic conditions.
VERSIT+	VERSIT+ is a state-of-the art emission model developed by TNO to predict

Term	Description
	emission factors and energy use factors on national, regional and local scales.
VT-CPFM	VT-CPFM is a new power-based microscopic fuel consumption model. It was developed in order to provide reliable fuel consumption estimation and convenience of easy calibration.
UDRIVE	EU FP7 project (2012-2016) aiming to increase understanding of road user behaviour by systematically studying road user behaviour in real life conditions. First and foremost it focused on the identification of relevant measures to improve road safety up to the Horizon 2020 and beyond. Secondly, it focused on the identification of promising approaches for reducing harmful emissions and fuel consumption in order to make road traffic more sustainable.
USA-RDE	Research Data Exchange (RDE) is a transportation data sharing system that promotes sharing of archived and real-time data from multiple sources and multiple modes. This new data sharing capability will support the needs of Intelligent Transportation System researchers and developers while reducing costs and encouraging innovation. Data accessible through the RDE is quality-checked, well-documented, and available to the public.

List of abbreviations and acronyms

Abbreviation/acronyms	Meaning
AA	Advisor Accelerator
Acc	Accelerometer
ACC	Adaptive Cruise Control
AMS	Auto Motor und Sport
ANN	Artificial Neural Networks
Ba	Barium
BC	Bluetooth classic
BLE	Bluetooth Low Energy
BN	Bayesian Network
Ca	Calcium
CD	Cross day
CLD	Cloudy
CLD	Chemiluminescence Detector
CLR	Clear
CMEM	Comprehensive Modal Emissions Model
CNG	Compressed Natural Gas
CO	Carbon Monoxide
CO_2	Carbon Dioxide
CPF	Catalyst Pass Fraction
Cu	Copper

Abbreviation/acronyms	Meaning
CVS	Constant Volume Sampler
DALED	Mobile App for Low-Emission Driving
DTCs	Diagnostic Trouble Codes
ECG	Electrocardiography
EF	Frequency of Events
Efs	Emission Factors
EGR	Exhaust Gas Recirculation
EPA	Environmental Protection Agency
EU	European Union
EV	Electric Vehicle
Fe	Ferrum
FEV	Fully Electric Vehicle
FF MLP	Feedforward Multi-Layer Perceptron
FID	Flame Ionization Detector
FL	Fuzzy Logic
FOT	Field Operational Test
FP7	EU Seventh Framework Programme for Research and Development
FVT	Forschungsgesellschaft für Verbrennungskraftmaschinen und Thermodynamik
GDI	Gasoline (petrol) Direct Injection
GPS	Global Positioning System
Gyr.	Gyroscope
HBEFA	Handbook Emission Factors for Road Transport
H2O	Hydrogenoxide
HC	Hydrocarbons
HDV	Heavy-duty Vehicles
HEVs	Hybrid-electric Vehicles
HIL	Hardware-in-the-Loop
HMI	Human Machine Interface
ICE	Internal Combustion Engine
ICP-MS	Inductively Coupled Plasma Mass Spectrometry
IEs	Innovation Elements
IMU	Inertial Measurement Unit
INEA	Innovation and Networks Executive Agency
k-NN	k-nearest neighbours algorithm
KPI(s)	Key Performance Indicator(s)
LACT	Los Angeles City Traffic
LDV	Light-duty Vehicles (i.e. Passenger Cars)
LNT	Lean NOx Trap

Abbreviation/acronyms	Meaning
lpm	Litres per Minute
MAC	Media Access Control
MIL	Model-in-the-Loop
Mob	Mobile
NAEI	National Atmospheric Emission Inventory
NAO	Non-Asbestos-Organic
NDIR	Non-Dispersive Infrared
NDS	Naturalistic Driving Study
NEE	Non-Exhaust Emissions
NOx	Nitrogen Oxides
NP	Non-Professional
NSC	NOx Storage Catalyst
O3	Ozone
OBD	On-Board Diagnostics
OBD2	Bluetooth-based (mostly) On-Board Diagnostic
OC	Organic Carbon
PAH	Polycyclic Aromatic Hydrocarbons
PCA	Principal Component Analysis
PCC	Predictive Cruise Control
PEMS	Portable Emissions Measuring System
PHEV	Plug-in Hybrid Electric Vehicle
PM	Particulate Matter
PM10	Particulate Matter 10 Micrometres or Less in Diameter
PMP	Particle Measurement Program
PN	Particle Number
PPG	Photoplethysmography Sensors
RA	Rainy
RBS	Regenerative Braking System
RDE	Research Data Exchange
RF	Random Forest
SCOOT	Split Cycle Offset Optimisation Technique
SCR	Selective Catalytic Reduction
SD	Same day
SIL	Software-in-the-Loop
SIPs	State Implementation Plans
SS	Sensation-Seeking
S/S	Start/Stop
SVM	Support Vector Machines

Abbreviation/acronyms	Meaning
SW	Smartwatch
TEN-T	Trans-European Transport Network
Ti	Titanium
TRWP	Tire and Road Wear Particles
TSP	Total Suspended Particles
TU Graz	Graz University of Technology
UDP	Urban Driving Program
UK	United Kingdom
UNECE	The United Nations Economic Commission for Europe
VIN	Vehicle Identification Number
VMT	Vehicle Miles Travelled
WLTP	Worldwide Harmonized Light-duty Vehicles Test Procedure
XRF	X-ray Fluorescence
Zn	Zinc

List of mathematical symbols

Symbols	Meaning
a	Vehicle acceleration
A_f	Vehicle frontal area
A_r	Frequency of injury crashes
c_1, c_2	Rolling parameters
$C_{Cu\text{-}pad}$	Concentration of copper in pads
C_D	Drag coefficient
$C_{Fe\text{-}disc}$	Concentration of iron in discs
$C_{Fe\text{-}pad}$	Concentration of iron in pads
C_h	Altitude
C_r	Rolling resistance factor
$e_{TIRE,TSP,j}$	TSP mass emission factor from tyre wear
e	Proportion speed limit offenders
E	Emission rates
$E_{TIRE,i,j}$	Total emissions for the defined time period and spatial boundary
$(E_{TIRE})_{PC}$	TSP emission factor for cars
$EF_{TIRE(v)}$	Tyre wear particle factor for a vehicle in class v
EO_i	Exhaust emission rate of i
ER_{CO2}, ER_{CO}, and ER_{HC}	Emission rate of CO_2, CO, and HC
F	Force applied during the slip
f_{Bi}	The fraction of TSP (total suspended particle) that can be classified as

Symbols	Meaning
	PM10, PM2.5, PM1 or PM0.1.
fl	Traffic flow
$f_{TIRE,i}$	Mass fraction of tyre-wear TSP that can be attributed to particle size class *i*
F_{TIRE}	Fraction of particles less than or equal to the particle size cut-off
FR	Fuel rate
g	Gravity
$G(t)$	Slope
H	Hardness of the softer material in contact pair
I_r	Injury crash rate
j	Number of junctions per road section
IVEHWL(v)	Average number of wheels on a vehicle of class *v*
K	Engine friction factor
k1, k2	Wear constants
K_{idle}	Constant idle engine friction factor
l	Length of the road section
LCF_{TIRE}	Load correction factor
L_g	Sliding length
LF	Load factor for the truck
M	Vehicle weight
M_j	Mileage driven (km) by vehicles in the defined class during the defined time period
M_v	Vehicle mass
n	Number of samples
N	Engine speed
N_{axle}	Number of truck axles
N_{idle}	Constant idle engine speed
N_j	Number of vehicles in the defined class within the defined spatial boundary
P	Engine power output
p_1, p_2, p_3…	Corresponding weight of x_1, x_2, x_3….
P_{acc}	Engine power requirement for accessories
$P(t)$	Energy consumption by vehicle wheels
P_{tract}	Tractive power
R_{CO}	CO emission rate
$R_{Fe/Cu}$	Mass ratio between iron and copper
R_{NOx}	NO_x emission rate
R_T	Total tractive force required to drive the vehicle
$S_{T(v)}$	Tyre-wear correction factor for a mean vehicle travelling speed *V*
***SB*(V)**	Speed correction factor
v	Vehicle speed

Symbols	Meaning
V	Engine displacement
v_{limit}	Speed limit
VSP	Vehicle specific power
W	Wear rate
Wd	Wear rate of discs
W_p	Wear rate of pads
$x_1, x_2, x_3....$	Sample in the study
ΔA	Contact area
ΔF_N	Normal load at profile peak of contact point
Δv	Difference between individual vehicle speed and average traffic speed
%C	Carbon percentage of gasoline (petrol) by weight
$\overline{v}$	Average speed
α	Constant idle emission rate
$\alpha_0, \alpha_1, \alpha_2$	Fitted coefficients using test data
β_1	Emission rate per unit of engine energy
β_2	Emission rate per unit of energy-acceleration
ε	Vehicle drivetrain efficiency
η	Indicated efficiency for diesel engines
η_d	Driveline efficiency
θ	Road grade
λ	Rotl masses
μ	Mean
ρ	Density
σ	Variance
$\emptyset$	Fuel/air equivalence ratio

Executive Summary

The purpose of the work reported in this deliverable was to review the existing state of knowledge related to the MODALES project, and to thereby set out a set of recommendations for subsequent work packages, and specifically to guide the emission measurement campaigns planned for WP3 (Impact of user behaviours). In particular the review conducted in WP2 (Knowledge of low-emission factors) focused on two key aspects: variability in driving behaviours (from task T2.1) and low emission driving requirements (from Task T2.4). The first element sets out our understanding of the link between driving behaviours and emissions, and the second builds on the understanding of existing low-emission driving programmes/projects to help set out what we need in order to realise the objective of low emission driving.

The literature review of **driving behaviour variability** was performed through a meta-analysis with the aim to identify typical driving patterns and practices. By reviewing and collating the findings from world-wide studies (e.g. Naturalistic Driving Studies, Field Operational Tests), its aims were to provide scientific evidence to the MODALES project on the characterisation of driver aggressiveness profiles, and to establish the link between vehicle emissions and driving behaviour based on both real world measurement and laboratory tests. The review demonstrated that we have a clear empirical understanding of many of the factors that influence different driving behaviours, ranging over characteristics of the driver (e.g. age, gender and experience), of the vehicle type (e.g. performance characteristics of the vehicle), and of the environmental conditions experienced (e.g. road type, gradient, curvature, surrounding landscape). As a consequence, and as demonstrated in the reviewed studies, driving behaviours vary from time to time, place to place and most importantly driver to driver, and the reviewed studies provide an understanding of the mechanisms underlying this variation.

Alongside the analysis above, individual reviews were conducted of the evidence of air pollution caused by **exhaust emissions**, **brake wear** and **tyre wear**. The emissions from exhausts have been widely studied, and various prediction models have been proposed and used for the development of policy interventions and traffic management measures aimed at improving air quality. The review showed, however, that there is a need for these predictive models to be validated with real monitoring data from real-world road tests under various conditions, in particular under different road environments, traffic characteristics, weather conditions, vehicle conditions, and most drivers with different driving styles (e.g. vehicle speed, acceleration and deceleration). On the brake wear side, the influence of different measurement methods was found to be the main source of the high variability in brake emission factors deduced from different studies. This leads to the implication that selection of the correct brake sequence for testing brake emissions is fundamental to the measurement of real-world emission factors.

As a general conclusion from these studies, it is clear that any general guidelines for decreasing brake emissions should be based around encouraging a defensive and conservative driving style, characterised by the use of engine brake torque to limit the initial brake speed and the temperature of the braking system. On the tyre wear side, the review of the key factors related to tyre emissions indicated a wide variety of factors that influence the generation of tyre wear particles, and thus any future efforts at reducing this source would need to consider not only the characteristics of the tyre, but also the vehicle to which it is mounted, the manner in which the vehicle is operated and the type of pavement on which the vehicle is driven. It was found that very few studies had been carried out to simultaneously correlate driving behaviour variability with the three emission sources. It was also not clear from these studies how driving guidelines and practices should be developed to reduce

vehicle emissions from all three sources in a consistent and optimised manner. This is actually one of the challenges to be addressed in MODALES.

Many **mobile apps** have already been developed for helping drivers to reduce their emissions, both through academic or industrial projects. Unlike the existing apps, the DALED solution will be aimed at developing an exclusively local application, one that is not based on online services, which are rarely adapted to real-time assistance. Also, MODALES will create an individually tailored learning strategy that interacts with them safely and actively while they are driving and uses gamification techniques to provide proactive follow-up strategies.

To define and specify **low-emission driving requirements**, this deliverable reviewed existing low emission driving programmes/projects and critically discussed the set of requirements derived from the previous tasks. It carried out a mapping of eco-driving and low-emission characteristics and identified overlaps where requirements and driving techniques coincide in both.

Finally, each of the above reviews made a set of **recommendations and guidelines** for the collection of new real driving data (both exhaust and non-exhaust), to be addressed in the subsequent MODALES work-packages such as WP3. These recommendations and guidelines are presented in detail in Chapter 9 and key highlights are summarised as follows:

- Driving behaviour variability exists between gender, age and experience. It also changes under different traffic conditions. Therefore, as result any on-road or in-lab measurement tests should make sure that these groups are well-balanced and well-represented. In addition, the modelling work in Task 3.5 needs to ensure that the correlation between driving behaviour and vehicle emissions can be interpolated or extrapolated when scaling up the impact of the MODALES innovation solutions.
- Brake wear emissions studies are normally carried out in a laboratory with pre-defined driving cycles and vehicle parameters. It is recommended that such experimental settings should be designed to be as close to the conditions of the real-world trials as possible.
- More work is needed on validating tyre wear emission models in real-life studies. It can be anticipated that the results of the planned periodic (8-week) measurement of real-world tyre emissions may be difficult to correlate with instantaneous driving behaviour characteristics (e.g. speed, acceleration and braking). It is therefore recommended that the correlation model to be developed in Task 3.5 should be validated and calibrated to ensure that its estimation of tyre emissions is compatible with the periodic measurements.
- The evidence is that the effect of driver training programmes to reduce emissions can be considerable, and but may vary significantly from person to person. The DALED app to be developed in the project should therefore consider personalised features in its design, and ensure that it monitors impacts to ensure that it is effective in achieving low-emission driving in the long run.

Fulfilment of deliverable / related task objective:

All the activities specified in Tasks 2.1 and 2.4 have been carried out and their objectives have been fulfilled as summarised below, together with the chapters in which they are presented:

- Derive highly accurate information about various driving behaviours using data collected from large-scale FOTs (Field Operational Tests), NDSs (Naturalistic Driving Studies) carried out worldwide (**Chapter 2**)
- Carry out a meta-analysis of the results of exhaust emissions from available data sources to improve estimates of emission rates for commonly used driving patterns (**Chapter 3**)
- Undertake a thorough state-of-the-art review of limited number of published studies on brake wear and the activity carried out by the PMP, together with in-house data, to identify brake wear data (**Chapter 4**)
- Review published and in-house data/models to identify tyre wear data for later correlation analysis (**Chapter 5**)
- Conduct a state-of-the-art review of published partner studies and external projects to identify the correlation between phone sensors and user driving profiles (**Chapter 6**)
- Produce recommendations and guidelines for new real driving data (both exhaust and non-exhaust) to be collected in WP3 (**Chapter 9**)
- **Chapter 8** details the activities carried out in Task 2.4, namely:
    - Define in detail the term "low emission driving" and report how this term is perceived by the drivers in several countries;
    - Perform an in-depth review of projects findings and distinguish the key factors between eco driving and low emission driving;
    - Do the mapping of eco-driving and low emission characteristics and check the areas were requirements and driving techniques coincide in both;
    - Categorise the requirements taking into account the vehicle and driver profile: e.g. vehicle type, driver experience, professional or normal user, gender, age, etc.

An additional chapter (**Chapter 7**) was devoted to the discussion about the correlation of driving behaviours variability with vehicle emissions, fuel consumption and safety. It aims to shed some lights on how to make sure that the driver is clear about which driving practice should be used and when.

1 Introduction

1.1 Background of MODALES

The impact of road traffic on local air quality is a major policy concern. There have been numerous technological advances and policy initiatives aimed at improving underlying vehicle and fuel technologies, reducing emissions through traffic management and seeking improvements through enforcement. Zero tailpipe emission technologies may solve the problem in the long term, as it is rolled out to the full vehicle population, but fleet renewal takes time. We need also to make more immediate changes, during periods in which road traffic continues to be dominated by internal combustion fleets (with its current share more than 95%).

However, such advances are hampered by a lack of understanding of the links between driving behaviour and emissions, and inconsistencies between laboratory tests and real-world emissions levels. A programme funded by the UK Department for Transport in 2016 showed that on-road emissions are significantly different from laboratory measurements. The study revealed that some cars emit up to 12 times the permitted EU maximum. Real-world emissions can be affected by many factors including vehicle characteristics, ambient temperature, traffic, road layout and driver behaviour. Recent studies have aimed to undertake large scale activity monitoring of engines to quantify these factors. Driver behaviour is regarded as the single biggest determinant of vehicle emissions.

The MODALES project was therefore created to advance the understanding of the co-variability of user behaviour and vehicular emissions, in particular from powertrains, brakes and tyres. From the understanding thus gleaned, the project aims to modify user behaviour via dedicated training, to help local and national authorities develop effective air quality plans and enforcement strategies. Over a 36-month timeframe, MODALES will study driving behavioural variability and recognise typical driving patterns and practises. Based upon that knowledge, it will establish the link between real vehicle emissions and driving behaviour through a combination of real-world measurement and laboratory tests.

Furthermore, MODALES will create training courses for low-emission driving, which will be taught and validated in pilot exercises. Poor maintenance and tampering aspects will be investigated with a fleet of cars whose emissions are intentionally influenced by lack of maintenance and/or by tampering, and MODALES will observe whether present OBD or inspections are able to detect those. Finally, an assessment of the potential impacts of retrofits for light- and heavy-duty road vehicles and for Non-Road Mobile Machinery (NRMM) will be performed, including promotion of their application in the selected pilot cities with relevant pollution problems.

Relation to eco-driving:

Eco-driving, which has been the subject of different projects as well as currently available applications and training activities, targets a reduction in target a reduction in CO_2 emissions and fuel consumption in road transport by encouraging the adoption of green driving behaviour. CO_2 is indeed strongly correlated with certain air pollutants emitted from a vehicle such as CO. However, there exists a substantial discrepancy between CO and CO_2 due to a number of factors including air-fuel ratio, highlighting that a best eco-driving practice may not be the best for low-emission driving.

MODALES typically focuses on other air pollutants (e.g. NOx, O3, PM, PN) due to their significant exceedances found particularly in many European cities affected by specific environmental or industrial conditions. These pollutants are much loosely correlated with CO_2. Also, MODALES addresses the particle emission from brake and tyre wear. Zero tailpipe emission technologies might be able to solve the emission from fuel but not from brake and tyre wear. The latter may be even more problematic with newer vehicles (e.g. electric vehicles) when they become heavier. Therefore, MODALES will make sure that the driver is clear about which driving practice should be used and when.

1.2 Purpose of this document

WP2 is the technical kick-off activity for MODALES, aimed at synthesising the state-of-the-art in current international knowledge of vehicular emissions, in order to define key contributory factors. The factors considered vary from the driving and maintenance behaviour of individual car users, to the real effectiveness of OBD systems and retrofits, as well as assessing the legal situation of tampering in different member states.

The present deliverable focuses on two specific objectives of WP2, namely quantification of driving behaviour variability (independent variable for correlation with vehicle emissions) in Task 2.1 and identification of low-emission driving requirements for training courses for various users in Task 2.4. The first part aims to ensure that a full range of driving behaviours is considered in subsequent parts of the project, and specifically has the role of guiding the emission measurement campaigns in WP3. The second part reviews existing low-emission driving programmes and projects, and will critically discuss and amend the set of requirements derived by the review.

1.3 Document structure

This deliverable begins in Chapter 2 with a review of various driving behaviours observed in research and innovation projects worldwide, such as large-scale Naturalistic Driving Studies (NDS) and Field Operational Tests (FOT). It then reviews vehicle emissions from three main sources, namely powertrain, brake wear and tyre wear, in Chapters 3, 4 and 5 respectively.

Chapter 6 is devoted to a state-of-the-art review of published partner studies and external projects, with the aim to identify the correlation between phone sensors and user driving profiles, to serve as input to WP3 and WP5.

Chapters 7 and 8 address the common issues of driving behaviour in relation to vehicle emissions, energy consumption and safety, in order to identify the areas where requirements and driving techniques coincide in them.

2 Variability of driving behaviour

Drivers have quite different driving behaviours which are determined by a number of factors such as the drivers' characteristics (e.g. age, gender and experience), the environment conditions (e.g. road types, gradient and curvature, surrounding landscape) as well as vehicle types. Driver behaviour impacts not only traffic safety but also fuel consumption and gas emissions.

This chapter presents a thorough literature review of driving behaviours which vary from time to time, place to place and more importantly driver to driver. This meta-analysis of driving behaviour variability recognises typical driving patterns and practices. It was made to review and collate the findings from world-wide studies (e.g. Naturalistic Driving Studies, Field Operational Tests) and aimed at providing scientific evidence to MODALES to characterise driver aggressiveness profiles and establish the link between vehicle emissions and driving behaviour with measurement campaigns in both real world and laboratory tests.

2.1 Driving behaviour variability by vehicle type

Table 2.1 shows the speed characteristics for various types of vehicles on different highway class. The obvious driving pattern is that mean speeds vary from one road category to another and are generally higher in rural roads than urban roads, given a particular road class. Private cars are the fastest mode of transport, travelling at 103 km/h, 90 km/h and 92 km/h on rural sections of national, inter-regional and regional highways, respectively. It is observed that trucks are the slowest. Among the highway class, the national roads record the highest rural mean speed of 90 km/h because they have favourable geometric characteristics and generally provide a direct service between cities and larger towns. In contrast, the inter-regional and regional roads possess limited sight distances, narrow and weedy shoulders, thus accounting for speed differentials on highway types. Figure 2-1 shows the speed variations on a major highway for different types of vehicles in Ghana.

Table 2.1: Mean speed and standard deviation by vehicle class and road class (James et al., 2008)

	Speed (mean value± standard deviation)/ km/h					
	National roads		Inter-regional		Regional	
Vehicle class	Urban	Rural	Urban	Rural	Urban	Rural
Taxi	74.3 ± 15	85.7 ± 18	63.7 ± 12	75.2 ± 14	65.3 ± 11	75.2 ± 16
Private car	89.3 ± 18	102.7 ± 19	69.4 ± 14	90.0 ± 17	78.2 ± 14	91.8 ± 19
Medium bus	80.1 ± 14	86.5 ± 13	63.4 ± 10	79.4 ± 13	71.9 ± 11	81.3 ± 11
Large bus	88.5 ± 16	89.4 ± 15	67.8 ± 13	79.6 ± 14	73.7 ± 10	81.5 ± 10
Light truck	71.5 ± 13	75.3 ± 14	61.1 ± 9	73.0 ± 14	67.0 ± 13	75.9 ± 12
Heavy truck	68.1 ± 14	68.9 ± 13	58.9 ± 12	69.0 ± 13	70.2 ± 15	73.2 ± 9

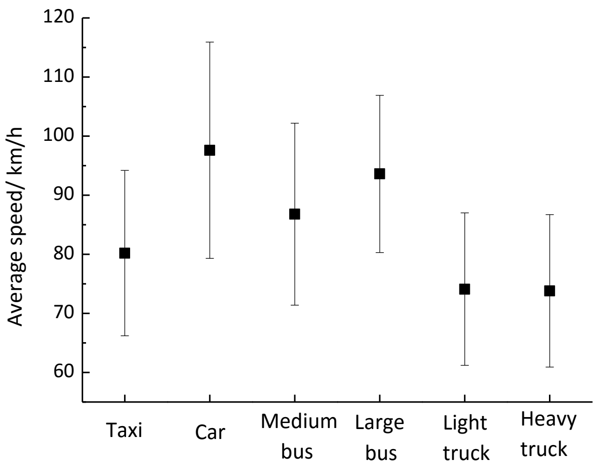


Figure 2-1: Vehicle speed variations on a major highway (James et al., 2007)

During acceleration manoeuvre, acceleration time and acceleration distance for all vehicle type increase with maximum speed in all speed ranges as observed in Indian traffic stream (see Table 2.2). The acceleration time and distance are related to the capability of vehicles. The maximum accelerations observed are 1.0 m/s^2, 0.64 m/s^2, 2.23 m/s^2, 2.87 m/s^2 for truck, motorised three-wheeler, diesel car and petrol car respectively. In the deceleration process, the petrol car has the highest capacity of deceleration among these types of vehicles (see

Table 2.3).

Table 2.2: Driving behaviours of all vehicle types during acceleration (Bokare and Maurya, 2017)

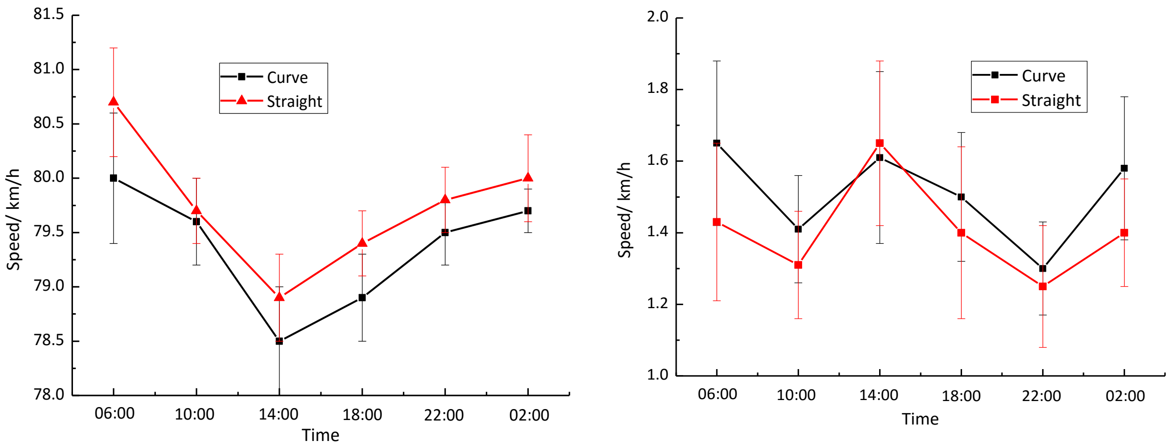
Vehicle Type	Maximum Speed Range (km/h)	Acceleration Time (sec)	Acceleration Distance (m)	Maximum Acceleration (m/s^2)	Mean Acceleration (m/s^2)
Truck	20-30	11.00	56.98	0.75	0.28
	30-40	17.00	98.26	1.00	0.29
	40-50	34.00	259.08	0.96	0.24
	50-60	35.00	361.20	0.87	0.24
Motorised three wheeler	15-25	27.00	94.50	0.54	0.21
	25-32	36.00	156.24	0.45	0.22
	32-36	40.00	220.80	0.60	0.22
	36-43	50.00	308.50	0.64	0.20
Diesel Car	68-76	34.80	519.18	1.89	0.55
	76-84	45.70	766.22	2.23	0.47
	84-92	52.50	923.64	1.97	0.52
Petrol Car	80-84	28.80	425.99	2.24	0.82
	84-88	31.60	545.01	2.47	0.64
	88-92	34.80	620.90	2.87	0.70

Table 2.3: Driving behaviours of all vehicle types during deceleration (Bokare and Maurya, 2017)

Vehicle Type	Maximum Speed Range (km/h)	Deceleration Time (sec)	Deceleration Distance (m)	Maximum Deceleration (m/s^2)	Mean Deceleration (m/s^2)
Truck	20-30	16.00	70.88	0.72	0.47
	30-40	21.30	124.39	0.75	0.46
	40-50	20.33	148.81	0.88	0.52
	50-60	30.75	243.54	0.88	0.51
Motorised three wheeler	27-31	19.85	107.52	0.85	0.35
	31-35	27.33	159.33	1.12	0.31
	35-39	26.45	172.31	1.14	0.36
	39-43	28.42	201.05	1.06	0.36
Diesel Car	92-94	8.08	83.38	4.30	3.19
	94-96	8.52	108.80	4.33	3.11
	96-98	8.60	113.04	5.00	3.36
	98-100	8.87	129.59	4.52	3.72
Petrol Car	61-72	7.61	85	3.36	2.42
	72-83	9.96	129	3.97	2.52
	83-91	10.27	134	4.33	2.59

2.2 Driving behaviour variability by time of day

The average vehicle speed and speed deviations across the time of the day for straight and curved roads are presented in Figure 2-2 (Lenné et al., 1997). The average vehicle speed is in the range of 78.5~80 km/h and 79~80 .5 km/h for straight and curved roads from 6 am to 2 am of the next day. Average speed at 2 pm shows the lowest value for both the straight and curved roads; meanwhile the speed fluctuations at 2 pm are high, which indicates frequent accelerations and decelerations.



(a) Average speed (b) Speed deviations

Figure 2-2: Average vehicle speed and speed deviations across the time of the day

Figure 2-3 shows the hourly distributions of speed parameters for rural sections of the national highways. Vehicle speed is generally higher during day time than night time. Speed reductions for the first 4 hours of the night are particularly significant. Speed dispersions are generally higher throughout the 16-hour period, ranging between 17 and 20 km/h.

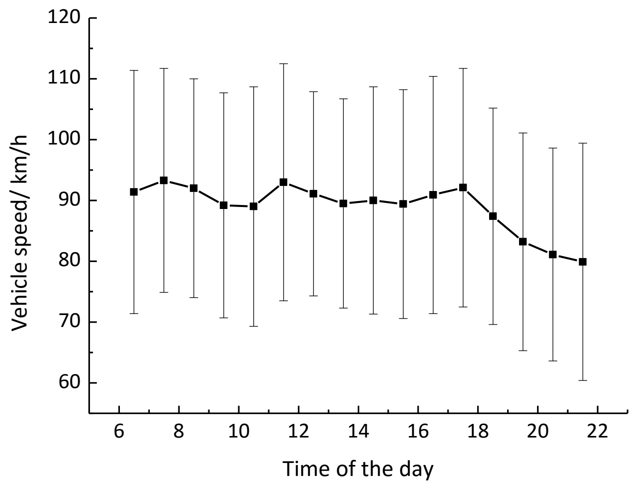


Figure 2-3: Vehicle speed distributions as the hour of the day (James et al. 2007)

2.3 Driving behaviour variability by road type

In DaCoTa project (http://www.dacota-project.eu/), vehicle movements are monitored to investigate the driver behaviours. Pilgerstorfer et al. (2011) shows that speeds in “regional” and “interurban 1” are more evenly distributed than other types of road (see Figure 2-4). High speed measurements are mainly concentrated on highway, and low speed measurements (lower than 40 km/h) mainly happen in “collector” and “arterial”, which account for more than 58% of driving time in their corresponding speed ranges.

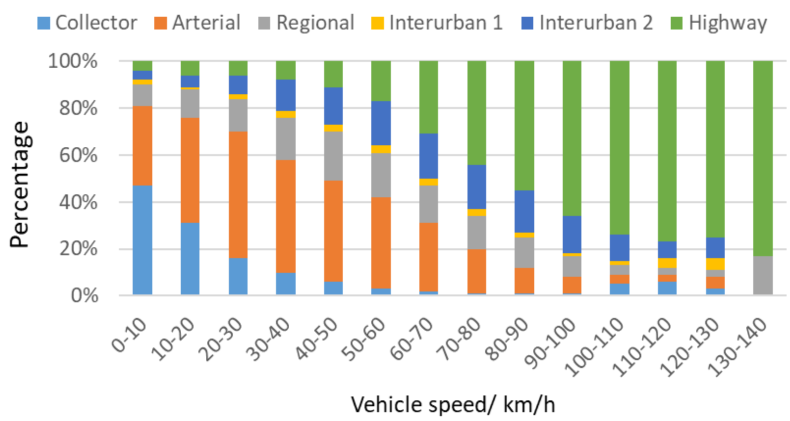


Figure 2-4: Speed distributions vs. road type

The Chinese Ecological Driving project (Yao et al., 2019) aims at driving behaviour corrections using a deep learning method to achieve the ecological driving. In this project, video training is used to correct the driving behaviours.

Table 2.4 (Yao et al., 2019) shows the driving behaviour changes after the adoptions of video training over different road types, such as uphill, downhill, and passing a curve. Positive values in this table show the decrease of non-ecological driving behaviour in the percentage of time compared to the values before training, and negative values are corresponding to the increase.

Table 2.4: Percentage of non-ecological driving behaviours decreased after training

	Accelerating sharply	Decelerating sharply	Low gears with high speed	Speed is too high
Uphill	0.00%	10.77%	23.61%	-40.00%
Downhill	44.74%	8.70%	40.00%	23.08%
Pass a curve	13.46%	-29.41%	23.75%	-50.00%

Table 2.5 (Pierre et al., 2016) lists part of the value changes of all kinds of driving behaviour key performance indicators (KPIs) after using eco-technologies over different road types. As we can see, the changes in driving behaviours differ significantly even using the same technology over various types of roads. Positive values mean the increase compared to without training. The data is from the ecoDriver (http://wiki.fot-net.eu/index.php/EcoDRIVER), which aims to achieve a reduction of CO_2 emissions and fuel consumption in road transport.

Table 2.5: Changes in KPIs of driver behaviours in ecoDriver

KPI abbreviated	Road type	Technology 1	Technology 2
Average speed when cruising/ %	Urban	3.30	4.76
	Rural	1.82	1.71
	Motorway	3.32	3.50
Average speed when freely driving/ %	Urban	10.61	9.83
	Rural	0.37	0.37
	Motorway	0.67	0.62
Average rpm when shifting gear up/ %	Urban	5.63	6.68
	Rural	9.97	12.23
	Motorway	3.42	3.32
Weighted average engine rpm/ %	Urban	9.12	9.39
	Rural	13.95	14.20
	Motorway	4.41	3.72

2.4 Geographical differences

Based on the database provided in Research Data Exchange (RDE), the variations in driving behaviours on the same type of road (rural roads) between two regions are compared. Figure 2-5 and Figure 2-6 (https://data.transportation.gov/) show the vehicle speed and acceleration distributions from Los Angeles and Northern Virginia road testing. Most of the vehicle speed is lower than 80 km/h, and the peak values are in the range of 35~40 km/h and 50~60 km/h for Northern Virginia and Los Angeles respectively. The testing conducted for Northern Virginia shows a greater proportion of low-speed driving than that of Los Angeles, and there is more than 70% of the acceleration being in the range of -0.5~0.5 m/s^2, suggesting gentle driving behaviour during the test. There is a higher percentage in time for rush acceleration and deceleration in Los Angeles, located in the regions of higher than 1 m/s^2 and lower than -2 m/s^2. It means driving behaviours in Los Angeles are more aggressive than that of Northern Virginia. The driving variability caused by regions including the factors of traffic conditions, road conditions, driver habits, also weather conditions. This data is from the Research Data Exchange (RDE) (https://its.dot.gov/).

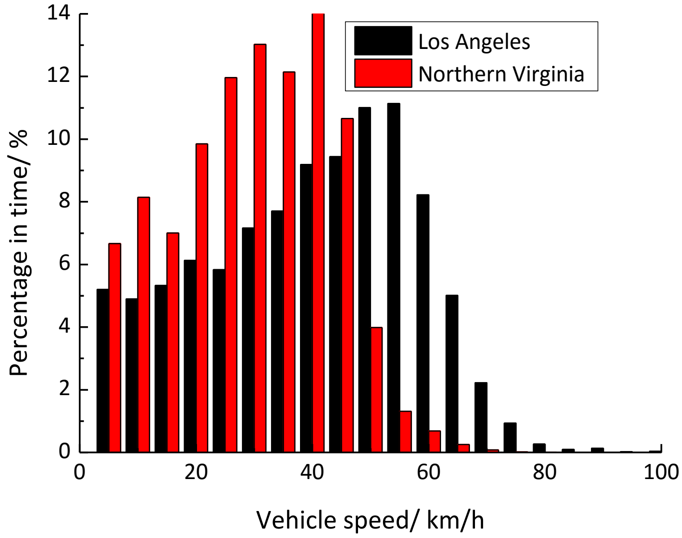


Figure 2-5: Speed distributions of vehicles testing in Northern Virginia

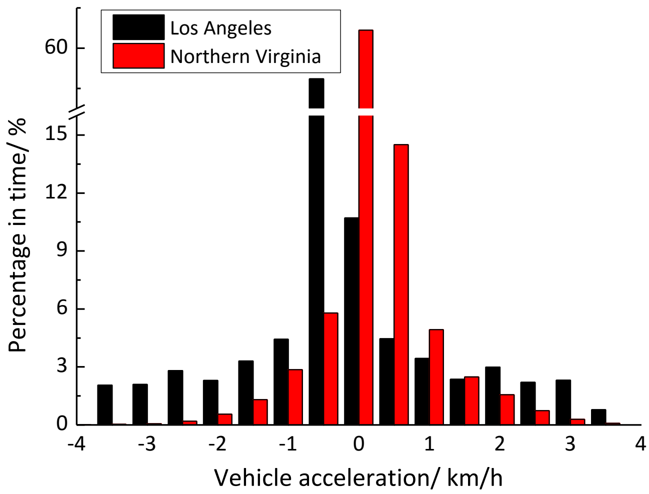


Figure 2-6: Acceleration distributions of vehicle testing in Northern Virginia

2.5 Impact of weather conditions

Figure 2-7 (Kilpeläinen et al., 2007) presents vehicle speed reductions over various weather situations compared to very good weather condition. It indicates that bad weather conditions reduce the average traffic and vehicle speeds. Figure 2-8 shows the effect of weather conditions, for example cloudy, clear, rainy and foggy on the driving behaviours (e.g. vehicle speed, acceleration and deceleration). Average vehicle speed appears sometimes to be dependent on the weather conditions, meanwhile, the deceleration and acceleration happen more frequently at foggy weather. The effect of weather conditions on the driving behaviour variability is not consistent; it can be caused by the road types and traffic conditions.

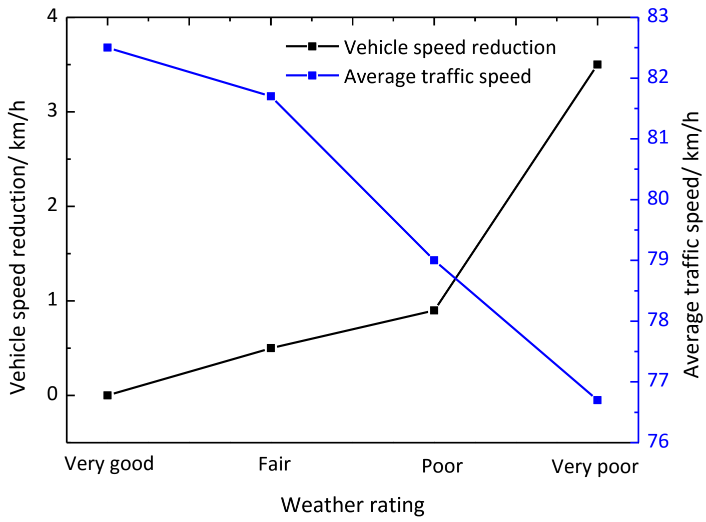


Figure 2-7: Drivers' speed reductions compared to very good weather condition

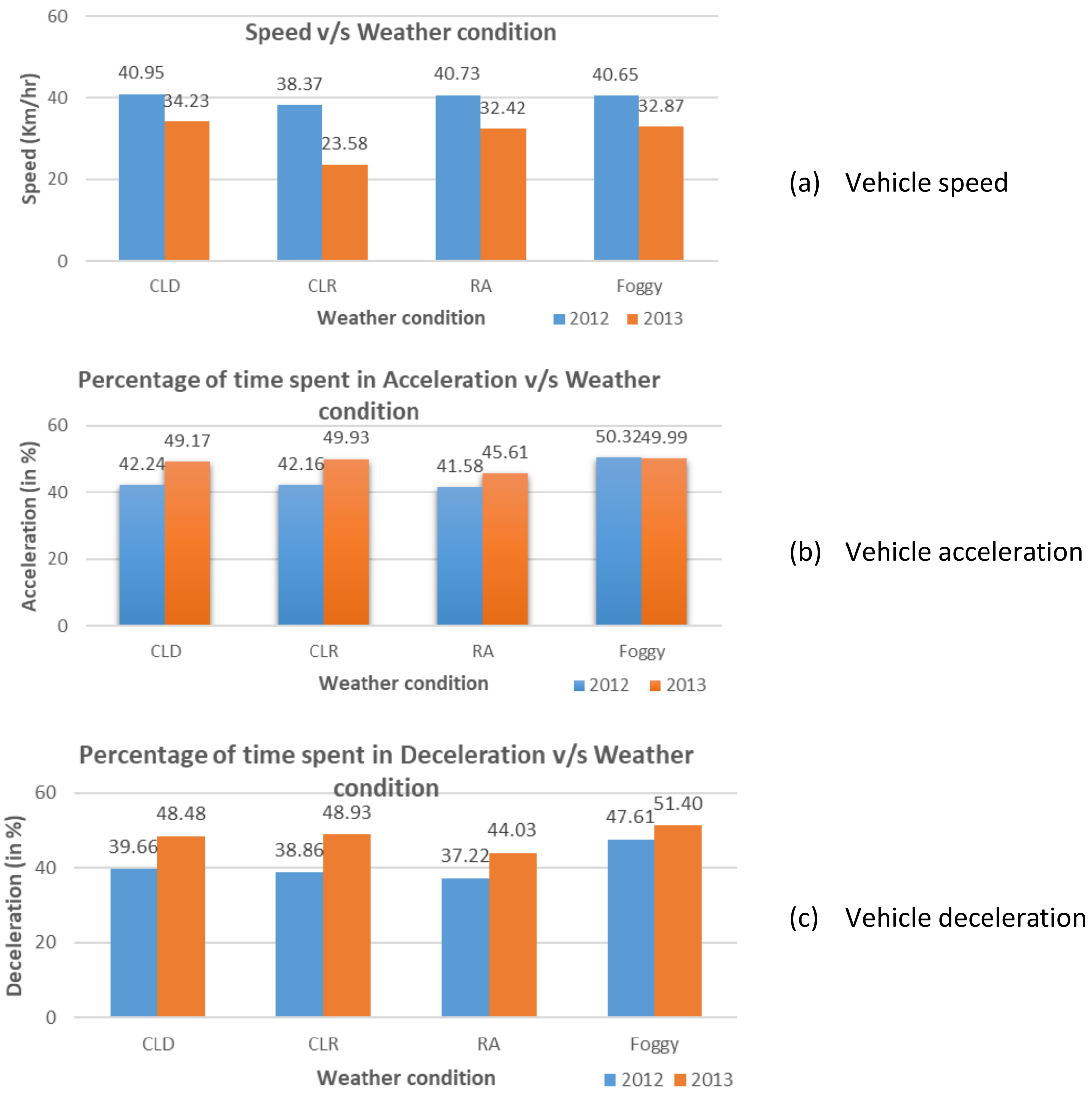


Figure 2-8: The effect of the weather conditions on driving behaviour variability: CLD, cloudy; CLR, clear; RA, rainy (Kilpeläinen et al., 2007)

2.6 Gender differences

Lightfoot company investigated the drivers behaviour differences based on 100 drivers (https://www.lightfoot.co.uk/news/2018/09/20/men-vs-women-driving-debate/#). When Lightfoot device is first installed, it takes 100 miles (161 km) of driving or two weeks from the date of installation to learn your vehicle and driving style. After 100 miles/two weeks, Lightfoot goes 'live' – providing real-time feedback through its system. This is the point at which drivers get feedback on their driving and can begin to adapt their driving habits to best suit their engine's design and needs. The test data appears to show that women are, without assistance, better drivers than men. However, once both groups are guided to a smoother driving style, men score slightly higher than women. The test results also indicate that men leave their vehicles idling 13% more than women in learning mode, and it is 50% in "live" mode.

From the speed profiles of female and male drivers on the same road (see Figure 2-9), it can be seen that male drivers prefer travelling at higher speed compared to the female drivers. At the first section of the given road, the female drivers travel at a lower speed than the male drivers. While travelling in the middle section of the road, there is no significant difference among the drivers. In the last section of the test road, the male drivers speed up faster than that of female drivers. The female drivers tend to drive smoothly than male drivers by comparing the two speed profiles. The fact is also demonstrated by Rohani et al., (2014) on a road segment for both male and female drivers with 30 participants in total. The average speed is slightly higher for male drivers than that of female drivers, with the average speed being 29.00 and 28.80 km/h for male and female drives respectively.

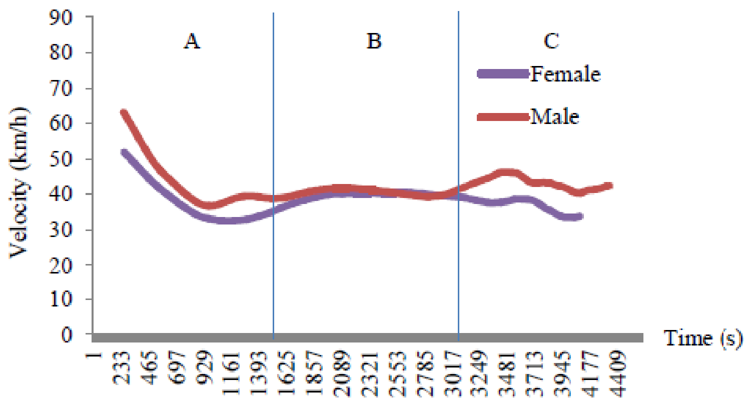


Figure 2-9: Vehicle speed difference between female and male drivers (Teo et al., 2016)

2.7 Effects of age

Different age drivers generally exhibit various driving behaviours. For example, compared to young drivers, older drivers drive slower. Meanwhile, older drivers have much more driving experience, and they know better how to drive within their limits. Table 2.6 lists the different driving behaviours in different age range. It can be obtained that older drivers make fewer steering and speed than the young control group. Younger drivers drive significantly faster and execute more braking applications than older drivers.

Figure 2-10 shows mean speed as a function of driver age range. Mean speed for drivers in the age range of 20-24 is the fastest than that in other age range. In addition, mean speed for male drivers in the same age range is faster than that for female drivers, except for the age range of 40-54.

Table 2.6: The driving behaviours in different age ranges (Perryman et al., 1996)

Group*	Average range	Speed/ mile/h	Braking	Steering
Young	24-34	15.0±1.3	244.1±23.4	1.52±0.5
Young/Aged	64-69	13.0±2.0	236.9±35.8	1.22±0.04
Old/Aged	69-91	11.8±1.0	203.2±33.8	1.23±0.05

*: Other age groups were not reported in the paper.

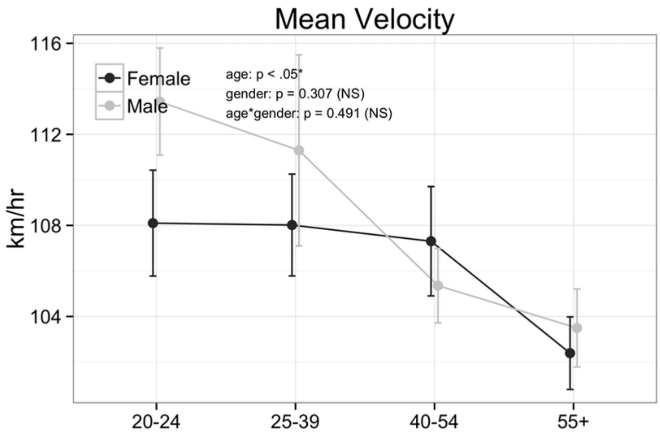


Figure 2-10: Mean driving speed as a function of driver age range

2.8 Influence of driving experience

The interactions between experience level and sensation-seeking (SS) on mean speed are significant (see Figure 2.11). Low sensation-seeking participants with 10+ years of driving experience drive slower overall when compared to both groups of less experienced drivers (Christina et al., 2014). It is disagreed with results of Li et al., (2015), who indicates that professional drivers have faster speed than non-professional ones (see Figure 2.12).

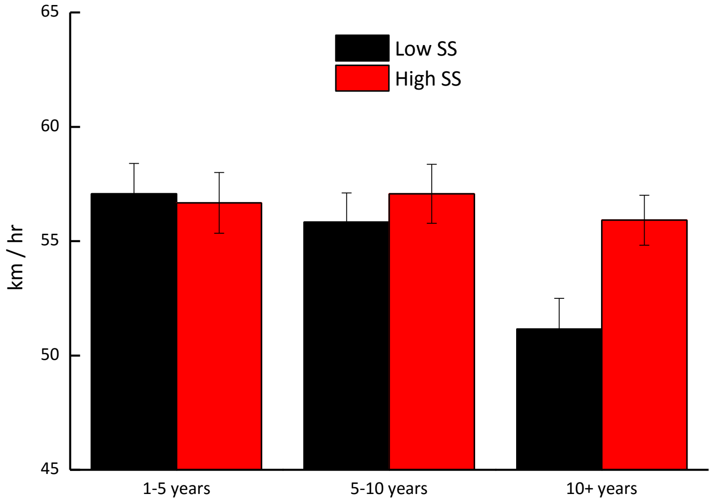


Figure 2.11: Effect of sensation-seeking and experience level on mean speed: SS, sensation-seeking

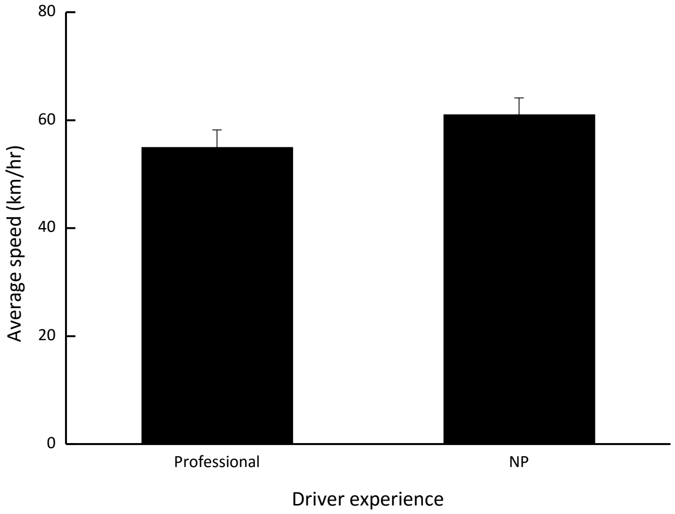


Figure 2.12: Average speed for different driver experience on the straight segment: NP, non-professional

Greater experience produces significantly smaller standard deviations ($p<0.05$) of velocity for real car and simulator (see Table 2.7). Consequently, the experienced drivers maintain a more constant velocity than inexperienced driver.

Table 2.7: Vehicle speed for inexperienced and experienced driver over real car and simulator

Performance index	Real car		Simulator	
	Inexperienced	Experienced	Inexperienced	Experienced
Velocity/ km/h	104.3	109.7	104.9	103.4
SD velocity	1.1	0.8	1.3	1.0

3 Exhaust emissions

In this chapter, the detailed analysis of the in-house data sources (e.g. MOVES, PHEM, VERSIT+, RETEMM and Motor Vehicle Emission Control Programs in China) are analysed, especially the equations developed within these tools. Key performance indicators (KPIs) of driving behaviours are included in these equations and used for analysing the relationship between driving behaviours and exhaust emissions to provide the evidence of low emission driving in MODALES project. Further, the preliminary meta-analysis is conducted to further uncover the relationship between driving behaviour and exhaust emission under given conditions.

3.1 Exhaust emissions from diesel and petrol engines and influence factors

3.1.1 Exhaust emissions from diesel engines and influence factors

Although the diesel engines, as the main power train, bring us great convenience, the petroleum fuel combustion in the diesel engines yields a great number of air pollutants that affect air quality and human health (Ristovski et al. 2012, Khair and Majewski 2006). These pollutants primarily include carbon dioxide (CO_2), carbon monoxide (CO), nitrogen oxide (NO_x), hydrocarbons (HC), aldehyde, and particulate matter (PM), as shown in Figure 3.1. Among these pollutants, the composition of PM is extremely complicated and involves the presence of broad classes of particle constituents such as organics, sulphates and elemental carbon, the presence of metallic ash and metal oxides, inorganic ions, and also the presence of toxic compounds such as polycyclic aromatic hydrocarbons (PAH), reactive oxygen species, carbonyls and quinones (Mayer et al. 2010, Cheung et al. 2010, Surawski et al. 2010).

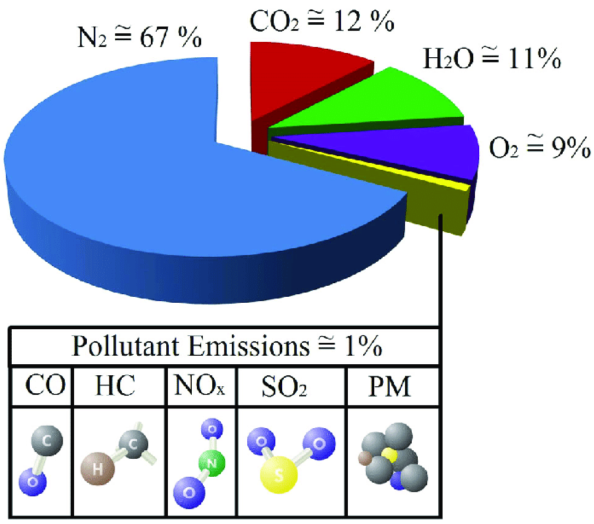


Figure 3.1: Main composition of pollutant emissions from diesel engines (Reşitoğlu, Altinişik and Keskin 2015)

The generation of these pollutants greatly depends on fuel used, engine operating conditions and so on. As fuel sulphur content reducing, the HC, CO and SO_2 emissions reduced, and the PM emission decreased remarkably, while NO_x emissions was not affected obviously. With fuel aromatic content decreasing, emissions including the PM, NO_x, HC and CO reduced significantly (Clark et al. 2002). In addition, the addition of biodiesel resulted in lower emissions of HC, PM, and CO and increased emissions of CO_2 and NO_x (Shirneshan 2013). Generally, an increase in diesel load led to the reduction in HC and CO but the increase in the CO_2, PM and NOx (Shirneshan 2013).

The vehicle age also significantly affects the emissions produced. As a vehicle ages and accumulates high mileage, the engine will slowly wear and produce higher emissions.

3.1.2 Exhaust emissions from petrol engines and influence factors

Compared to diesel engines, the pollutant emissions generated from petrol engines are similar. However, the nature of the high temperature combustion of petrol engines results in significant production of NO_x (Carslaw et al. 2011). Similarly, the increase in load and speed causes an increase in CO_2 and NO_x concentrations and reduces CO and HC concentrations. Additionally, increasing the compression ratio results in an increase of CO_2 and NO_x emissions and a decrease of CO and HC emissions. As for petrol engines, two main types of the fuel injection technology exist for petrol-fuelled vehicles: gasoline direct injection (GDI) and port fuel injection (PFI), which affects vehicle emissions. GDI generally provides better fuel economy and lower CO_2 emissions, because direct fuel injection technology can more accurately control the fuel volume and injection timing (Maricq, Szente and Jahr 2012). However, GDI vehicles have been reported to emit more particulate emissions than PFI vehicles, because there is limited time for fuel and air to be thoroughly mixed (Yinhui et al. 2016). A large percentage of particles emitted from GDI vehicles are smaller than 100 nm.

Another important factor that affects vehicle emissions is the ambient temperature. Extensive experiments have been conducted at ambient temperatures between 20 ^{o}C and 25 ^{o}C (Fu et al. 2014). However, the results from room-temperature tests may not reflect actual vehicular emission levels, because the average temperature of most places is below this temperature, especially during the winter. Some studies were reported to lead to the increase in emissions at low ambient temperatures. For example, Weilenmann et al. (Weilenmann, Favez and Alvarez 2009) found that gaseous emissions from light-duty vehicles increased at -7 ^{o}C and -20 ^{o}C, compared with those at 30 ^{o}C. In general, the ambient temperature had a significant effect on the cold-start emissions, and some emissions could increase by 10 times as the temperature varied from +22 ^{o}C to -18 ^{o}C (Chan et al. 2013). Dardiotis et al. (Dardiotis et al. 2013) obtained the similar variation tendency of the exhaust emissions with the ambient temperature decrease. This increase of the vehicle emissions at cold environment is mainly the result of 1) poor evaporation of fuel and sub-optimal combustion that need enrichment of fuel-to-air mixture to reach stable combustion, 2) this offsetting the needed stoichiometric AFR for three-way catalytic converter to work, and 3) too low temperatures, both exhaust and emission control systems, for reactions.

3.2 Monitoring of exhaust emissions

Real-world vehicle emission monitoring approaches can be divided into two main categories: in situ methods, in which monitoring equipment is deployed at fixed points (typically roadside or near roadside) and emissions are measured for multiple passing vehicles, and in-vehicle methods, in which monitoring equipment is deployed in instrumented vehicles that monitor emissions (either same-vehicle monitoring in conventional probe vehicle studies or other nearby vehicles, such as in car chaser studies) as the instrumented vehicle is driven within the local traffic flow.

3.2.1 In-situ real-world emissions monitoring

In situ real-world vehicle emissions monitoring methods categorised here according to the type of monitoring method used: road tunnel, across-road, and remote sensor studies. To date, road tunnel studies are widely applied class of real-world emission factor measurement methods, having been used by various researchers/research groups and in several countries. In road tunnel studies, the road tunnel is effectively treated as a large dilution tunnel. Tunnel air intake and outlets (or points near these) are used as sampling locations to mass balance model emissions.

After road tunnel methods, across-road measurement methods appear to have been most widely used to study real-world vehicle emissions. Across-road measurement methods are basically one application of open path techniques. Unlike most conventional monitoring techniques that provide single-point measurements at the analyser, integrated path techniques provide an average measure for a given area or transect, using a modification of the conventional spectrophotometric principle that light absorption is proportional to concentration.

By comparison to other emission measurement of real-world vehicle, remote sensing can dramatically alter the way we monitor emissions from on-road vehicles and allow more efficient screening of highly polluting vehicles, as shown in Figure 3.2 (https://www.downtoearth.org.in/blog/air/remote-sensing-smart-policing-of-emissions-on-road 60539). Remote sensing is a light source and a detector that is placed on the side of the road or at a height to transmit a laser beam to measure exhaust emissions remotely via spectroscopy as vehicles pass by and cross the light path. This can not only measure exhaust plume, and detect opacity, nitric oxide, carbon monoxide, hydrocarbons, and carbon monoxide in the exhaust plumes of vehicles but also record emission rates from thousands of individual vehicles along with speed and acceleration across all driving conditions daily. The big benefit of this system is that it helps to detect individual high-emitting vehicles, where high emissions result from poor vehicle maintenance by the vehicle owner or are caused by the removal and tampering of emission control systems and accidental malfunctioning of emission control equipment among others. However, the measurement accuracy is greatly dependent on the number of vehicles per time unit and screening criteria (Huang et al. 2018).

Figure 3.2: Remote sensor devices for emission test

3.2.2 In-Vehicle real-world vehicle exhaust emissions monitoring

Although it is easier to determine vehicle emission values in controlled and relatively narrow laboratory conditions and the testing ensures reproducibility and comparability of results, it covers only a small range of the ambient, driving, and engine operating conditions that typically occur on the road. For this reason, it is necessary to verify gaseous pollutant and particle number emissions during a wide range of normal operating conditions on the road using the Portable Emissions Measurement Systems (PEMS), as shown in Figure 3.3. So far, emission monitoring of in-vehicle real-world is also subject to limitations. First, on-road emission measurements are subject to larger uncertainty margins than emission measurements in the laboratory (Giechaskiel et al. 2015). Second, the handling of PEMS equipment requires training; conducting emission tests on the road is not yet plug-and-play.

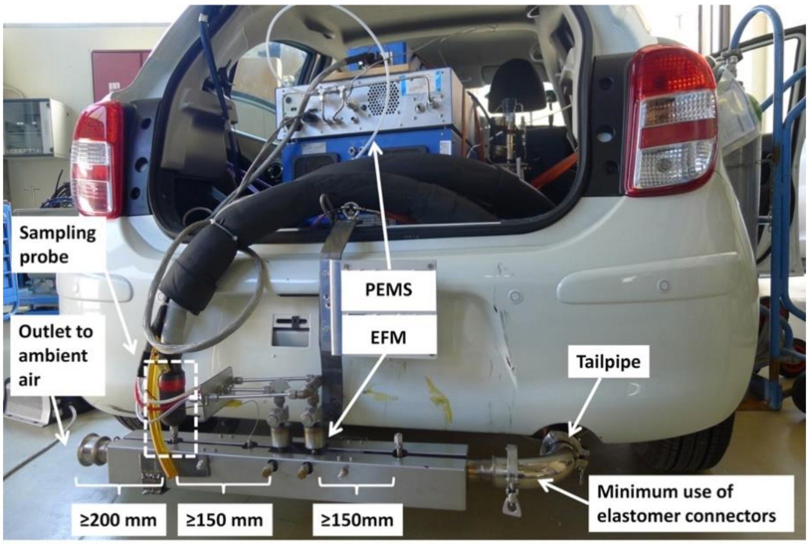


Figure 3.3: Portable emissions measurement system for real driving conditions (Giechaskiel et al. 2016)

In-vehicle real-world vehicle emissions monitoring methods are readily categorised according to the type of monitoring being conducted (i.e., either same vehicle monitoring, as in conventional probe vehicle studies, or other nearby vehicles, as in the case of car chaser and in-traffic flow studies). To date, most published probe vehicle work has tended to relate to driver behaviour research and/or traffic flow management, such as floating car studies where only limited parameters are logged, most often only Global Positioning System (GPS) position at real-time to near-real-time (1–5 seconds resolution).

In car chaser studies, specific vehicles (e.g., likely high-emitting vehicles) are targeted and followed directly by the probe vehicle for a given period of time, and elevated concentrations are inferred to result from the target vehicle. In in-traffic flow studies, the probe vehicle is driven in traffic (not keeping pace with any particular vehicle) and ambient concentrations are inferred to result from general vehicle emissions.

Figure 3.4 shows the on-road plume chasing and analysis system (OPCAS) for on-road vehicle emission. This system that is used for chasing and analysing real-time vehicle emission factors and volatile organic compounds (VOC) was developed by the School of Energy and Environment at City University of Hong Kong. It can be installed on any kind of automobile and includes a condensation particle counter, a real-time aerosol monitor, an Aethalometer, an air analyser, a VOC analyser, a global positioning system and a video camera. The OPCAS collects real-time plume samples from a target vehicle on the road. It takes about two minutes to determine pollutant concentrations, including VOC, fine suspended particulates, nitrogen oxides and black carbon, in the plume of the vehicle and the emission rates, based on carbon balance and fuel carbon content.

Figure 3.4: On-road plume chasing and analysis system

3.2.3 Lab monitoring of exhaust emissions

Now, all the test procedures in emission regulations are dependent on the chassis dynamometer, although the real-world emission test is also introduced in the Euro 6. Figure 3.5 shows the setup of the chassis dynamometer, which is used for the exhaust emission measurement. A chassis dynamometer, gaseous emission analyser, and full-flow constant volume sampler (CVS) exhaust dilution tunnel system are necessary to measure the regulated gaseous emissions, PM, CO_2 emissions, and fuel economy. CO and CO_2 were estimated using the non-dispersive infrared (NDIR) method; total hydrocarbon was measured using a heated flame ionization detector (FID); and the NO_x emissions were determined using a chemiluminescence detector (CLD). One of the other devices was a NO_x logger, which received the signal from the NO_x sensors, and the other was an FTIR analyser. The additional NO_x sensors used in the NO_x logger were installed both before and after the lean NO_x trap (LNT) in the vehicle. Exhaust from vehicles should be diluted before doing to the gaseous emissions analyser.

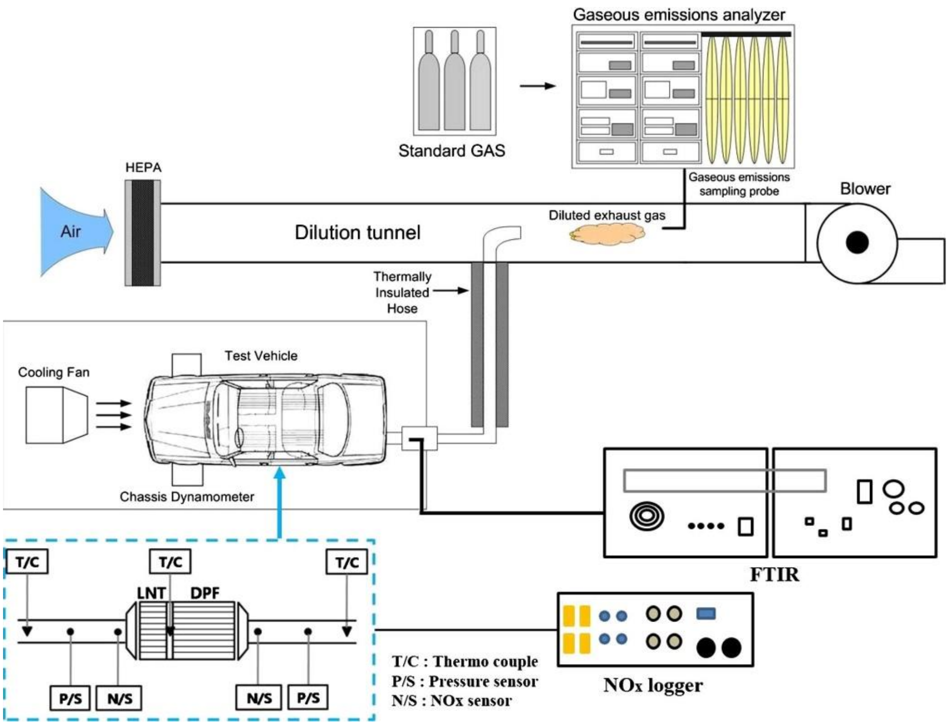


Figure 3.5: Setup of the chassis dynamometer (Ko et al., 2017)

3.3 Modelling of exhaust emissions

3.3.1 Instantaneous power-based emission models – PHEM

3.3.1.1 Introduction of PHEM (Austria)

Passenger Car and Heavy Duty Emission Model (PHEM) simulation tool was developed by Graz University of Technology (TU Graz) in cooperation with Forschungsgesellschaft für Verbrennungskraftmaschinen und Thermodynamik (FVT). PHEM is a detailed model for 1Hz simulation of single motor vehicles and vehicle fleets. Features of the PHEM are as the follows:

- Vehicle longitudinal dynamics simulation using a "backward" approach.
- Engine emission behaviour characterised by "emission maps" via engine speed and power (or torque).
- Additional model elements for exhaust after-treatment simulations (e.g. SCR, NSC), electrified powertrains (HEV, PHEV, EV), and emission behaviour in transient conditions.
- Time resolution: 1 Hz.
- Main model outputs: fuel consumption, CO_2, and pollutant emissions
- Interface to micro-scale traffic models (e.g. VISSIM, Aimsun)

Typical Model Applications

- Used for elaborations of Handbook Emission Factors for Road Transport (HBEFA) emission factors for passenger cars, light commercial vehicles and heavy-duty vehicles.
- Using HBEFA for generation of emission factors for special conditions (user defined data on driving cycles, road gradient, and ambient conditions).
- Research and engineering tool. Example: simulation of thermal conditions in the exhaust system for layouts of waste heat recovery systems.
- Link with micro-scale traffic models (e.g. VISSIM, Aimsun).

PHEM has a huge database for different cars, heavy duty vehicle (HDV), and light duty vehicle (LDV) from which input files for the "average" vehicle categories are elaborated. Data files can be provided for the following vehicle categories:

- Passenger Cars (diesel, petrol, EURO 0 to EURO 6d)
- Light Duty Vehicles (diesel, petrol, EURO 0 to EURO 6)
- Heavy Duty Vehicles (diesel, EURO 0 to EURO VI, split into weight categories)
- Buses
- Coaches

3.3.1.2 Inputs and outputs of PHEM

Basic inputs and outputs of this emission model are presented in Tables 3.1 and 3.2. It is similar to commercial software.

Table 3.1: Input variables of PHEM model

Variables	Related aspects
Vehicle parameters	Vehicle type
	Engine fuel consumption map (brake specific fuel consumption (bsfc) vs. engine speed and torque)
	Engine exhaust emission maps (emissions (CO, CH, NOx and PM) vs. engine speed and torque)
	Fuel types
	Gear shift strategies
	Transmission system parameters (gear number, gear ratio, and main reduction ratio)
	Tyre size
	Aerodynamic factor
	Vehicle mass
	Front surface area
	Auxiliaries use situations
	Aftertreatment system parameters
	Aftertreatment system thermal model
Road types	Rolling resistance factor
	Slope vs. distance
Speed profiles	Vehicle speed vs. time

Table 3.2: Outputs of the MOVE model

Outputs	Unit
Fuel consumption	g/km
CO_2 emission	g/km
HC emission	mg/km
CO emission	mg/km
NO_x emission	mg/km
PM emission	mg/km

3.3.1.3 Mathematical equations in PHEM

Theory of exhaust emission calculations in PHEM is to consult exhaust emission maps of internal combustion engines based on engine torque and speed required. The required engine speed is determined by vehicle speed, tyre radius, gear ratio and main reduction ratio of transmission system; however, more information is needed for engine torque calculation (related to engine power output if engine speed is given), such as rolling resistance factor between tyre and road, air dynamic drag coefficient and road slope.

Calculations of the energy consumption by wheelers are shown in the following equations (Rexeis & Hausberger, 2016),

$$P_e = P_{Air} + P_{Roll} + P_{Acc} + P_{Grd} + P_{Loss} + P_{Aux} \quad \text{(Eq. 3-1)}$$

Where, P_{Air}, P_{Roll}, P_{Acc}, P_{Grd}, P_{Loss}, and P_{Aux} are energy consumed by air dynamic drag, rolling resistance, vehicle acceleration, road grade, energy loss by friction in all the system (except for engine), and auxiliary, respectively.

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

(Eq. 3-2)

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.

3.3.2 Instantaneous power-based emission models – NDDBEM

3.3.2.1 Introduction of NDDBEM (US)

Emissions during a trip often depend on transient vehicle dynamics that influence instantaneous engine loads. Vehicle specific power (VSP) is a proxy variable for engine load that has been shown to be highly correlated with emissions. Newly defined diesel bus emission model (NDDBEM) estimates emission rates for diesel-fuelled transit buses using speed profiles, and validated using a portable emission monitoring system.

Engines can operate at different conditions (engine speed and torque) even though vehicle speed and engine power outputs are the same. It can be achieved by different gearshift strategies. In addition, vehicle emissions are significantly dependent on aftertreatment performance. Efficiency of the after-treatments is excellent if the engine is fully warmed up. Gao et al. (Gao et al., 2019) also indicated that majority of vehicle emissions are emitted during engine cold start and warm up process. But all these important factors are neglected in this emission model, which leads to a low precision of emission estimations. Meanwhile, this model fails to estimate exhaust emissions under idle conditions.

3.3.2.2 Mathematical equations in NDDBEM

Equations provided in NDDBEM (Zhai et al., 2008) to estimate exhaust emissions are shown in the following equations. This estimation is based on vehicle speed profile. This model provides the relations of vehicle speed and emissions, which is linked by vehicle power. It has an assumption that CO and NO_x emissions are only related to vehicle power outputs. The vehicle power estimation is similar to other work, where vehicle speed, acceleration, road grade, and vehicle parameters are used. However, this model convers limited information of the engine operation situations.

$$VSP = v \cdot (a + 9.81 \cdot \sin(\varphi) + 0.092) + 0.00021 \cdot v^3 \quad \text{(Eq. 3-3)}$$

$$R_{CO} = -0.001 \cdot VSP^2 + 0.0179 \cdot VSP + 0.0105 \quad \text{(Eq. 3-4)}$$

$$R_{NOx} = -0.0014 \cdot VSP^2 + 0.0349 \cdot VSP + 0.0711 \quad \text{(Eq. 3-5)}$$

Where:

- VSP: vehicle specific power (kW);
- v: vehicle speed (m/s);
- a: vehicle acceleration (m/s^2);
- φ: road grade (°);
- CO emission rate (g/s);
- NOx emission rate (g/s).

3.3.3 Instantaneous fuel-based emission model – CMEM

3.3.3.1 Introduction of CMEM (US)

Comprehensive modal emissions model (CMEM) was initially developed in the late 1990's with sponsorship from the National Cooperative Highway Research Program (NCHRP) and the U.S. Environmental Protection Agency (EPA) to fulfil the need for microscopic emissions modelling (https://www.cert.ucr.edu/cmem). This type of model is necessary for evaluating emissions benefits of project-level or corridor-specific transportation control measures (e.g. HOV lanes), intelligent transportation systems (ITS) implementations (e.g. electronic toll collection), and traffic flow improvements (e.g. traffic signal coordination).

CMEM is microscopic in the sense that it predicts second-by-second tailpipe emissions based on different modal operations from in-use vehicle fleet. One of the most important features of CMEM is that it uses a physical, power-demand approach based on a parameterised analytical representation of emissions production. In this type of model, the emissions process is broken down into components that correspond to physical phenomena associated with vehicle operation and emissions production. Each component is modelled as an analytical representation consisting of various parameters that are characteristic of the process. These parameters vary according to the vehicle type, engine, emission technology, and level of deterioration. One distinct advantage of this physical approach is that it is possible to adjust many of these physical parameters to predict emissions of future vehicle models and applications of new technology (e.g., after-treatment devices).

3.3.3.2 Mathematical equations in CMEM

CMEM is composed of six modules: engine power, engine speed, air–fuel ratio, fuel use, engine-out emissions, and catalyst pass fraction (CPF). This model estimates emission rates under different vehicle operating conditions (stoichiometric, cold-start, and enrichment conditions) (Barth et al., 2000). This model estimates second-by-second tailpipe emissions as the products of fuel rate (FR), engine-out emissions index ($g_{emissions}/g_{fuel}$), and CPF by using the form (Barth et al., 2000),

$$\text{Tailpipe emissions} = FR \times \left(\frac{g_{emissions}}{g_{fuel}}\right) \times CPF \quad \text{(Eq. 3-6)}$$

Engine-out emissions index ($g_{emissions}/g_{fuel}$) is the values of engine out emission rate over fuel rate. Catalyst pass fraction (CPF) value for all the heavy duty trucks (HDDTs) is considered to be 100%. FR value is estimated using the following equation (Barth et al., 2000),

$$FR = \left(K \cdot N \cdot V + \frac{P}{\eta}\right)\frac{1}{43.2} \cdot [1 + b_1 \cdot (N - N_0)^2] \qquad \text{(Eq. 3-7)}$$

Where:

- FR is fuel rate (g/s);
- P is engine power output (kW);
- K is engine friction factor;
- N is engine speed (revolutions per second);
- N_0 is engine speed under idle conditions;
- V is engine displacement (L);
- η is indicated efficiency for diesel engines;
- $b_1=10^{-4}$, and 43.2 kJ/g is the lower heating value of diesel fuel.

In the equation, the indicated efficiency of the diesel engine is considered as a constant value, which is completely different from the real life. In the real driving conditions, the indicated engine efficiency differs a lot, especially under various engine load conditions.

The engine out emissions for CO, HC, and NOx are modelled according to linear equation, as the following

$$Engine\ out = a \cdot FR + r \qquad \text{(Eq. 3-8)}$$

Where,

a and *r* are coefficients, which are determined by regression and calibration procedures.

3.3.4 Regression-based emission model – VERSIT+

3.3.4.1 Introduction of VERSIT+ (Netherlands)

TNO has developed the state-of-the art emission model VERSIT+[1]. This suite of models is used to predict emission factors and energy use factors that are representative for vehicle fleets in different countries. Emission factors are differentiated for various vehicle types and traffic situations, and take into account real-world driving conditions. VERSIT+ is unique in that it yields consistent results on national, regional and local scales. It can be used for investigating national greenhouse gas reduction strategies but also for local air quality improvement. The emission factors are used by public and private organisations for environmental monitoring as well as for assessment of environmental effects of traffic measures and vehicle technology incentives.

Based on measurements of current vehicles and sound knowledge of future emission reduction technologies, VERSIT+ can project car emissions into the future. Emission prediction for road traffic (trucks, buses, passenger cars and motorcycles) is important for governments to make well-informed decisions regarding clean vehicle technology incentives.

Emissions per car can vary widely, due to differences in vehicle technology and driving behaviour. VERSIT+ is based on a database of 12,000 measured driving cycles, mimicking all aspects of real-time

[1] https://www.tno.nl/media/2451/lowres_tno_versit.pdf

driving behaviour. Using advanced statistical modelling techniques, VERSIT+ finds the best fitting emission factor equation for any given driving pattern.

The newest development is to link VERSIT+ directly to traffic simulation models. This allows for direct evaluations of impact of traffic measures (such as green wave, or trajectory control) on the air quality. This is vital information for local governments in their battle against local air pollution

3.3.4.2 Theory of VERSIT+

VERSIT+ is a "cycle-variable" emission model that it can generate exhaust emissions based on the provided vehicle speed profiles. Inputs and outputs of the emission model are shown in Table 3.3. VERSIT+ is more often used for microscale simulations where it is coupled with traffic simulation model, for example VESSIM to conduct the co-simulation, as indicated in Figure 3.6 (Borge et al., 2015). The emission factors for emission calculations are provided by VERSIT+, and it is based on the vehicle types, and is limited to cars, trucks and buses.

Table 3.3: Input variables of VERSIT+ emission model

Inputs	Outputs
Vehicle speed profiles Vehicle parameters (vehicle mass, front area, aerodynamic drag, rolling resistance factor) Emission factors	NO_x emission PM emission CO emission HC emission

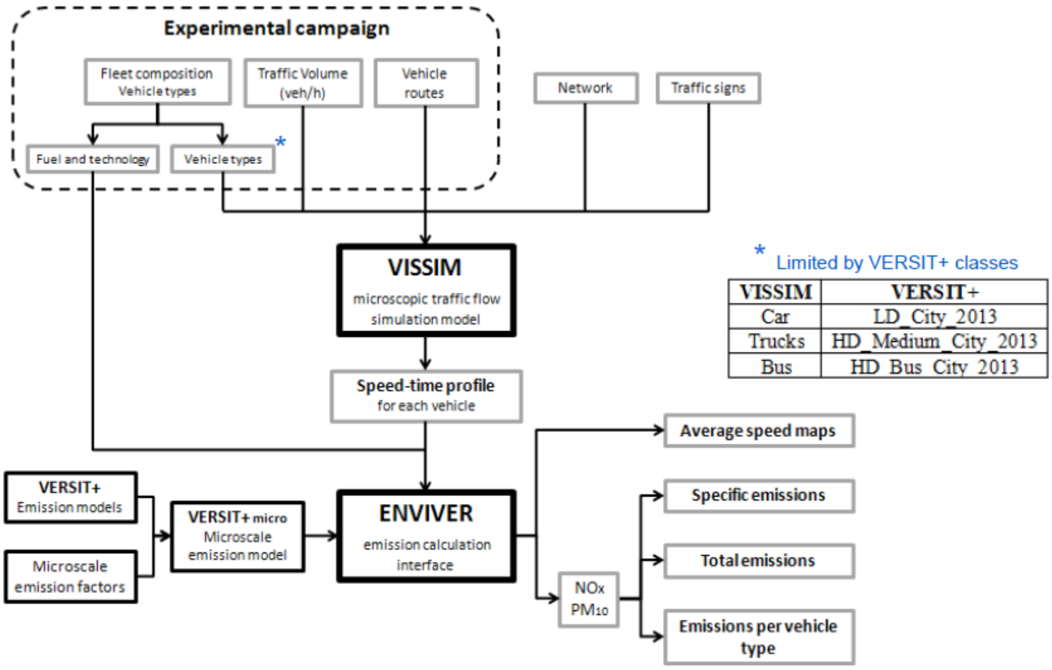


Figure 3.6: Co-simulation of the emission model and traffic model

3.3.5 Traffic simulation-based emission models – HBEFA

3.3.5.1 Introduction of HBEFA (EU)

Handbook Emission Factors for Road Transport (HBEFA) is a Microsoft Access database application providing emission factors, i.e. the specific emission factors in g/km, for all current road vehicle categories (passenger cars, light duty vehicles, heavy duty vehicles, buses, and motorcycles). Emission factors are provided for all regulated and the most important non-regulated air pollutants as well as for fuel consumption and CO_2. HBEFA is used to estimate road transport emissions on different spatial aggregation levels from national to street level. Factors for the following components are provided: CO, NO_x, HC and several components of hydrocarbons (CH_4, non-methane hydrocarbons (NMHC), benzene, toluene, xylene), fuel consumption (petrol, diesel), CO_2, NH_3 and N_2O, NO_2, particle numbers (PN) and particle mass (PM).

HBEFA consists of four sub-modules:

- The emission factor database (expert version only) containing the base emission factors from various sources (such as vehicle emission measurements, emission factor models, etc.)
- The fleet model (expert version only) providing weighting factors for the base emission factors in order to produce fleet compositions for a particular location (e.g. a country or a city) and a particular time period (one or more years).
- The emission factor module (public and expert version) allowing access to the emission factor database by calculating weighted emission factors for particular traffic situations in a particular area and time period using the specified fleet compositions provided by the fleet model.
- The emission model (expert version only) for the computation of overall emissions either on an aggregated spatial level for a particular area (e.g. a country or a city) or for a specific road network ("linkwise"). Inputs of the emission model are the descriptions of the traffic activity (typically the vehicle kilometres travelled or the vehicle volume per road link) per vehicle category and the emission factors from the emission factor module. By multiplying these inputs, the overall emissions are calculated.

3.3.5.2 Mathematical equations in HBEFA

HBEFA (Schmied et al., 2014) is an emission model based on the regression technique for warm engines (excluding cold start). It includes separate polynomial models for NOx, CO and HC emissions, respectively. Vehicles are classified into three types, namely car, SUV and Truck. Each vehicle type is represented by the model with its own coefficients.

These models don't consider the variation of vehicles in the same category. For example, the emission rate of petrol cars is the same as that of the diesel cars.

The exhaust emissions under hot conditions are as the general form,

$$f(x)=\mathrm{a}\cdot x^2+\mathrm{b}\cdot x+\mathrm{c} \qquad \text{(Eq. 3-9)}$$

Where:

- x is vehicle speed;
- a, b and c are coefficient, the coefficient is shown in Table 3.4 over various types of vehicles.

Table 3.4: Coefficient of the hot emissions model (HBEFA)

Pollutant	Vehicle	Coefficients		
		a	b	c
NOx	CAR	0.000249	-0.00933	0.1405
	SUV	0.001264	-0.1118	3.448
	TRUCK	0.006815	-0.8451	27.55
CO	CAR	0.0029	-0.288	10
	SUV	0.001679	-0.1611	3.957
	TRUCK	0.0002483	-0.04091	1.698
HC	CAR	0.0002	-0.211	0.6974
	SUV	0.0006109	-0.05325	1.384
	TRUCK	0.001957	-0.02933	1.139

3.3.6 Average speed-based emission models – COPERT

3.3.6.1 Introduction of COPERT (Greece)

COPERT is the EU standard vehicle emissions calculator. It uses vehicle population, mileage, speed and other data to calculate emissions and energy consumption for a specific country or region. COPERT methodology is part of European Monitoring and Evaluation Programme (EMEP) and European Environment Agency (EEA) air pollutant emission inventory guidebook for calculations of air pollutant emissions. It is consistent with 2006 Intergovernmental Panel on Climate Change (IPCC) Guidelines for calculations of greenhouse gas emissions.

COPERT (https://www.emisia.com/utilities/copert/) has the following advantages:

- Internationally recognised — used by many European countries for reporting official emissions data.
- A research tool — calculating emissions at a national, regional or local scale, and for annual to daily estimates.
- Technologically advanced and transparent — COPERT's methodology is published and peer-reviewed by experts.
- Include all main pollutants: greenhouse gases, air pollutants and toxic species.

COPERT has the following technical features:

- Estimates emissions from all relevant road vehicle operation modes.
- Includes thermal stabilised engine operation ('hot' emissions).
- Covers the warming-up phase ('cold start' emissions);
- Can calculate non-exhaust emissions (from fuel evaporation, tyre and brake wear emissions).
- Contains emission factors for more than 450 individual vehicle types including passenger cars; light commercial vehicles; heavy duty vehicles (including trucks and buses); L-category vehicles (including mopeds, motorcycles, quads and mini-cars).

3.3.6.2 Mathematical equations in COPERT

Emission factor calculations in CORPERT are based on characteristics of individual vehicle, coefficients in emission calculation equations are calibrated using real test data under various scenarios (https://www.emisia.com/utilities/copert/documentation/). Vehicle category, fuel type, vehicle segment, vehicle emission level, fuel injection technology, and warm up situations are necessary to estimate vehicle emission factors using mathematical equations. Following equation gives an example of the exhaust emission after engine fully warmed up conditions,

$$EF=(a\cdot v2+b\cdot v+c+(d/v))/(e\cdot v2+f\cdot v+g)\cdot(1-h) \qquad \text{(Eq. 3-10)}$$

Where:

v is average vehicle speed;

EF is vehicle emission rate;

A~ h are coefficients from CORPERT (https://www.emisia.com/utilities/copert/documentation/).

3.3.7 Average speed-based emission model – NAEI

3.3.7.1 Introduction of NAEI (UK)

In National Atmospheric Emissions Inventory (NAEI), emissions from different types of vehicles can be estimated, e.g. cars, light goods vehicles (LGVs), heavy duty vehicles & buses, and motorcycles. However, the format of the equations is different for various categories of vehicles.

- The cars worksheet provides the parameters for calculation of emission factors for passenger cars, for different fuel types, engine sizes and Euro standards.
- The LGVs worksheet provides the parameters for calculation of emission factors for LGVs, for different fuel types, weight classes, and Euro standards.
- The heavy goods vehicles (HGVs) & Buses worksheet provides the parameters for calculations of emission factors for HGVs and buses, for different vehicle weight classes and Euro standards and different load factors and road gradients.
- The motorcycles worksheet provides the parameters for calculation of emission factors for mopeds and motorcycles of different engine sizes and Euro standards.

3.3.7.2 Mathematical equations in NAEI

This model describes the exhaust emission rates for different types of vehicles, based on their speed. The estimated exhaust emission rates are for hot engine conditions. It means a high efficiency of aftertreatments. This model is obtained based on large amounts of test data, which then is used for the regression. Users need to refer the coefficients from the NAEI websites based on the vehicle type, engine size, fuel type, and emission levels. This model is only suitable for part of roads, because the coefficients under various road grades are not available for parts of vehicle types in NAEI. The following equation shows NO_x emission of motorcycles,

$$EF = (a+b\cdot v+c\cdot v^2+d\cdot v^e+f\cdot \ln(v)+g\cdot v^3+h/v+i/v^2+j/v^3)\cdot x \qquad \text{(Eq. 3-11)}$$

Where:

- *EF* is exhaust emission rate (g/km) (CO, HC, NO_x, and PM emission)
- *V* is average speed (km/h)
- a~j and x are coefficients from NAEI (https://naei.beis.gov.uk/data/ef-transport); the coefficients are different for various types of motorcycles.

3.3.8 MOVES

3.3.8.1 Introduction of MOVES (US)

EPA's MOtor Vehicle Emission Simulator (MOVES) (https://www.epa.gov/moves) is a state-of-the-science emission modelling system that estimates emissions for mobile sources at the national, county, and project levels for criteria air pollutants and greenhouse gases. It is used to create emission factors or emission inventories for both on-road motor vehicles and off-road equipment. The purpose of MOVES is to provide an accurate estimation of emissions from cars, trucks and non-highway mobile sources under a wide range of user-defined conditions. In the modelling process, users specified vehicle types, time periods, geographical areas, pollutants, vehicle operating characteristics, and road types are included. The model then performs a series of calculations, which have been carefully developed to accurately reflect vehicle operating processes, such as running, starts, or stopping, and provide estimations of total emissions or emission rates per vehicle. In addition, the MOVES model includes a default database that summarises emission relevant information for the entire United States. The MOVES team continually works to improve this database, but, for many uses, up-to-date local inputs will be more appropriate, especially for analyses supporting State Implementation Plans (SIPs) and conformity determinations.

3.3.8.2 Mathematical equations in MOVES

MOVES estimates emissions of both exhaust and evaporative emissions. Outputs from the model are in the form of emission factors expressed as grams of pollutants per vehicle per hour (g/hr), or per vehicle mile travelled (g/mile). Thus, emission factors from MOVES can be combined with estimations of total vehicle miles travelled (VMT) to develop highway vehicle emission inventories. For the emission models in MOVE, different emission outputs require different input variables. Table 3.5 presents the basic input variables for model operations. The MOVES model is similar to a lookup table based on thousands of real-world tests, such that you can find the corresponding emission rate when the tested conditions are given.

Table 3.5: Input variables of the MOVE model

Input variables	Output
Time spans Geographic Bounds Vehicle type Fuel type Road type Target pollutions	NO_x emission PM emission CO emission HC emission

The theory of the emission calculation in the MOVES model is to consult a series of tables, which indicates all the coefficients created based on the real-world tests. The following equation is an example of NO_x emission calculation.

$$\text{Emission Quant} = NO_x\text{Ratio} * \text{Oxides of Nitrogen} \quad \text{(Eq. 3-12)}$$

NO_x ratio comes from a table in MOVES; Oxides of Nitrogen is calculated by a series of coefficients for example nono2ratio, ppa, ppmy, sourceusetype, which are provided by the code in the model.

3.4 Meta-analysis

A meta-analysis is a statistical analysis that combines the results of multiple scientific studies. Meta-analysis can be performed when there are multiple scientific studies addressing the same question, with each individual study reporting measurements that are expected to have some degree of error. The aim is to use approaches from statistics to derive a pooled estimate closest to the unknown common truth based on how this error is perceived. Existing methods for meta-analysis yield a weighted average from the results of the individual studies, and what differs is the manner in which these weights are allocated and also the manner in which the uncertainty is computed around the point estimate thus generated. In addition to providing an estimate of the unknown common truth, meta-analysis has the capacity to contrast results from different studies and identify patterns among study results, sources of disagreement among those results, or other interesting relationships that may come to light in the context of multiple studies.

The purpose of meta-analysis is to estimate the overall or combined effect based on the published and unpublished data. The combined effect analysis includes fixed effects meta- analysis and random effect meta-analysis (Kelley and Kelley, 2012). The definitions and their characteristics are shown in Figure 3.7. The first step of meta-analysis is to summarise related data from both published and unpublished papers. Then, the analysis of the summarised data will be done is based on the distribution characteristics.

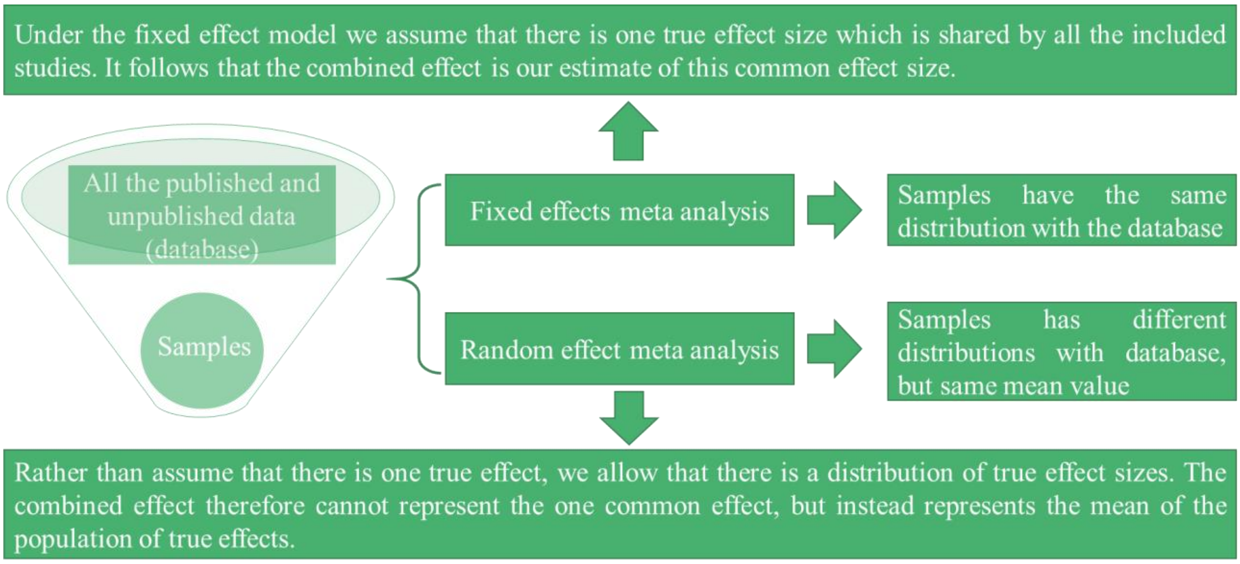


Figure 3.7: Definitions and characteristics of fixed and random effect meta-analysis

3.4.1 Fix effect meta-analysis model

In a fixed effect analysis, the distributions of the studies are considered to meet the normal distributions. The observed effects are distributed about the common effect of μ, with a variance σ^2. The variance mainly depends on the sample size. The normal distributions are shown in Figure 3.8 (https://en.wikipedia.org/wiki/Normal_distribution).

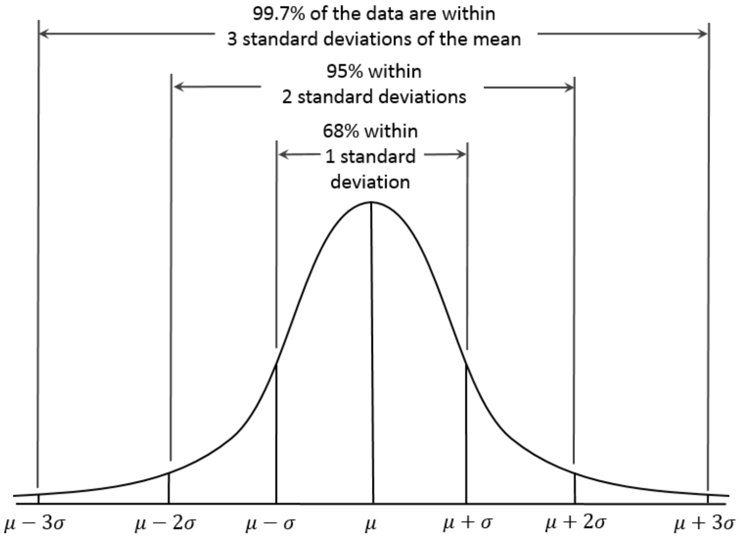


Figure 3.8: Distributions of the fixed effect analysis

The normal distribution equation is as the follows,

$$\boldsymbol{f(x)} = \frac{\mathbf{1}}{\sqrt{\mathbf{2}\boldsymbol{\pi\sigma}}}\mathbf{exp}\left(-\frac{(\boldsymbol{x}-\boldsymbol{\mu})^{\mathbf{2}}}{\mathbf{2}\boldsymbol{\sigma}^{\mathbf{2}}}\right) \quad \text{(Eq. 3-13)}$$

μ: mean

σ: variance

$$\mu = x_1p_1+x_2p_2+\ldots\ldots+x_np_n \quad \text{(Eq. 3-14)}$$

$$\sigma^2=1/n[(x_1-x)^2+(x_2-x)^2+\ldots\ldots+(x_n-x)^2] \quad \text{(Eq. 3-15)}$$

x_1, x_2, x_3....are the sample in the study;

p_1, p_2, p_3...are their corresponding weight;

n is the number of samples.

If the significance level is α, it satisfies the following equation

$$\Pr\ (c_1 < \mu < c_2) = 1- \alpha \quad \text{(Eq. 3-16)}$$

c_1 and c_2 are lower limit and upper limit of the confidence interval.

3.4.2 Random effects meta-analysis model

The observed effect T_1 (box) is sampled from a distribution with true effect θ1, and variance σ2. The true effect θ1 is sampled from a distribution with mean μ and variance *T*2. The random effects model is shown in Figure 3.9 (Borenstein et al., 2011). Under the conditions, it meets the γ^2 distribution.

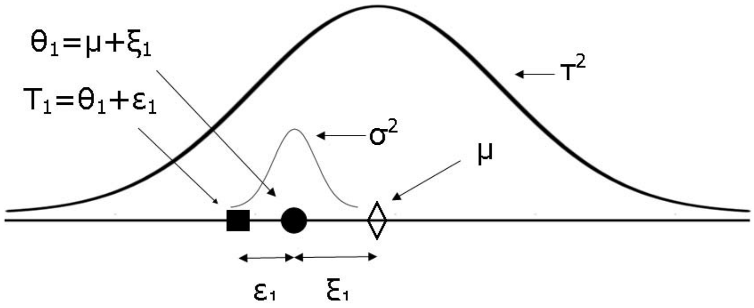


Figure 3.9: Distributions of the random effect analysis

3.4.3 Meta-analysis review related to exhaust emission and closed filed

In this sub-section, the applications of meta-analysis to exhaust emissions and similar research will be reviewed. In the meta-analysis, errors are evitable due to different test conditions and targets, consequently thorough error analysis is commonly carried out in such research.

Robin et al., (2010) reviewed the traffic emission models and conducted meta-analysis, which was driven by the increasing need to estimate the contributions of road transport to air pollutants. In this work, 50 studies with different emission models from the literature are used, including the information of average speed, traffic situation, cycle variable and traffic variable. These emission models are validated or partially validated including test data from tunnels, laboratory and remote sensing. Consequently, prediction errors vary for different emissions. The authors argue that a more complex model cannot ensure a better performance of error predictions.

Aplllonia et al., (2011) analysed ship emission modelling approaches using meta-analysis based on available data sources. An effective approach is based on the geographic characteristic of the world being divided into 0.1° × 0.1° cells. The intensity of the ship traffic is obtained based on AMVER and ICOADS datasets, then the emissions are calculated for each cell. Another method involves estimating the emissions based on the international marine fuel usage reported by Energy Information Administration. This method illustrates the magnitude of maritime transport on the impact of atmosphere emissions. Based on the meta-analysis of the current methods of estimating emissions, a more effective method is proposed.

In the work (Belis et al., 2013), consistent records were identified for source contribution estimates of PM mass concentrations for 272 records and of organic carbon (OC) in PM for 60 records. The focus of the receptor models is shifting from the component analysis and classical factor analysis to Positive Matrix Factorisation. The compositions of PM from six major categories are analysed to identify the sources of PM that the atmosphere formation of secondary organic aerosol, biomass burning, and fossil fuel combustion are the three main sources of organic carbon. In addition, the factors of seasonal and geographical variations are discussed.

Zhou and Levy (2012) investigate factors influencing the spatial extent of mobile source air pollution impacts using meta-analysis. Data in the study is taken from published papers and reports detailing, the significant pollutants; carbon monoxide, benzene, nitrogen oxides, and particulate matter (particle counts and mass). The findings from the meta-analysis are that the spatial extension of the impact for mobile sources is in the order of 100-400 meter for elemental carbon, and 200-500 meters for nitrogen dioxide.

Singh et al., (2017) investigated the PM2.5 source apportionment over South Asia using meta-analysis method. This work summarised 51 studies, of which 90% are performed in the period of

2007-2015, and more than half of the studied area are focused on typical urban stations (Delhi, Dhaka, Mumbai, Agra and Lahore). The findings of the work are that the vehicle emissions are the biggest contributors to the PM2.5, followed by industry and secondary aerosol. Geography and seasonality significantly affect the particle source strength.

3.4.4 Preliminary meta-analysis results of vehicle emissions

In this part, the relations of exhaust emissions and driver behaviours, for example average speed, average positive acceleration, average negative acceleration, and percentage of vehicle stops, acceleration, and deceleration in time are analysed. Table 3.6 show the template for summarising the published data about the driving behaviours and exhaust emissions. Figure 3.10 presents the preliminary analysis results. The relations between the driving behaviours and exhaust emissions are clearly presented. In this section, the exhaust emission factors are normalised based the vehicle emission level and engine displacement (the engine displace reflect the vehicle size to some extend).

Table 3.6: Template of the reported data

<table>
<tr><th colspan="2">Items</th><th>Values</th></tr>
<tr><td colspan="2">Year of manufacture, brand</td><td>e.g. 2010, Skoda Octavia; 1996, Ford Galaxy Tdi</td></tr>
<tr><td colspan="2">Engine tech</td><td>e.g. turbocharger; after-treatment; common rail</td></tr>
<tr><td colspan="2">Fuel type</td><td>e.g. diesel; petrol (gasoline); natural gas</td></tr>
<tr><td colspan="2">Test cycle</td><td>e.g. real-word; NEDC; WLTC</td></tr>
<tr><td rowspan="4">Emission type and emission factors/ g/km</td><td>HC</td><td>e.g. 0.09</td></tr>
<tr><td>CO</td><td>e.g. 0.05</td></tr>
<tr><td>NO_x</td><td>e.g. 0.97</td></tr>
<tr><td>PM</td><td>e.g. 0.01</td></tr>
<tr><td colspan="2">Fuel consumption/ L/100km</td><td>e.g. 7.15</td></tr>
<tr><td rowspan="3">Speed, acceleration, deceleration</td><td>Average speed/ km/h</td><td>e.g. 33.6</td></tr>
<tr><td>Average acceleration/ m/s^2</td><td>e.g. 0.59</td></tr>
<tr><td>Average deceleration/ m/s^2</td><td>e.g. -0.82</td></tr>
<tr><td rowspan="3">Percentage in time for vehicle operation process</td><td>Acceleration process/ %</td><td>e.g. 25</td></tr>
<tr><td>Deceleration process/ %</td><td>e.g. 20</td></tr>
<tr><td>Idle/ %</td><td>e.g. 10</td></tr>
<tr><td colspan="2">Reference</td><td>e.g. Vlieger et al., 2000</td></tr>
</table>

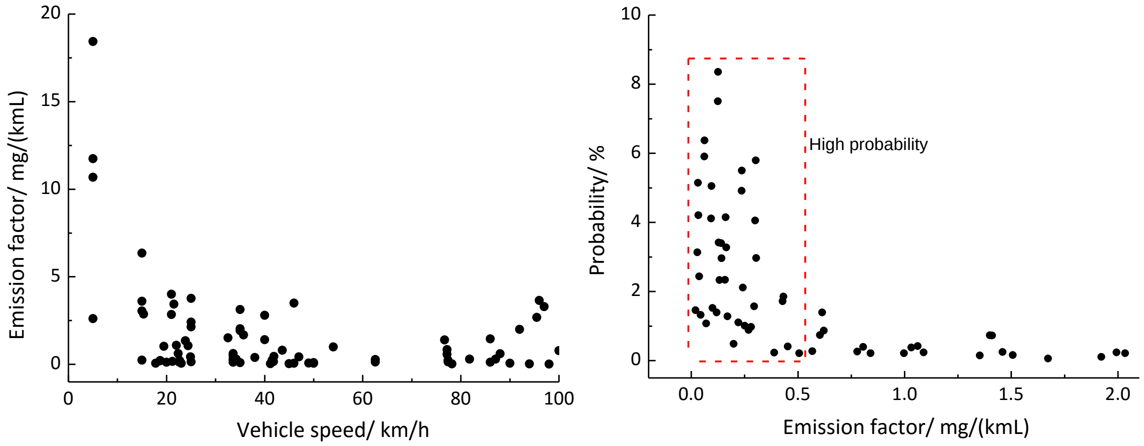


Figure 3.10: Preliminary results of meta-analysis: NO_x emission

4 Emissions from brake wear

This chapter reports a thorough state-of-the-art review of the published studies on brake wear and the activity carried out by the PMP (Particle Measurement Program) by UNECE Informal Working Group, together with in-house data (provided by BREMBO), to identify brake wear data needed to quantify the correlation of brake emission with the variability of vehicle characteristics, speed and driving behaviour.

4.1 Background

While fuel and engine technologies have been improved for the last three decades, reducing particulate matter (PM) emissions from vehicle exhausts, no policies are currently in place to limit or reduce non-exhaust emissions (NEE) such as the particles released into the air from brake wear, road surface wear, tyre wear and resuspension of road dust. The non-exhaust emissions currently constitute 60% and 73% (by mass), respectively, of primary PM2.5 and PM10 emissions from road transport (AirQualityExpertGroup, 2019), and their magnitude and contribution to ambient PM concentration in cities are bound to increase in the future, posing obvious research and policy challenges aiming for improving air quality.

Non-exhaust particulate matters can be generated either from brake, tyre, clutch and road wear, or already exist in the form of deposited materials on road surface, which become re-suspended due to traffic-induced turbulence. The coarse parts of the PM from road traffic are believed to originate mainly from non-exhaust sources, although thermal and/or chemical process also result in the decomposition of brake lining materials under high temperature at the brake-rotor interface, which generate fine particles (Grigoratos and Martini, 2015). The proportions vary with geography. Road wear contribution to PM is larger in Scandinavian countries, owing to the use of winter tyres whose high abrasion generate more airborne minerals dust (Kupiainen et al., 2005). Its share is also found higher in Mediterranean countries due to dry climate (Querol et al., 2004).

PM concentration due to brake wear is associated with the vehicle deceleration, often seen in urban traffic environments with high vehicle density and braking frequency (Harrison et al., 2012). Abu-Allaban (Abu-Allaban et al., 2003) observed higher contribution of brake wear at freeway exit sites using a DustTrak to sample the emissions, see Figure 4-1. The sampling pairs were located at 0.5m, 1.0m, 1.7m and 3.0m above ground. He then used a multi-leg regression approach to calculate emission factors (EF) from light-duty vehicles (LDV) and heavy-duty vehicles (HDV). Another study by Mathissen (Mathissen et al., 2012) using a mobile measuring unit, see Figure 4-2, found that although emission factors increase with an increase in vehicle velocity, the lowest EFs were measured on motorways. Both studies indicated the significance of braking on the PM10 emission.

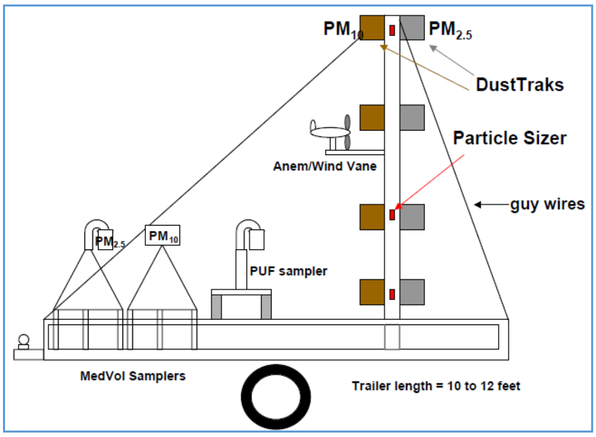


Figure 4-1: Experimental setup of DustTrak

Figure 4-2: Mobile brake wear measurement

4.2 Size and chemical composition of brake emissions

The majority of vehicle brake systems use cast iron and composite lining. Brake wear PM10 usually displays an unimodal mass size distribution with median particle diameter between 1.5µm and 6µm (Pant and Harrison, 2013).

Iron (Fe), copper (Cu), Barium (Ba) and lead (Pb) and zinc (Zn) are repeatedly reported to display high concentrations in brake wear, see Table 4.1 (Grigoratos and Martini, 2015). The same research also found that approximately 50% of brake wear PM10 is emitted as airborne particles. The rest may deposit on the road or be attracted by the vehicle. Sanders (Sanders et al., 2003) also found that 50-70% of abraded brake wear becomes airborne. In contrast, Garg estimated that 35% of brake wear was released as airborne (Garg et al., 2000). This value was corrected to 64% by Sanders, after consideration of the defects in Garg's sample collection (Sanders et al., 2003). There is uncertainty of how accurately the physical properties of brake wear are simulated in dynamometer laboratory facilities (Blau and Jolly, 2005).

Table 4.1: Chemical constituents of brake wear

Metal	Brake dust (mg/kg)	Metal	Brake dust (mg/kg)
Al	330-20,000	Mg	(1700)-83,000
As	<2.0-(100)	Mn	620-5640
Ba	(5800)-140,000	Mo	5.0-740
Ca	500-8600	Na	80-(5100)
Cd	<0.06-11	Ni	80-730
Co	12-42.4	Pb	4.0-1290
Cr	135-12,000	Sb	4.0-19,000
Cu	70-210,000	Sn	230-2600
Fe	1300-637,000	Ti	100-110,000
K	190-39,000	Zn	120-27,300

Hulskotte (Hulskotte et al., 2014) collected 65 brake pads and 15 brake discs from car maintenance shops, and analysed their composition, using X-ray Fluorescence (XRF) and Inductively Coupled Plasma Mass Spectrometry (ICP-MS) analysis, see Figure 4-3 and Figure 4-4. He found that brake pads contained about 50% of non-metal materials, Fe and Cu are the dominant metals in brake pads but their ratio varied considerably. Brake discs consisted almost entirely of metal with iron being the dominant (>95%). Hulskotte estimated that 70% of the brake wear originates from the discs and 30% from the pads. His paper gives the following equation for calculating brake pad emissions:

$$R_{Cu/Fe} = \frac{W_p \times C_{Cu-pad}}{W_d \times C_{Fe-disc} + W_p \times C_{Fe-pad}} \quad \textbf{(Eq. 4-1)}$$

Where:

- RFe/Cu = mass ratio between iron and copper
- CCu-pad = Concentration of copper in pads (m/m%)
- CFe-disc = Concentration of iron in discs (m/m%)
- CFe-pad = Concentration of iron in pads (m/m%)
- Wp = wear rate of pads, (units of mass)
- Wd = wear rate of discs, (units of mass)

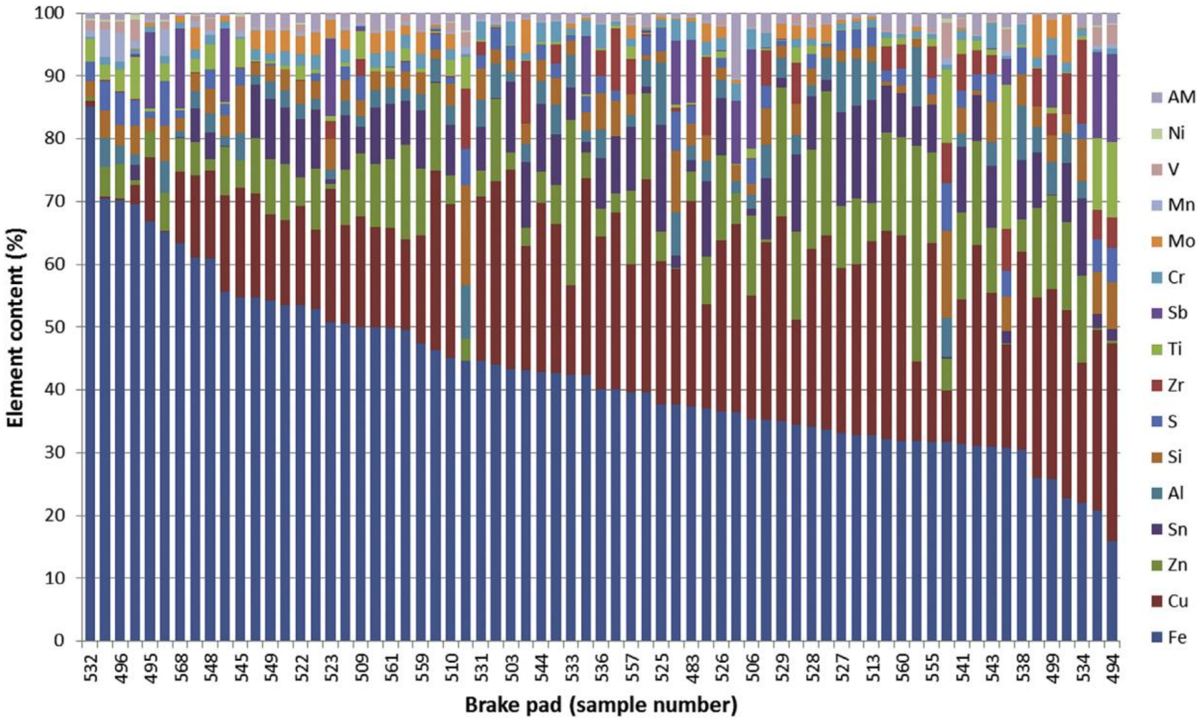


Figure 4-3: Element contents of brake pads

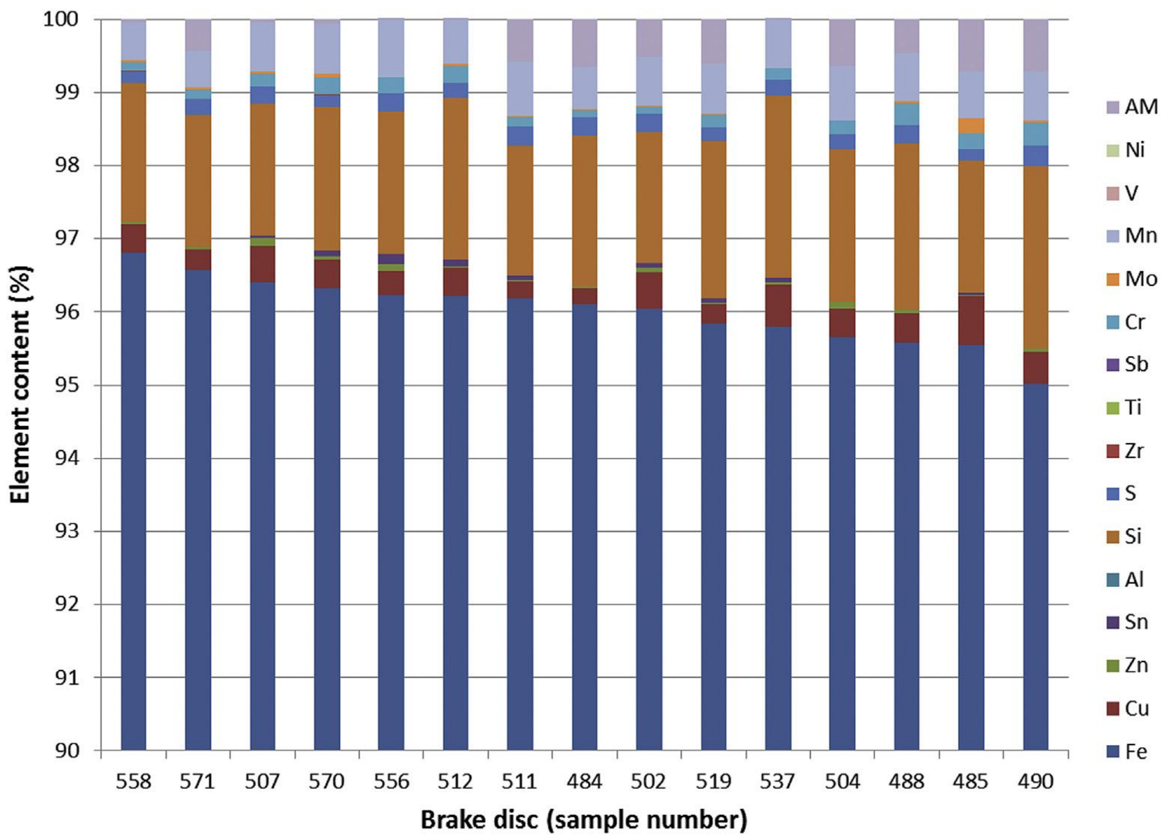


Figure 4-4: Element contents of brake discs

4.3 Influencing factors to brake wear

The brake wear emissions from internal combustion engine (ICE) vehicles depend on a number of factors such as the friction materials, vehicle mass, driving behaviour, and disc temperature. The combination of different materials and driving behaviours leads to a high variability of the measured brake-wear emission factors (Grigoratos and Martini, 2015).

4.3.1 Friction materials

In order to identify the role of the different friction materials on the brake emission factors, Sanders (Sanders et al., 2003) studied the wear behaviour of three different types of friction material. The materials were subjected to a brake sequence named Urban Driving Program (UDP) in a brake dynamometer. The UDP test consisted of 24 stops characterised by an initial brake speed between 37 and 89 km/h, a vehicle deceleration within the range 0.6-1.6 m/s^2 and an initial brake disc temperature between 54 and 177°C. The calculated emission factors are listed in Table 4.2.

Table 4.2: Emission factors measured with different classes of friction materials (Sanders et al. 2003)

Friction Material Class	Total Mass [mg/stop brake]	PM10 mass [mg/stop brake]
Low Metallic	8.2	7.0
Semimetallic	2.0	1.7
Non-Asbestos-Organic	1.8	1.5

As can be noted from the data in Table 4.2, the Non-Asbestos-Organic (NAO) composition showed the lowest emission factors while the low metallic formulation exhibited the highest ones. According to the results listed in Table 4.2, the emission factors vary about 4.6 times for the total mass and about 4.7 times for the PM10 mass from a low metallic formulation to a NAO one.

The role of braking behaviour on the particle emissions was analysed in the same study (Sanders et al., 2003) by testing the low metallic friction material with two more severe brake sequences. The first sequence consisted of full stops at a 1.8 m/s^2 deceleration-level from an initial speed of 96 km/h. The second one, that is also the harshest one, consisted of ten full stops from 100 km/h at a deceleration level of 10 m/s^2. This last procedure is internationally known as Auto Motor und Sport (AMS) test and aims at characterising the braking materials in particularly severe conditions, i.e. the typical temperatures reached during this test exceed 700°C.

The results obtained with the UDP, the 1.8 m/s^2 deceleration stops and the AMS testing procedures with the low metallic friction material are listed in Table 4.3.

Table 4.3: Emission factors measured from different brake sequences with the same low metallic friction material (Sanders et al., 2003)

Brake Sequence	Total Mass [mg/stop brake]	PM10 mass [mg/stop brake]
UDP	8.2	7.0
1.8 m/s^2 deceleration	49.0	45.0
AMS	from 3 to 3000	from 0.6 to 1500

From the data in Table 4.2 and Table 4.3, it is possible to state that the highest variability in the emission factors is related to the different testing conditions; from mild braking conditions such as the UDP test to the severe AMS ones, the emission factors increased by three orders of magnitude. Furthermore, from the data collected in Table 4.3, results of the AMS procedure are widely varying due to the increase of the initial brake temperature that occurred during the test. This temperature-rise lead to an increase of the emission factors from 3 to 3000 mg/stop brake for the total mass and from 0.6 to 1500 mg/stop brake for the PM10 mass.

4.3.2 Vehicle mass

The influence of vehicle mass on brake emissions can be found in Table 4.5. Grigoratos (Grigoratos and Martini, 2015) found that emission factors of HDVs are approximately one order of magnitude higher than of LDVs. Taking into account the difference in activity levels (vehicle kilometre), NAEI estimated that the brake wear emissions from cars are responsible for 64% of all PM10 from non-exhaust emissions, see Fig.4.7 (NAEI, 2017).

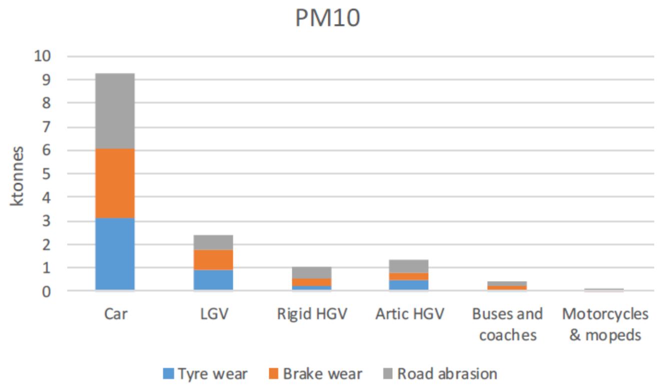


Figure 4-5: PM10 emissions by vehicle type

Figure 4-6: Test track measurement

4.3.3 Braking-related driving behaviour

Kwak (Kwak et al., 2013) investigated the properties of non-exhaust particles generated by on-road driving in a laboratory setting using a mobile sampling system. Chemical analysis of PM samples indicated that: 1) the concentrations of Fe and Ca were highest in the coarse fraction emitted under constant speed and cornering conditions; 2) the concentrations of Fe, Ba, and Ti were highest in the fine fraction emitted during braking. Table 4.4 illustrated the wide range of driving and braking applications that have been found in the literature (Mathissen et al., 2018). The initial speed and deceleration rate are considered the main influencing factors.

Table 4.4: Effects of speed and braking pattern on brake emissions

Reference	Type of study	Braking pattern	Initial speed [km/h]	Deceleration [m/s^2]
Garg et al.	Brake Dyno	Full stop braking from a set speed	50	2.9
Sanders et al.	Brake Dyno	Full stop braking from a set speed	100	7.9
Sanders et al.	Brake Dyno	Full stop braking within a cycle	34-96	0.6-1.6
Sanders et al.	On-Road	Full stop braking from a set speed	96	1.8
Von Uexküll et al.	Brake Dyno	Full stop braking from a set speed	60	2.1
Iijima et al.	Brake Dyno	Full stop braking from a set speed	50-80	3.0
Iijima et al.	Brake Dyno	Full stop braking from a set speed	40-60	1.0-3.0
Mathissen et al.	On-Road	Full stop braking from a set speed Different Patterns	30-120	-
Kukutschová et al.	Brake Dyno	Light Deceleration	73	0.1
Kwak et al.	On-Road	Full stop braking Different Patterns	50-150	3.0
Hagino et al.	Brake Dyno	Full stop braking from a set speed	20-60	0.5-3.0
Hagino et al.	Brake Dyno	Japanese JC08 Transient Cycle	-	-
Gramstat et al.; Lugovyy,	Brake Dyno	AK Master Transient Cycle	-	-
Farwick zum Hagen et al.	Brake Dyno	3h-LACT Transient Cycle	17-154	0.2-2.9
Agudelo et al.	Brake Dyno	NEDC, WLTC Transient Cycles	-	-

In the test track measurement, see Fig.4.8, carried out on cars and LDVs by Sanders (Sanders et al., 2003), the deceleration rate was set at 1.47 m/s^2 to 2.45 m/s^2 and 3.43 m/s^2, from an initial speed of

96 km/h. This represented the deceleration values used in highway design in the UK (2.45 m/s^2) and USA (3.4 m/s^2).

4.3.4 Brake disc temperature

Mathissen (Mathissen et al., 2018) found that below a disc temperature of 160 °C, particle number emission is same as at background level, and it sharply increases at brake temperatures above it. Brake temperature was also measured in Sanders' experiment, but the role of elevated temperature on brake wear increase was limited to hypothesis (Sanders et al., 2003).

Regenerative braking system (RBS) used in hybrid and electric vehicles were tested on the dynamometer, see Fig.4.9 (Wager et al., 2018), for their braking efficiency and wear debris. Results showed that the RBS achieved required braking efficiency at temperatures lower than friction-based braking system, see Fig.4.10, which has the potential to reduce the brake wear because higher brake disc temperatures are associated with higher wear rates.

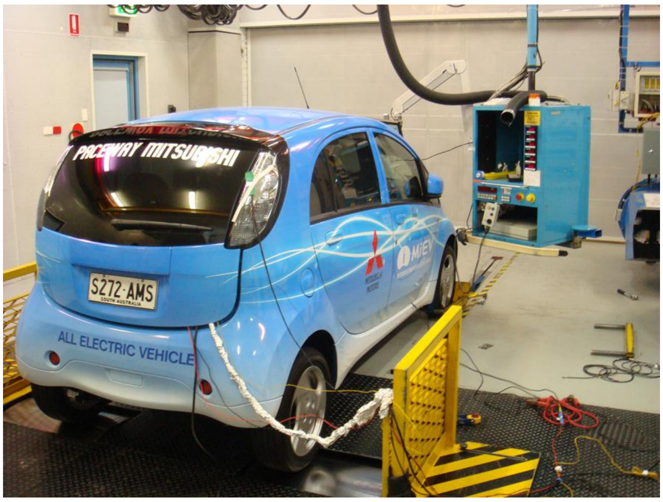


Figure 4-7: Electric vehicle on the chassis dynamometer

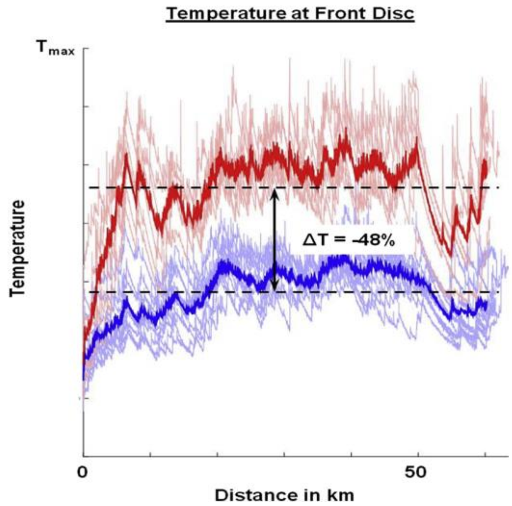


Figure 4-8: Disc temperature with and without regenerative braking

4.4 Estimation of brake emissions

While many research (either in laboratory or in field) measured the total emissions from vehicles (Wåhlin et al., 2006), separating the source are faced with a number of challenges. According to Pant (Pant and Harrison, 2013), one of the main difficulties in analysis of non-exhaust PM using field data is the difficulty in distinguishing between wear emissions and road re-suspended dust.

Methods for calculating emissions from tyre and brake wear are provided in the EMEP/EEA Emissions Inventory Guidebook, derived from a review of measurements by the UNECE Task Force on Emissions Inventories (http://vergina.eng.auth.gr/mech0/lat/PM10/), which give the methodology for calculating total emissions (TE) from brake wear in [mg] as following equation:

$$TE_{Bij} = N_j \times M_j \times f_{Bi} \times (EF_{B\,TSP})_j \times S_B(V) \qquad \textbf{(Eq. 4-2)}$$

Where

- i = PM10, PM2.5, PM1, PM0.1 depending on the fraction used in the equation each time.

- N = the number of vehicles.
- M = the mileage per vehicle for the period considered [km].
- fBi = the fraction of TSP (total suspended particle) that can be classified as PM10, PM2.5, PM1 or PM0.1.
- (EF B TSP)j = the TSP emission rate in [mg/veh*km] at a speed of 65 km/h for vehicle category j = PC (passenger car), LDV (light duty vehicle), HDV (heavy duty vehicle) or MC (motorcycle).
- SB(V) = the speed correction factor which depends on the mean vehicle velocity.

Emission factors (EFs) are used by researchers and regulating agencies as a tool to quantify the emission of a specified pollutant by an individual vehicle. Emission factors for PM10 are provided in mg/km for different vehicle types with correction factors for speed and vehicle mass, see Table 4.5 (Brown et al., 2018). Emission of PM2.5 is estimated as a weight ratio to the PM10 of 40%, 70% and 54%, respectively, for brake wear, tyre wear and road abrasion.

Table 4.5: Estimation of brake, tyre and road wear by vehicle kilometres

Emission Factors (mg/km)	From Brake			From Tyre			From Road Abrasion
	Motorway	Rural	Urban	Motorway	Rural	Urban	
Car	1.4	5.5	11.7	5.8	6.8	8.7	7.5
Motorcycle	0.7	2.8	5.8	2.5	2.9	3.7	3.0
Bus	8.4	27.1	53.6	14.0	17.4	21.2	38.0
LGV	2.1	8.6	18.2	9.2	10.7	13.8	7.5
HGV-rigid	8.4	27.1	51.0	14.0	17.4	20.7	38.0
HGV-articulated	8.4	27.1	51.0	31.5	38.2	47.1	38.0

UK National Atmospheric Emission Inventory (NAEI) calculated a PM10 brake wear EF of 7.0 mg/veh*km for passenger cars, and 11.0 mg/veh*km for LGVs (NAEI, 2017). For comparison, Sanders (Sanders et al., 2003) estimated the emission factor to be 20.9 mg/veh*km (converted from 13 mg/veh*mile) for PM10 brake wear. According to Grigoratos (Grigoratos and Martini, 2015), most studies find PM10 emission factors of some 6.0-7.0 mg/veh*km, see Table 4.6, which is close to the standard for exhaust emissions of Euro 5/6 diesel vehicles, i.e. 4.5-5.0 mg/veh*km.

Table 4.6: Emission factors of brake wear

Reference	Type of study	Emission factor
Garg et al. 2000	Brake dynamometer study	2.9-7.5
Sanders et al. 2003	Brake dynamometer study	8.1
Iijima et al. 2008	Brake dynamometer study	5.8
Rauterberg-Wulff 1999	Receptor modelling (highway-tunnel)	1.0
Abu-Allaban et al. 2003	Receptor modelling	0-80
Luhana et al. 2004	Receptor modelling	8.8
Bukowiecki et al. 2009a	Receptor modelling (urban street canyon)	8.0
Bukowiecki et al. 2009a	Receptor modelling (highway)	1.6
USEPA 1995	Emission inventory	7.9
Lükewille et al. 2001	Emission inventory	1.8-4.9
Boulter et al. 2006	Emission inventory (RAINS model)	3.8
Boulter et al. 2006	Emission inventory (CEPMEIP model)	6.0
Boulter et al. 2006	Emission inventory (MOBILE 6.2 model)	7.8
Boulter et al. 2007	Emission inventory	4.0-8.0
NAEI 2012	Emission inventory	7.0

4.5 Measurement of brake emissions

4.5.1 In laboratory

Probably the wide range of results can be explained by the lack of standardised sampling procedure and measurement techniques. This often leads to different experimental approaches by researchers and therefore in non-comparable results and conclusions. Largely, three ways of measuring brake wear emissions are found from literature.

- in the laboratory by means of a brake dynamometer test, see Figure 4-9 (Iijima et al., 2008, Garg et al., 2000, Sanders et al., 2003);
- using a special brake wear tracer (receptor modelling), see Figure 4-10 (Kwak et al., 2013); and
- sampled on road under real-world traffic conditions by means of a mobile unit, see Figure 4-2 (Mathissen et al., 2012).

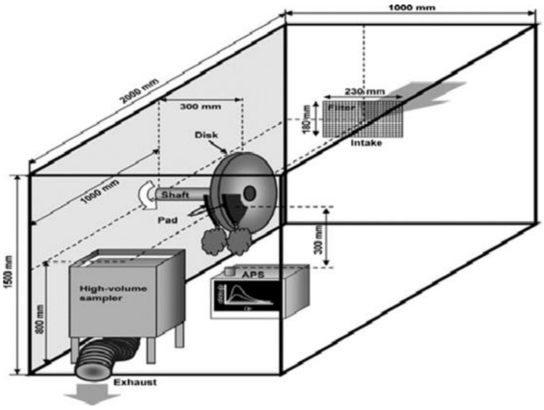


Figure 4-9: Brake dynamometer

Figure 4-10: Brake wear tracer

4.5.2 Real-world monitoring of brake emissions

Brake wear emissions were measured by Ferdinand (2019) during on-road driving in a mid-size passenger car, with a novel sampling system (see Figure 4-11) attached to the outer side of the wheel rim, to monitor the entire aspiration of brake wear particles. The test found that the PM10 emission factors are ranging from 1.4 mg km^{-1} $brake^{-1}$ to 2.1 mg km^{-1} $brake^{-1}$, although the fixed driving behaviour and the unusually high brake disc temperatures (exceeding 170 °C) limited the generalisation of the results.

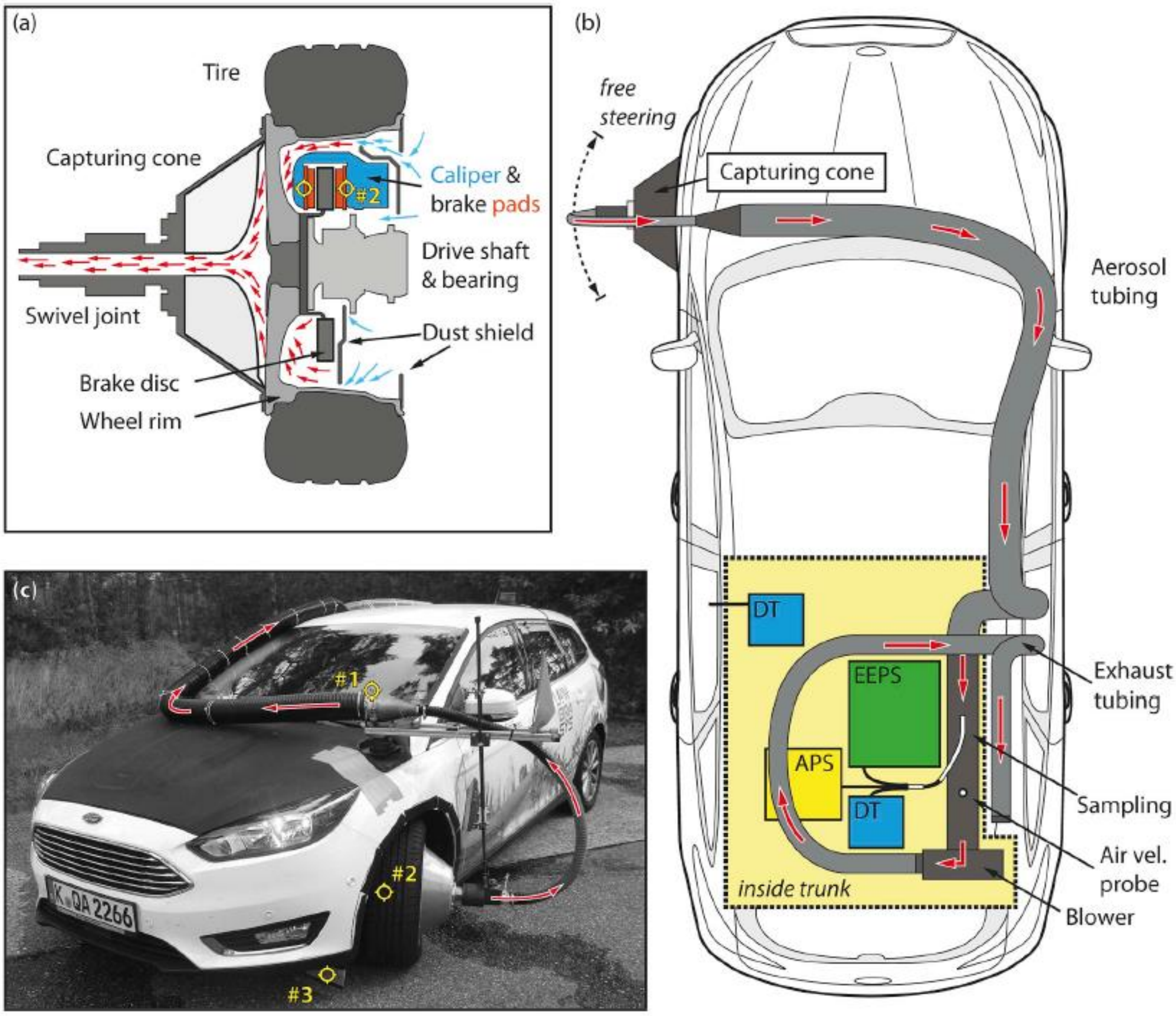


Figure 4-11: On-road driving investigation of brake wear particles in a semi-closed vehicle setup

4.6 Brake test cycles

According to these results, it is clear that the selection of the most representative brake test cycle is of paramount importance to the measurement of the real-world brake emissions. Based on this consideration, Perricone (Perricone G., 2016) modified the SAE-J 2707 Method B procedure to better reproduce the on-road conditions during dynamometer-bench tests. The novel cycle is summarised in Table 4.7.

Table 4.7: Reduced SAE-J 2707 Method B cycle (Perricone G., 2016)

Section	Initial Vehicle Speed [km/h]	Vehicle Deceleration [m/s^2]	Initial Brake Temperature [°C]	Number of Stops
Burnish	50	2.4	100	100
Town Block 1	50	2.4	150	20
Country Road Block 1	80	3.4	200	20
Country Road Block 2	100	3.9	125	20
Town Block 2	50	2.4	150	20
Country Road Block 3	100	3.9	125	20

The authors tested one non-asbestos-organic (NAO), and four low-steel friction materials. Consistently with the data of Sanders (Sanders et al., 2003), the detected emission factors ranged from 8.9 to 42.4 mg/stop brake. Moreover, the PM emission factors of the low-steel materials were from 1.7 to 4.8 times higher than the NAO ones. This suggests that the brake cycle used by (Perricone G., 2016) was representative of conditions close to the 1.8 m/s^2 deceleration-level stops used by Sanders (Sanders et al., 2003).

The study of a testing cycle capable of reproducing real-world conditions has been continued within the EU co-funded LOWBRASYS project; Mathissen (Mathissen & Evans, 2019) proposed a reduced brake sequence that has been based on an existing brake test procedure called Los Angeles City Traffic (LACT). This reduced cycle was named 3h-LACT and it has been generated from the actual on-road driving data acquired in the Los Angeles urban and sub-urban area. The parameters of this brake sequence that has been used to study the brake emissions of a passenger car during chassis-dyno tests, are summarised in Table 4.8.

Table 4.8: Parameters of the 3h-LACT brake test procedure (Mathissen & Grigoratos, 2019)

Initial Vehicle Speed [km/h]	Vehicle Deceleration [m/s^2]	Initial Brake Temperature [°C]	Number of Stops
from 17 to 154	from 0.2 to 2.9	from 54 to 187	217

The emission factors identified by (Mathissen & Grigoratos, 2019) were within the range of (3-7) x 10^9 mg/km stop for a low metallic friction material.

Although the 3h-LACT procedure has been generated from the actual on-road data of vehicles circulating in the Los Angeles area, a brake cycle, closer to the European driving behaviour, has been developed thanks to the work of the PMP (Particle Measurement Programme) by UNECE Informal Working Group. The selected database for the creation of the novel brake cycle has been the worldwide harmonized light-duty vehicles test procedure (WLTP); it consists of in-use data of light-duty vehicles coming from five different regions (EU, USA, India, Korea and Japan). Steven (Steven, 2016) and Mathissen (Mathissen et al., 2018) have analysed the WLTP database generating a testing procedure representative of the European braking behaviour. The final cycle has been published under a free license in 2018 (Mathissen, et al., 2018). The main parameters of the brake cycle are listed in Table 4.9.

Table 4.9: Parameters of the WLTP-based cycle (Mathissen et al., 2018)

Average Initial Vehicle Speed [km/h]	Vehicle Deceleration [m/s2]	Initial Brake Temperature [°C]	Number of Stops
43.7	from 0.49 to 2.2	from 35 to 175	303

The comparison between the initial braking speed, the vehicle deceleration, the in stop duration and the time between the braking actions of the novel WLTP-Based, the 3h-LACT and the complete WLTP database brake cycles are reported in Figure 4-12.

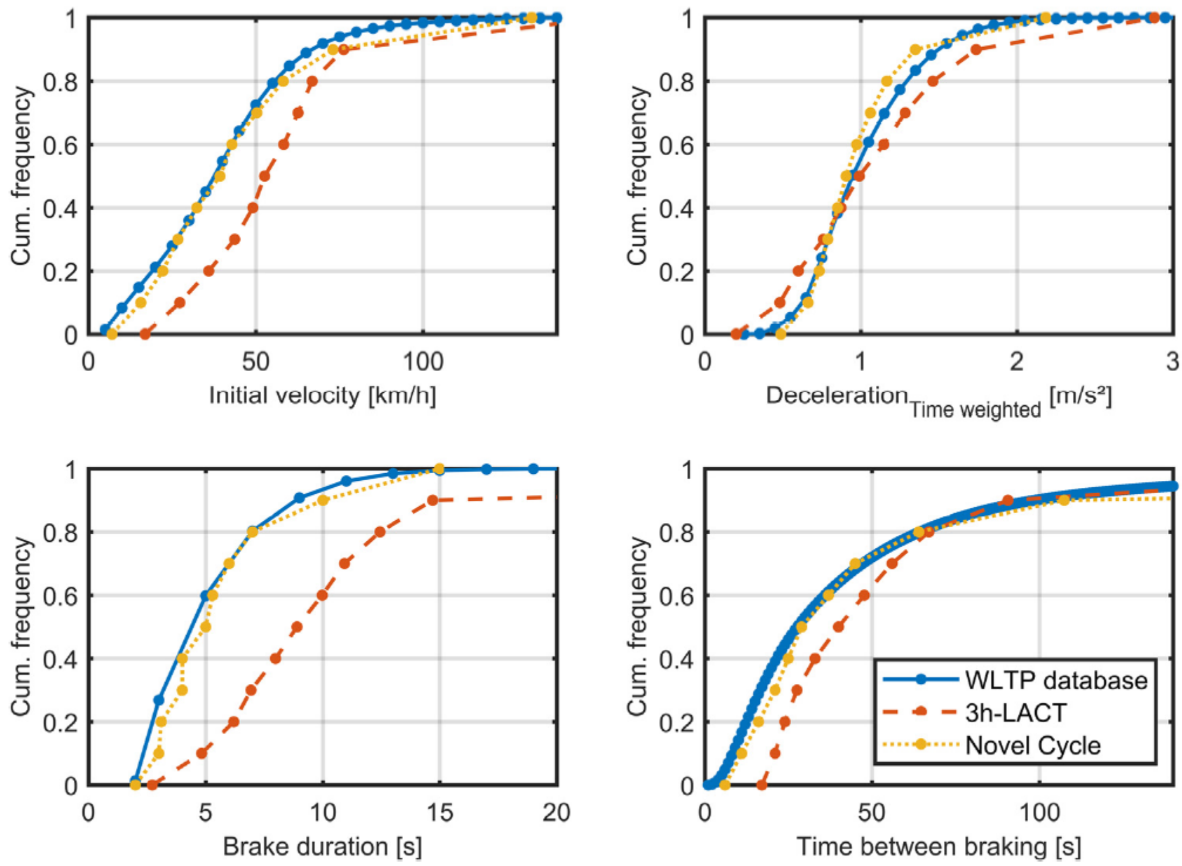


Figure 4-12: Vehicle velocity profile during the WLTP-based cycle (Mathissen et al., 2018)

As can be noted from Figure 4-12, the novel cycle is characterised by a higher number of stops at a lower initial brake speed with respect to the 3h-LACT procedure. The time-weighted deceleration curves showed a higher number of stops at lower deceleration levels of the novel WLTP-based cycle with respect to the 3h-LACT one. Furthermore, the brake duration during both the WLTP and the novel cycle are lower than in the case of the 3h-LACT cycle such as the time between the braking actions. As a general consideration, the novel cycle, which is considered as the most representative of the average European driving behaviour, consists of mild braking actions at slow speeds that are repeated more frequently than during the 3h-LACT cycle.

Figure 4-13 highlights the differences in the recorded emissions of the two testing procedures, from different braking conditions.

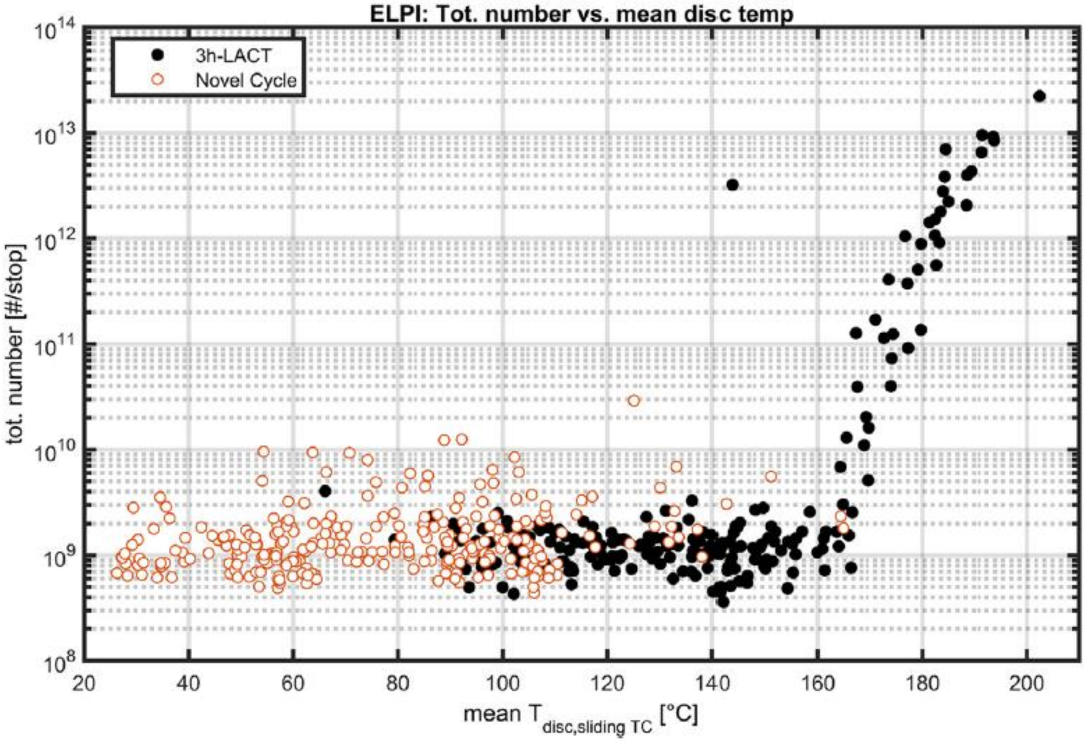


Figure 4-13: Vehicle velocity profile during the WLTP-based cycle (Mathissen et al., 2018)

As can be noted from Figure 4-13, the mild braking parameters, typical of the European driving behaviour, lead to lower emissions during the WLTP-based tests than in the case of the 3h-LACT ones.

5 Emissions from tyre wear

5.1 Background

Exhaust and non-exhaust traffic-related sources contribute almost equally to traffic-related emissions (Grigoratos et al., 2015, Grigoratos et al., 2014). Exhaust traffic-related emissions are emitted as a result of incomplete fuel combustion and lubricant volatilisation during the combustion procedure, and non-exhaust traffic-related emissions are either generated from non-exhaust traffic-related sources or already exist in the environment as deposited material and become re-suspended due to traffic-induced turbulence (Grigoratos et al., 2015). Exhaust emissions have been very well studied and characterised, while technological improvements have resulted in a significant reduction of their emissions (van der Gon et al., 2013, Pant and Harrison, 2013, Amato et al., 2014). However, non-exhaust processes have not yet been adequately studied, and several questions regarding physical characteristics, chemical composition, emission rates, and emission model development of tyre wear particles remain unclear (van der Gon et al., 2013, Grigoratos et al., 2015, Grigoratos et al., 2014, Panko et al., 2018).

Among non-exhaust sources, tyre and road wear particles (contribution between tyre and road is difficult to distinguish) can contribute from 5% to 30 % by mass to non-exhaust traffic-related emissions (Grigoratos, 2014, Harrison et al., 2012). Tyre wear particles represents between 1%-8.5 % by mass to PM10 emissions (Panko, 2019). Among tyre wear particles, only up to 10% are PM (Grigoratos, 2014, Harrison et al., 2012).

Tyre wear particles are generated either by shear forces between the tread and the road pavement, in which case the emitted particles are mechanically generated and mainly distributed in the coarse size fraction (Kreider et al., 2010), or by volatilisation which results in the generation of much smaller particles, usually in the fine mode (Wagner et al., 2018). The generation of fine particles is described as a thermomechanical process with local hot spots on the tyre tread reaching high temperatures and resulting in evaporation of the volatile content of tyres (Mathissen et al., 2011). The interaction of tyres and pavement alters both the chemical composition and characteristics of the particles generated compared to the original tyre tread due to heat and friction, as well as incorporation of material from the road surface (Panko et al., 2013). Despite the difficulties in measuring and characterising tyre wear particles, an increasing number of researchers have already raised a discussion on the need for regulating emissions from non-exhaust sources including tyre wear (for example, Kreider et al., 2010, van der Gon et al., 2013, Grigoratos, 2014).

5.2 Tyre Wear

5.2.1 Definition and generation mechanisms

The available literature on tyre wear reports that tyre wear results from the friction between the rubber on the tread of the tyre and the ground. Various physical approaches exist to model the mechanisms of the rubber wear, but we can split these methods into two types of similar approaches:

- Frictional power

According to (Braghin et al. 2006) and (Lupker, 2004), wear can be modeled with a brush model using a physical Rigid Ring Tyre Model as below:

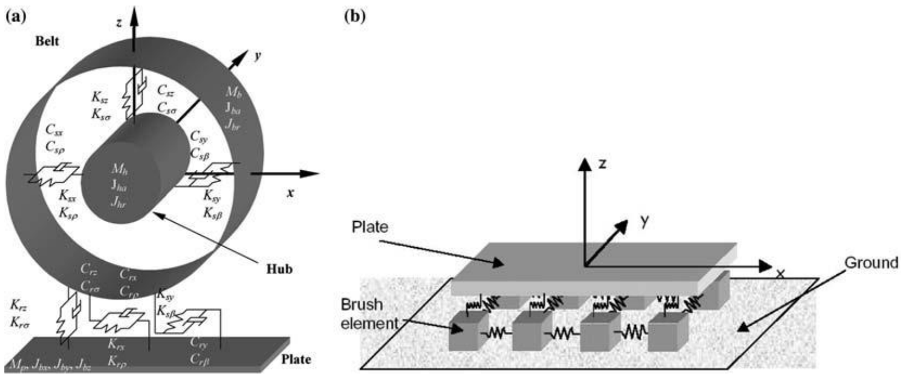


Figure 5-1: The tyre structural model and the tyre contact model

In this model, at the local scale, the relation between frictional power per unit contact area $\widetilde{\omega}$ and mass loss per unit covered area m may be approximated by the following expression (k1, k2 are wear constants):

$$m_{ij} = k_1 \, \widetilde{\omega}_{ij}^{k2} \qquad \text{(Eq. 5-1)}$$

The frictional power depends on the contact shear force τ and the slip velocity:

$$\widetilde{\omega}_{ij} = \tau_{x_{ij}} . \gamma_{x_{ij}} + \tau_{y_{ij}} . \gamma_{y_{ij}} \qquad \text{(Eq. 5-2)}$$

- Frictional energy (Archard approach) (Archard, 1953)

As well described in (Chang, 2011*)*, the Archard model is a mathematic model which is based on the theory that when two surfaces connect, the contacts are the sum of areas of all the profile peaks. It assumes that the profile peak of wear particle is hemispherical, with a radius equal to contact point. Contact area ΔA is:

$$\Delta A = \pi \cdot a^2 \qquad \text{(Eq. 5-3)}$$

Where, a is wear particle radius. If contact causes plastic deformation, then:

$$\Delta A = \frac{\Delta F_N}{H} \qquad \text{(Eq. 5-4)}$$

Where:

- ΔF_N is normal load at profile peak of contact point
- H is hardness of the softer material in contact pair.

If wear particle is proportional to the size of contact point, the volume of wear particle ΔV is:

$$\Delta V = \frac{2}{3} \pi \, a^3 \qquad \text{(Eq. 5-5)}$$

When slipping occurs between profile peaks of contact point the relative slipping distance at load N ΔF_N is ΔL = 2a.

For a pair of hemispherical wear particles, the wear volume under unit slipping distance is:

$$\Delta W = \frac{\Delta V}{\Delta L} = \frac{1}{3} \pi a^2 = \frac{1}{3} \frac{\Delta F_N}{H} \qquad \text{(Eq. 5-6)}$$

If we extend the previous equation to the entire contact surface the wear volume under unit slipping distance is obtained:

$$W = \sum_{i=1}^{n} \Delta W = K \frac{F_N}{3H} \qquad \text{(Eq. 5-7)}$$

Where:

- n represents the contact number on contact surface
- K is the wear factor.

The total wear volume V through slipping distance L is:

$$V = K \frac{F_N}{H} L \qquad \text{(Eq. 5-8)}$$

Tyre wear therefore depends on the slip of two surfaces in contact which could be led by the sliding length (Lg), the slipping speed (Vg), the force applied during the slip (F), and rubber abrasion resistance. Thus, the project focuses on driving behaviour aspects which impact the force in the contact patch as well as slip between tyre and ground.

5.2.2 Tyre wear particles

5.2.2.1 Definition and general knowledge

Tread rubber of tyres is emitted in the form of elongated particles. In real life, these particles do not consist of pure tread material but are instead a mixture including wear particles from the road and possibly from other sources. Therefore, the particles found on roadsides are usually referred to as tyre and road wear particles (TRWP) and contain a multitude of materials stemming from other traffic-related or environmental sources (R. Pohrt, 2019). Most studies agree that only 0.55%-10% of particle mass is below 10 µm (Figure 5-2). Instead the characteristic size is in the order of 65-80 µm and does not become airborne.

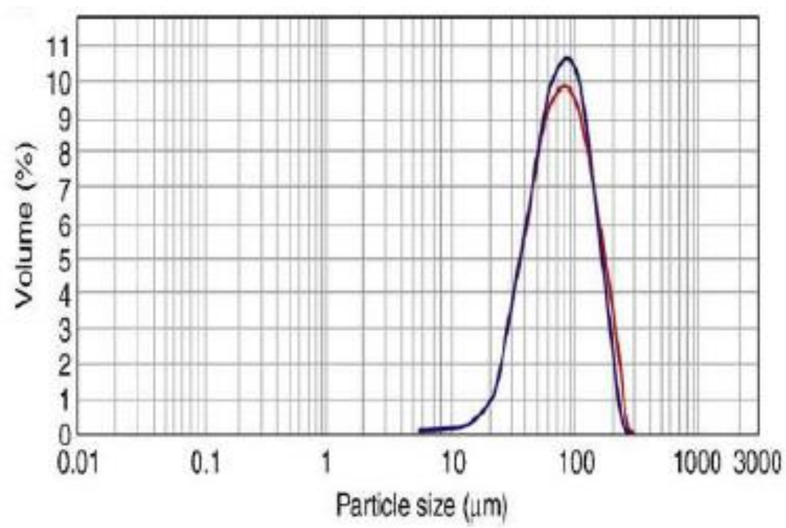


Figure 5-2: Particle size distribution determined by volume of particles according to laser diffraction and tyre wear particles (Kreider et al., 2010)

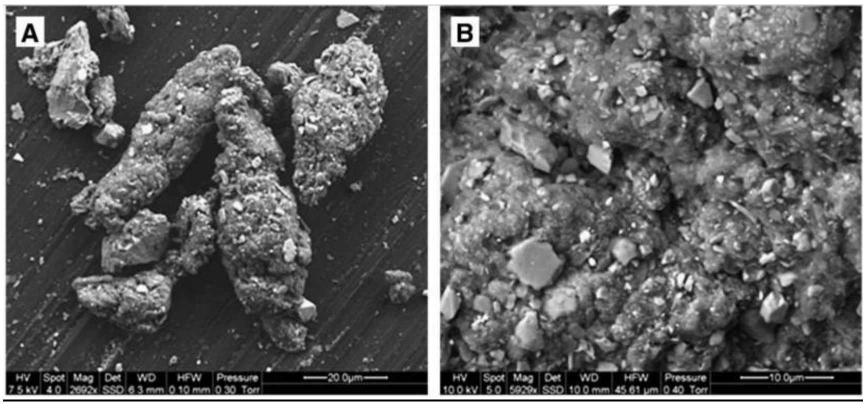


Figure 5-3: REM images of Tyre and road wear articles

5.2.2.2 How to measure it?

The aim of MODALES project is focused on tyre wear emission, consequently a tyre related criterion was created referred to as Wear rate (W) defined as the amount of tread material removed from the vehicle per unit road length travelled.

$$Wear\ rate = W = \frac{Amount\ of\ mass\ lost}{distance\ convered} \quad \text{(Eq. 5-9)}$$

No measurement technology is available to capture the wear rate directly on the vehicle during operation, researchers rely on measuring the remaining mass of the tyre after a certain operational duration:

$$Amount\ of\ mass\ lost = Mass_{newtire} - Mass_{after\ operational\ duration} \quad \text{(Eq. 5-10)}$$

In the MODALES project framework, wear is defined as the tyre wear of the complete vehicle set of tyres. Methods available to optimise tyre wear will be potentially more numerous than those optimising one single tyre.

5.3 Influencing factors on tyre wear and emissions

According to (Le Maitre, 1998) wear is dependent upon many parameters which take effect through a modification of the forces applied to the tyre of through a change of the rubber/ground interface. Each of them may induce wear rate variations from to 2 to 15.

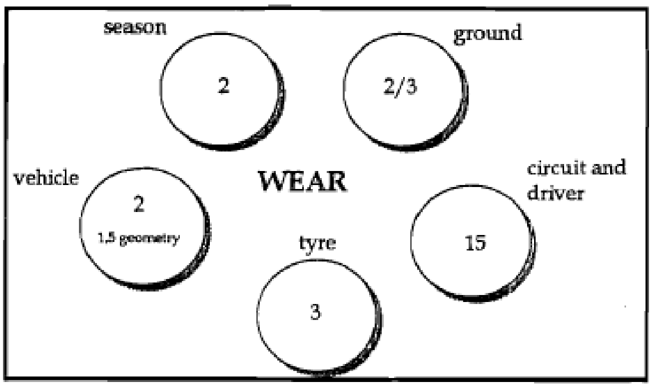


Figure 5-4: Important wear parameters

5.3.1 Routes and styles of driving

Depending upon the route and the style of driving, the acceleration levels reached by the vehicle may vary. These acceleration levels modify the forces applied to the tyre. The system of loads causing wear in the contact patch (sliding, stresses) is directly proportional to these forces.

The effect of driving style can be quantified by measuring the tyre wear on the same vehicle driven by different drivers over the same course. The variation in wear rates (in g/100km) is very significant (up to a factor of 6). It can be interpreted by the differences in acceleration levels (σ_{yx}, σ_{yx}) which each driver imposes on the vehicle (see Figure 5-5). Relevant wear differences can be seen between the vehicles driven by professional drivers and the vehicles driven by moderate use drivers. This comes from the fact that a professional driver will drive the vehicle at the speed limit with transversal acceleration levels much higher than those of moderate drivers.

	Professional			*Customer*	
Driver	1	2	3	4	5
Vkm/h	72.6	72.7	58.8	63.1	57.4
$\sigma_{\gamma x}$	1.22	0.92	0.75	0.69	0.62
$\sigma_{\gamma y}$	2.58	2.38	1.64	1.57	1.16
Wear	***28.5***	***19.0***	***8.8***	***7.6***	***4.6***

Figure 5-5: Driver influence on wear

5.3.2 Road surface

The ground impinges upon wear through a modification of the rubber/ground interface characteristics (friction, abrasion). The road abrasion is highly dependent upon the micro-roughness (but is roughly independent of macro-roughness) of the ground materials. A difference in magnitude of 2 to 3 may be seen for the same use, depending upon the ground characteristics.

5.3.3 Season effect

Environmental parameters such as temperature and humidity are very season-dependent. These parameters have a substantial influence on the rubber/ground interface characteristics and therefore on wear. Figure 5-6 indicates that tyre mass loss (in g/100km) may vary by a factor of 1 to 2 between summer and winter or within the same season, depending upon humidity. The amplitude of these variations is linked to the rubber compound chemical formula, hence the necessity to characterise the tyres on an annual basis in order to make a relevant evaluation of the tread compound wear performance taking into account seasonal variations.

Season's effect (similar use)

Rear-wheel drive vehicle
Wear on rear wheel (in g/100km)

tread compound A
(tread compound B)

SUMMER	AUTUMN	WINTER	
6.37 (5.92)	8.85 (7.92)	10.9 (9.42)	DRY
	5.06 (5.78)	7.13 (7.66)	WET

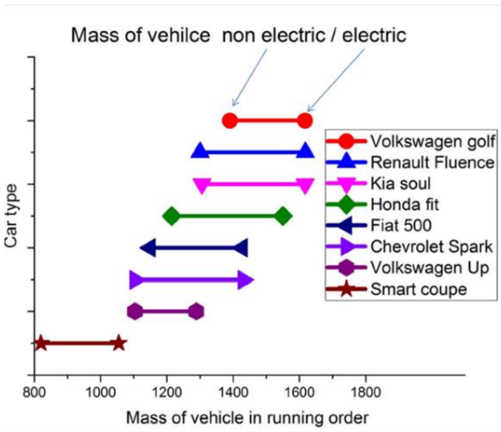
Figure 5-6: Seasonal effect

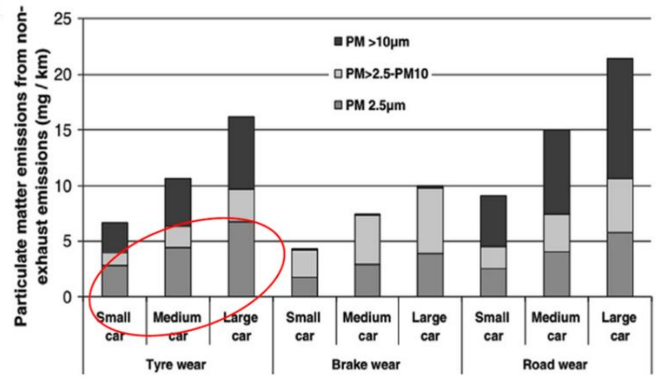
5.3.4 The vehicle

The vehicle acts directly on the forces applied to the tyre. The average life of a tyre may vary within a range of 50% or more, depending on the vehicle characteristics. The vehicle characteristics of the greatest influence are weight, suspension and steering geometry. The wear on an axle is quasi-proportional to the load imposed. The axle geometry (toe and camber) influences mass loss and wear profile. A 4mm difference on the axle toe leads to an average 1 mm difference in wear between the two shoulders of the worn tyre. Such differences are seen in actual use.

Focus on vehicle electrification:

Electric vehicles (EV) are heavier than the same vehicle with an internal combustion engine (ICE)due to the battery mass (around 25% of mass increase) (Horvath,2018). This mass increase has a direct impact on tyre wear and tyre emissions, for example there is a 1.5 factor difference between small and a large cars in term of wear rate (Figure 5-7).





Timmers and Achten 2016, Figure 1, From: Simons, A., 2013. Road transport: new life cycle inventories for fossil-fuelled passenger cars and non-exhaust emissions in ecoinvent v3. Int. J. Life Cycle Assess. 1-15; based on Ntziachristos, L., Boulter, P., 2013. EMEP/EEA Air Pollutant Emissions Inventory Guidebook 2013: Road Vehicle Tyre and Brake Wear; Road Surface Wear [Internet]. European Environmental Agency, Copenhagen [cited 11 August 2015]. Available from:http://www.eea.europa.eu/publications/emep-eeaguidebook- 2013/part-b-sectoral-guidance-chapters/1-energy/1-a-combustion/1-a-3-b-road-tyre.

Figure 5-7: EV vehicle mass increase and impact on tyre wear

5.3.5 The tyre

The tyre is the connection between the vehicle and the ground and tyre characteristics have a major effect on wear. The most important tyre parameters acting on wear are the following:

- the flexibility/rigidity determining the shape, stress and slip in the contact patch
- the rubber volume available for wear, which is correlated to geometrical characteristics of both tyre (width, diameter) and tread (rubber thickness and the tread pattern percentage)
- the material characteristics of the tread such as friction and abrasion

Hence, tyre size choice and inflation pressure are first order parameters for the wear performance of the tyre. For example, a switch from a 165/70 R14 to a 175/70 R14 on the same vehicle leads to a 20% increase in the tyre's life. This difference is due to the variation in rubber volume and stiffnesses between the two tyres. The inflation pressure of the tyres also has a great influence on wear and worn profile. It acts on the shape of the contact patch and on the tyre's stiffnesses.

5.4 Order of magnitude

5.4.1 Passenger car tyres

Few documents in the literature dealing with order of magnitude for passenger cars wear rate. For example (Pohrt, 2019) relates that during its service life, a typical modern tyre of the passenger car loses around Δm=1.4 kg of mass within approximately d=50000 km. The typical overall wear rate of the passenger car (with 4 tyres) is, therefore, approximately 112 µg/m (11.2g/100km).

5.4.2 Light duty vehicles tyres

There are few documents in the literature dealing with order of magnitude for wear rate for trucks, for example (Hillenbrand, 2005) presents a summary of distribution of wear rate coming from different studies:

Tabelle 4.4-2: Zusammenstellung der Abriebsmengen von Fahrzeugreifen [mg/FZkm] aus Literaturangaben

Fahrzeugart	PKW	Lieferwagen	Lastwagen	Sattelzug
Anzahl Reifen/FZ (Dunlop, 2002)	**4**	**5**	**9**	**12**
Pirelli (2002)	90	k. A.		
BUWAL (2001)	(152)[2]	(205)[2]	(2200)[2]	
Boller (2000)	60 - 120	k. A.		
Baumann/Ismeier (1998)	80			
Gebbe et al. (1997)[1]	53	107	539	1.092
CARB (1993)[1]	120	210 - 410		k. A.
BUWAL (1992)	64 - 200	685 - 1.500		
Mittlere Emissionsfaktoren und Schwankungsbreite	90 (53 - 200)	700 (107 - 1.500)		1.200 (1.000 - 1.500)

1) zitiert in Rauterberg-Wulff (1998);

2) Daten ermittelt durch die Schweizer Armee, deshalb nicht repräsentativ für den zivilen Bereich

Figure 5-8: Light trucks wear rates

Globally, we have an average value of wear rate between 107-1500 *µg/m (11-150 g/100km).*

5.5 How driving behaviour influences tyre wear

5.5.1 Electrification impact on driving behaviour

The available literature on tyre wear and electric vehicles indicate that the electrification of a vehicle has little influence on driving behaviour which would impact upon tyre wear. In (Helmbrecht, 2014), a study has been made using a Mini E vehicle on a mixed circuit composed of urban driving, highway and country road (Figure 5-9) in order to compare the usage severity between EV vehicle and combustion vehicle (average accelerations) in the first month of use and after five months of daily driving.

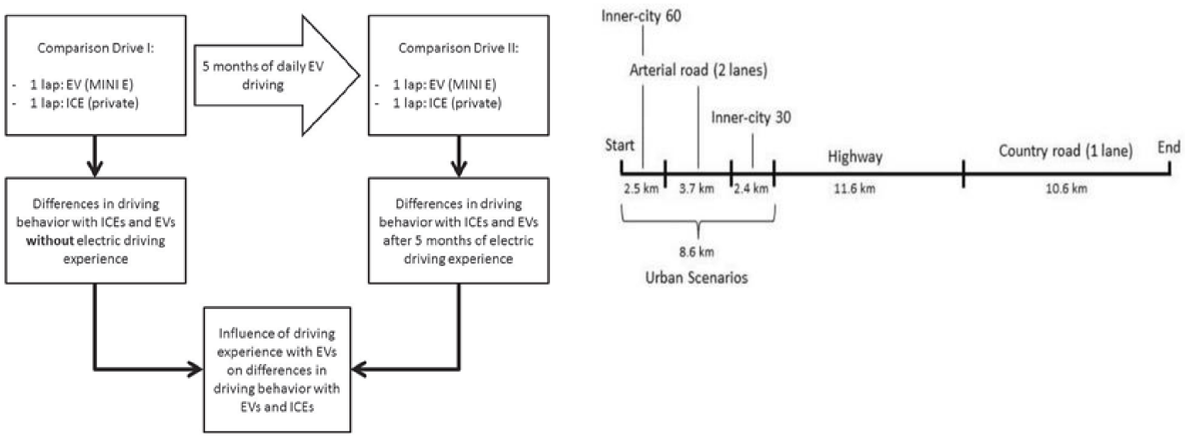


Figure 5-9: Study on electric vehicle driving behaviour impact

Results show that within the first month of the experiment, EV drivers have a stronger usage severity than the ICE driver (Figure 5-10, a) whereas after five months of daily driving this difference dissipates, and a calmer style of driving is noticeable between acceleration and braking manoeuvres (Figure 5-10, b).

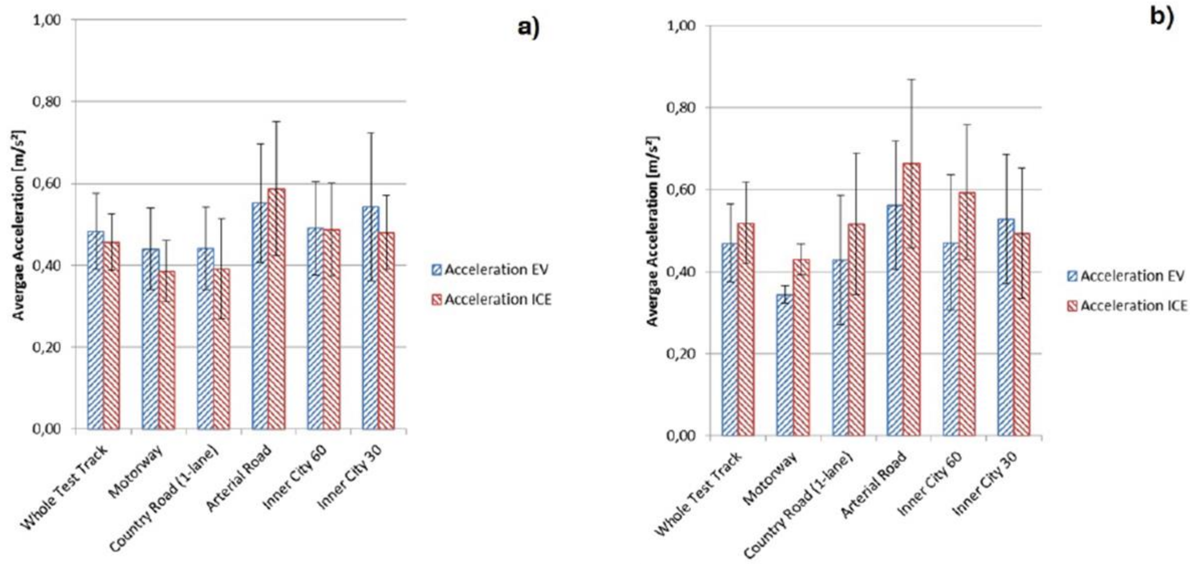


Figure 5-10: Electrification impact on driving behaviour

5.6 Measurement of tyre emissions

The standard measurement procedure for tyre wear particles is not available under either controlled laboratory or on-road direct measurement conditions, and is still under development stage. In this section, some representative measurement equipment for tyre wear particles are summarised.

5.6.1 Measurement equipment for tyre wear particles in the laboratory

In general, the tyre wear simulator in the laboratory consisted of a rotating drum, test tyre, and control system. Figure 11 shows the photo and schematic diagram of the tyre wear simulator (Kim &Lee 2018, Park et al. 2018). To simulate the roughness of asphalt pavement, a preconditioned safety walk with a grain size of 80 was used on the outer surface of the drum to reduce the influence of track abrasion. Driving speed can be easily controlled through the applied rotation speed of the drum. The tested tyre was connected tightly to the shaft of the driving control unit, which applied a lateral load of 4000 N to simulate the per-axel weight of a conventional passenger car. In addition, the tyre simulator can vary the slip angle from 0° to 4° to reflect cornering conditions. As shown in Figure 5-11, a controlled-volume chamber for TWP measurements was built to block aerosols from the atmosphere. The chamber was 4460mm long, 1908mm high, and 1680mm wide. All sides were sealed to prevent aerosol leakage and all inner surfaces of the walls were coated with anti-electrostatic paint to prevent the formation of electrostatic surface charges.

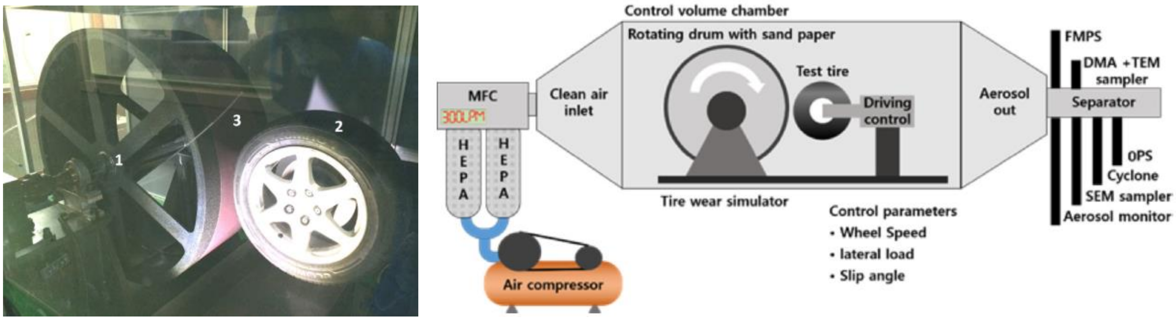


Figure 5-11: Photo and schematic diagram of the tyre wear simulator (Kim &Lee 2018, Park et al. 2018)

As shown in Figure 5-12, the tyre wear simulator comprises a vehicle wheel and tyre pressed under load against a large rotating metal wheel (Dall'Osto et al. 2014). Friction was generated by setting an angle between the vehicle wheel and the metal wheel, simulating a cornering manoeuvre. The sampling inlets were placed at distance of about 15 cm from the tyre/wheel interface and connected to the instruments via a 1 m long 1/4 inch conductive plastic tubing.

Figure 5-12: Photo of the tyre wear simulator. The arrow points towards the point of contact between the tyre (on the left) and the metal wheel (to the right) (Dall'Osto et al. 2014)

As shown in Figure 5-13, a road simulator (Swedish National Road and Transport Research Institute, Linköping) was used to generate wear particles from tyre running on two different pavements. Particle sampling in the simulator hall (10×8×5 m^3) makes it possible to sample wear particles with very low contamination from surrounding sources and no influence from tail-pipe emissions. The simulator consists of four wheels running a circular track with a diameter of 5.3 m. A DC motor is driving each wheel and the speed can be varied up to 70 km h^{-1}. At 50 km h^{-1} a radial movement of the wheels is started to force the tyres to wear evenly on the pavement. The simulator track can be equipped with any type of pavement and any type of tyre can be mounted on the axles.

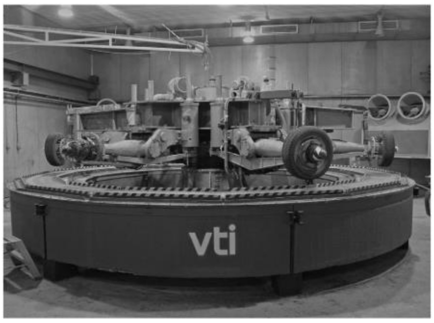


Figure 5-13: The road simulator of transport research institute (Gustafsson et al. 2008a)

5.6.2 On-road direct measurement for tyre wear particles

A schematic of the mobile sampling vehicle is provided in Figure 5-15. The vehicle had an unloaded weight of 1400 kg and was powered by a 2000 cc petrol engine. Sampling inlets were shown in Figure 5-14 (b), sampling inlet (1) is to measure the particles sampled from the front tyre, which could include tyre wear particles, road surface wear particles, road dust, atmospheric depositions, etc. Sampling inlet (2) is to measure background concentrations. The difference between (2) and (1) was considered to be the net concentrations of tyre wear particles.

(a)

(b)

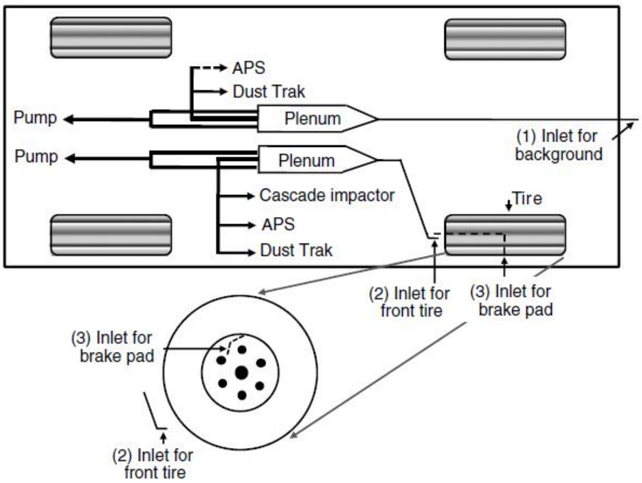


Figure 5-14: (a) Photograph showing two sampling sites: the ground proving ground (left) and road simulator (right), and (b) schematic of the current mobile sampling system (Kwak et al. 2013)

A Volkswagen van (LT 35, 2002) was used and equipped with three metal tube inlets: two were mounted behind the front tyres and one was mounted underneath the van that extended to sample background air bellow the front bumper (Figure 5-15). The three inlet lines entered the van compartment through the underbody. The three inlet lines entered the van compartment through the underbody. The front inlet was 0.4 cm in diameter and 300cm long; the flow rate in this inlet was 1.7 litres per minute (lpm). Both inlets behind the front tyres were mounted symmetrically and they were 1.9 cm in diameter and 230 cm long; the inlet was 21 cm above the ground, 5 cm behind the tyre, and 6.3 cm towards the centre of the vehicle from the outside edge of the tyre.

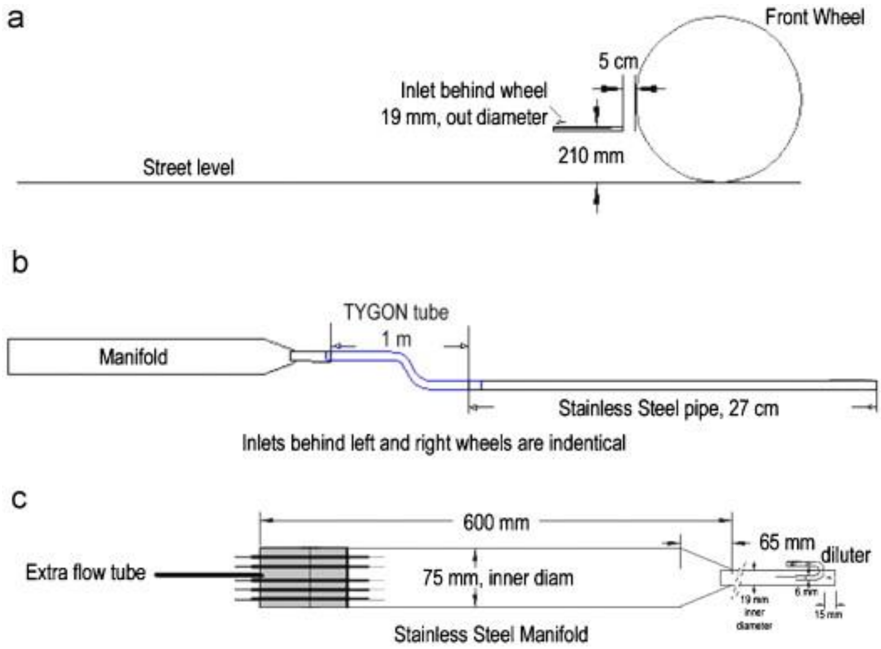


Figure 5-15: A schematic diagram showing the sampling lines setup behind the front tyres; note that both sampling lines are identical on the right and left sides: (a) distance and location of the inlet behind the tyre, (b) sampling lines between the inlet and the manifold, and (c) design of the manifold. (Hussein et al. 2008)

5.7 Tyre Emission models

So far, only a few emission models for tyre wear are available. The USEPA's AP-42 compilation of emission factors was presented in 1995 (USEPA 1995), which is probably the most widely-used models for predicting tyre wear particles. The tyre wear particle factor per vehicle is calculated as:

$$EF_{TYRE(v)} = 0.002 \times F_{TYRE} \times IVEHWL(v) \quad \textbf{(Eq. 5-11)}$$

Where $EF_{TIRE(v)}$ *is* the tyre wear particle factor for a vehicle in class v (g/mile), 0.002 is emission rate of airborne particulates from tyre wear for LDVs, F_{TIRE} is the fraction of particles less than or equal to the particle size cut-off, and *IVEHWL(v) is* the average number of wheels on a vehicle of class *v* and is listed in Table 5.1.

Table 5.1: Number of wheels per vehicle

Vehicle category	Average number of wheels
LDV	4
Small HGV	6
Medium HGV	6
Large HGV	18
Bus	4
Motorcycles	2

The particle size cut-off is the maximum aerodynamic diameter of the particles in the emission factor. For tyre wear (all vehicles), the value of F_{TIRE} for a particle size cut-off (10) is 1, and 0.01 for a particle size cut-off (0.1).

Venkatram (2000) indicated that the AP-42 model is not likely to provide adequate estimates of tyre wear particles. The model has little mechanistic basis and it relies on an input variable therefore the silt loading cannot be measured unambiguously. According to Fitz and Bufalino (2002), the AP-42 demonstrated that the silt loading reaches an equilibrium value without the addition of fresh material. If equilibrium is reached, then the emission rate should be zero, although this is not what the paved road equation predicts. Therefore, it is difficult to understand how this equation could be universally applicable unless the material is continuously replaced, a phenomenon which for most public roads is not likely.

EEA (2004) presented a more detailed methodology for estimating particle emissions from tyre wear using the following equation. This equation refers to a single vehicle category for a defined temporal and spatial resolution. Also, different particle size classes are considered.

$$E_{TYRE,i,j} = N_j \times M_j \times e_{TYRE,TSP,j} \times f_{TYRE,i} \times S_{T(v)} \qquad \textbf{(Eq. 5-12)}$$

Where $E_{TIRE,i,j}$ is total emissions (g) for the defined time period and spatial boundary, Nj is Number of vehicles in the defined class within the defined spatial boundary, Mj is mileage driven (km) by vehicles in the defined class during the defined time period, $e_{TIRE,TSP,j}$ is TSP mass emission factor from tyre wear (g/km). $f_{TIRE,i}$ is mass fraction of tyre-wear TSP that can be attributed to particle size class i, $S_{T(v)}$ is tyre-wear correction factor for a mean vehicle travelling speed V, i is size fraction (TSP, PM_{10}, $PM_{2.5}$, PM_1 and $PM_{0.1}$), j is vehicle category (two-wheel vehicle, passenger car, LVG, HDV).

TSP mass emission factors for different vehicle classes are listed in Table 5.2. Emission factors are based on available experimental data. It should be noted that the TSP emission rates do not assume that all tyre wear material is transformed into suspended particulate, as a large fraction of tyre rubber may be produced as a dust fall particles or larger shreds (e.g. under heavy braking). A value of 0.6 was selected as the PM_{10}/TSP ratio for tyre wear in order to derived TSP values where PM_{10} emission rates are available in the literature.

Table 5.2: TSP mass emission factors from tyre wear

Vehicle class (j)	Emission factor (g/km) ($e_{TIRE,TSP}$)
Two-wheel vehicles	0.0046
Cars	0.0107
LGV	0.0169
HDV	Equation (5.3)

For the heavy-duty vehicle case, emission factor needs to consider vehicle size. This can be obtained by the following equation:

$$\left(E_{TYRE}\right)_{HDV} = \frac{N_{axle}}{2} \times LCF_{TYRE} \times \left(E_{TYRE}\right)_{PC} \qquad \textbf{(Eq. 5-13)}$$

Where N_{axle} is number of truck axles, LCF_{TIRE} is Load correction factor, and $(E_{TIRE})_{PC}$ is the TSP emission factor for cars.

For heavy-duty vehicles, the number of axles is a parameter that can be used to differentiate size. Another parameter is a load correction factor, which accounts for the load carried by the truck or bus.

The load correction factor can be calculated based on the following equation which has been derived by linear regression on experimental data:

$$LCF_T = 1.41 + (1.38 \times LF) \qquad \textbf{(Eq. 5-14)}$$

Where *LF* is the load factor for the truck, ranging from 0 for an empty truck to 1 for a fully laden one. This equation can be used for urban busses and coaches.

Typical size profiles for TSP emitted by tyre wear have been obtained by combining information from the literature. According to this information, the mass fraction of TSP in the various particle size classes is listed in Table 5.3.

Table 5.3: Size distribution of tyre wear emitted particles

Particle size class (i)	Mass fraction (f_{TIRE}) of TSP
TSP	1.000
PM_{10}	0.600
$PM_{2.5}$	0.420
PM_1	0.060
$PM_{0.1}$	0.048

Winther et al., (2004) applied this detailed method to calculate tyre wear particles in Denmark. The emissions were compared with emission factors derived from roadside air pollution measurements. It was found that the emission factors for non-exhaust PM_{10} derived from the measurements were much higher than what could be expected from the model. For $PM_{2.5}$, the level of agreement between the two approaches was good, it was concluded that the underestimation of PM_{10} was due to a much higher contribution from the coarse mode to the measurements than accounted for in the model. Additionally, this reason may be ascribed to be the exclusion of resuspension from this method.

5.8 Recommendations and guidelines

5.8.1 Summary of key factors related to tyre emissions

The main conclusions drawn from the present literature study can be summarised below:

- Available data indicate exhaust and non-exhaust sources contribute almost equally to total traffic-related emissions. Among non-exhaust sources, tyre and road wear particles can contribute from 5% to 30 % by mass to non-exhaust traffic-related emissions. Tyre wear particles represents between 1%-8.5 % by mass to PM_{10} emissions. Among tyre wear particles, only up to 10% are PM.
- Given the variety of factors that influence the generation of tyre wear particles, any future efforts at reducing this source would need to consider not only the characteristics of the tyre, but also the vehicle to which it is mounted, the manner in which the vehicle is operated and the pavement on which the vehicle is driven.
- As varied sampling and analysis methodologies have produced non-comparable and, in some cases, even contradictory results, a single methodology should be developed to produce reliable and comparable results.
- The most important chemical constituents of tyre wear are comprised of both coarse and fine particle fractions. Despite the fact that some research regarding organic constituents of

wear particles has been conducted, there is very limited information regarding organic composition of tyre wear particles.

- The available information on tyre wear particles requires collation, and the methodologies currently employed to measure and model emissions should be summarised in order to provide general recommendations for model development.
- Tyre wear involves mechanical processes, thermos-mechanical and thermochemical processes. These processes result in different size distribution of tyre wear particles. Size distribution is extremely critical parameters, because the airborne particles generated from tyre wear seriously harm the environment and human health and are likely to become one of the restricted non-exhaust emissions. More detailed information regarding size distribution of tyre wear particles can be found in the literature (Gustafsson et al. 2008b, Harrison et al. 2012, Kim &Lee 2018, Kreider et al. 2009, Kreider et al. 2010, Kumar et al. 2013, Park et al. 2018, Sjödin et al. 2010)

5.8.2 Recommendations and guidelines for new driving data for tyre emissions

All the influencing factors on tyre wear presented in 5.1.3 are not related to driving behaviour. Since the MODALES project is focused on the link between particle emissions and driving behaviour, we propose to set up a classification (table 5.1) of these influencing factors which could be a method for the driver to reduce his tyre emissions.

This classification sort in term of influence domain for the driver:

- Methods that driver could activate **before driving**
- Methods that driver could activate **during driving**
- Methods that driver could activate **outside a driving phase**

Each factor is linked to a physical parameter which can be measured and ranked in term of knowledge maturity.

Since it is difficult to study all these factors in an experiment, we propose to focus on the more important parameters in the work package 3.3 (WP3.3).

Table 5.4: Driving behaviour influencing factors on wear rate classification

Influence domain	Controlled parameter	Physical parameter impacted	Knowledge maturity (0..2)*	Studied in WP3.3	Potential impact (1..3)**
Before driving (preparation)	Trip duration	Tyre thermic state --> tyre wear impact	2		2
	Route choice (grading)	Torque applied at the wheel	2		2
	Route choice (type of road)	Road roughness (μ)	1		2
	Load repartition	Tyre load repartition	2		1
During driving	Longitudinal acceleration	Ax	2	x	3
	Lateral acceleration	Ay	2	x	3
	Vertical acceleration	Az	2	x	3
	Average speed	< V >	2	x	3
Outside a driving phase	Inflation pressure	P	1		2
	Permutations	/	0		1

* 0: no scientific publication available | 1: one scientific publication available | 2: few scientific publications available

** 1: Moderate impact on tyre wear | 2: Intermediate impact on tyre wear | 3: Strong impact on tyre wear

6 Driving profiles based on smartphones

6.1 Introduction

This section provides a summary of the referenced literature on classifying driving behaviour using smartphone data. OBD (On-Board Diagnostics) data is also mentioned when it is considered by the reviewed literature, but is the subject of other deliverables (i.e., D2.2 and WP4 deliverables). Different methodologies are presented and discussed. This notably includes sensing schemes, types of data collected, classification algorithms, their accuracy and limitations. Challenges and possible solutions such as investigating the use of context-aware methods are also investigated.

It is important to note that this section provides:

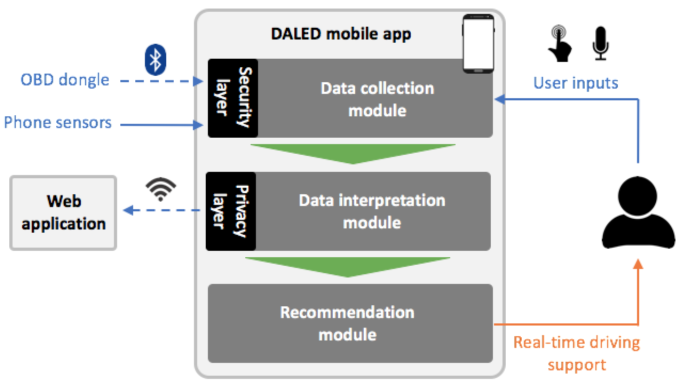
- an **initial** overview of the scientific and technical work that will be carried out for the mobile application and its data collection module, notably through OBD-II interfaces. This work will be completed and refined in the related work packages (WP4 and WP5).
- details on **determining a driving behaviour**, or **style**, in the broadest meaning. Wherever analogies exist with low-emission driving concerns, they are mentioned, but they are not the focus of this section. In more advanced WPs, driving style will be correlated with emission data in order to provide relevant recommendations.

6.2 Driving assistant for low-emission driving in MODALES: general approach

This part gives a brief description of the user-centric mobile intelligence that will be implemented in MODALES, so that the informed reader can make a link to the literature. This description is mostly based on the initial version of the Description of Action and is subject to evolve as the project and associated work packages evolve over time. More details will be formulated in WP4 and WP5 deliverables.

MODALES will implement a **mobile app for low-emission driving** (DALED, provisional name), which takes the role of **personal assistant** to the project's end-users. This app, transversal to the whole project, will profile a user's driving style and recommend attitudes to adopt or to avoid. It will naturally allow a large number of users to be reached easily and at a low cost, thus enabling experimentation and awareness campaigns to be conducted on a wide range of configurations (e.g., car types, engines, geographical areas).

Technically speaking, the app will be designed for the most popular platforms available on the market and adopt a modular approach, which allows several small components to be developed independently and then interact with each other to provide a unique driver experience. This approach makes it possible to technically feed the other elements of the project that require specific tools; it also facilitates collaborative development and validation. The app will be developed natively for Android and iOS. In order to prevent breaches of privacy, the processes developed will, as far as possible, be entirely local, and will not use services



external to the application (i.e., not using an Internet connectivity). For each app user, only anonymous indicators will be transmitted to a central collection point hosted by a project partner in Europe to collect usage statistics and performance metrics. The latter will be the subject of an independent web application that allows the authorities and the public to understand the benefits of the application, and view statistics by region or type of user.

The app would be broken down into three separate modules:

- A **data collection module**, which considers data from *(a)* OBD-II (e.g., engine type, emission data), *(b)* telephone sensors (e.g., accelerometer, wireless traces) and *(c)* the user, and which will provide information requested in a contextual manner to validate or provide input to a situation perceived by the application. Using an OBD dongle would be optional, in order to provide end users with a standalone application, and another – more accurate and detailed version – relying on additional data. The lack of data induced by the absence of OBD would be supplemented by specific machine learning techniques and by using the user's knowledge (for example by asking users for the reference of their car). Studies on sampling, recording, communication frequencies and safety aspects would complement the reliability of these approaches.
- The aforementioned data will be used as input for a **data interpretation module**, making it possible to create a local representation of the user's profile and distinguish different behaviours previously identified via laboratory tests and state-of-the-art reviews. Dimensionality reduction (e.g., PCA) and clustering detection (e.g., k-NN) techniques will be used to increase our understanding of the underlying data. This will enable creating meaningful and robust features to be used as inputs to supervised classification methods. Standard classification models (e.g., SVM, Decision Tree), flexible enough to be executed locally on a mobile device, would be used. Input data would come from OBD dongle and phone sensors, while ground truth data would be provided by the user and independent data, such as GPS.
- Finally, a **recommendation module** will advise the user to adopt particular attitudes depending on his/her perceived behaviour. A flexible Human-Machine Interface will be used to supplement the existing driver information panel. This HMI may be used to *(a)* provide visual/auditory feedback to the driver, *(b)* guide the driver using an advanced driving recommendation system Guidelines established with user groups will be used together with knowledge accumulated from the early phases of the project. Several strategies would be studied in parallel to the design of training courses to encourage users to follow these recommendations. A gamification layer will be implemented, which should for instance set up an eco-responsibility currency and competitions between different user groups.

The modules described above would be developed independently, then tested and validated under different conditions using several user groups whose nature will be redefined with each app release. For example, the first release will only be tested internally, while the two others will be tested on extended groups using traditional assessment principles: functional, usability, interaction, compatibility, performance and security testing. It should be noted that while other applications using similar concepts exist in the literature or on the market, to our knowledge, none is run exclusively locally and in real time. For the most part, users receive recommendations after their journey is over and based on aggregated historical measurements taken from several users. DALED will aim to assist users throughout their journeys, providing recommendations as they travel, and in ways that won't interfere with their driving (e.g., when stationary at a traffic light, or in the form of sound notifications). The app will also cover maintenance issues and not only on driving style analysis.

6.3 Sensing systems and sensors

Recent technological advances in communication technology and mobile computing have provided new ways to understand driving behaviour. All this requires setting up an **in-car sensing system** in order to collect relevant data and then use it. Detections performed by such a sensing system can be divided into two categories, namely **participatory sensing** and **opportunistic sensing**, preferred in the project and where the data collection process is performed automatically and based on sensors. Tri-axial accelerometers have for instance been used alone for several decades to monitor human movement and estimate energy expenditure – they are totally adapted to the present use-case since they have been embedded in all smartphones for several years.

Sensing applications can usually address three levels of detection depending on the data-sharing policies (Lane et al., 2010), namely the **individual** level, the **group** level and the **community** level. Depending on the level of detection, the level of data protection and privacy need to be adjusted, requiring the definition of rigorous data treatment systems. The usage of smartphone sensors in the context of driver behaviour is persistently shown in the literature and is mostly focused on the first level. The key challenge to conduct such research is therefore to select the most suitable sensors that are accepted by the driver (i.e., data collection process should be convenient to the end user, non-intrusive, and does not breach the user privacy).

With this in mind, Table 6.1 presents a comprehensive analysis to identify potential data collected through smartphones and OBD-II interfaces that can be used to analyse driving behaviour, and to show user acceptance of the technology (Faye et al., 2017, Hong et al., 2014, Júnior et al., 2017).

Table 6.1: List of smartphone and OBD data for the Driver Behaviour Analysis

Device	Sensor	Data	User Acceptance of Technology
Smartphone	Accelerometer	Acceleration, vibration, and tilt	High
	Gyroscope	Orientation details, rotation, and direction like up/down and left/right	High
	Barometer	Air pressure	High
	Network traces	Passive network data left by Wi-Fi, Bluetooth and cellular nodes	High
	Compass	Magnetic fields	Medium
	Camera	Facial Images	Low
	Microphone	Loudness of sound	Very low
	GPS	Location	Low
OBD-II dongle		Real-time parameters: Engine RPM, speed, pedal position, airflow rate, coolant temperature, Engine load, Throttle percentage.	Medium
		Vehicle Identification Number (VIN)	
		Status of "Check Engine" light	
		Emission readiness status	
		Oxygen sensor (maximum and, minimum voltage output, and switching rate)	
		Diagnostic trouble codes (DTCs)	
		Number of km or miles driven	
		Number of ignition cycles	

Among these entries, wireless traces collected passively through **wireless discovery** have an interesting potential. Network discovery (or scan) is the process through which nodes of a network announce their presence to each other. This is usually done through dedicated packets (i.e., traces), which contain relevant contextual information such as the MAC (Media Access Control) address of the device. Wi-Fi and Bluetooth are among the two most commonly used types of short-range networks. Wi-Fi nodes tend to be associated with places, whereas Bluetooth nodes with people (Faye et al., 2017).

Wi-Fi traces can for instance be analysed to discover places of interest or stop locations without explicit location information (Wind et al., 2016), for mobility and location profiling (Faye et al., 2017). Wi-Fi defines two discovery mechanisms:

- Passive scans, in which devices regularly send beacon management frames to announce their presence. Passive Wi-Fi scanning is an effective way to identify behavioural patterns and specific movements between buildings (Zhou et al., 2016).
- Active scans, in which devices send probe requests to explicitly request the presence of one or more access points. However, this causes privacy issues, as active scans imply that users are sending their own MAC addresses.

Bluetooth traces have already been used as a GPS substitute to classify different types of roads (Bronzi et al., 2017), reconstruct the path of a vehicle (Lees-Miller et al., 2013), or for behavioural pattern recognition. Devices using Bluetooth can broadcast discovery data, including their MAC address, RSSi and device or manufacturer specific data (e.g., type of device). Bluetooth is currently composed of two versions: Bluetooth classic (BC), offering a pairing mechanism between two devices, and Bluetooth Low Energy (BLE), which has been incorporated in Bluetooth 4.0, and no longer requires this mechanism. During MODALES, this will most certainly be the preferred communication technology to collect OBD-II data from the dongle to the smartphone. BLE is also used for running Bluetooth beacons, such as *iBeacons* and *Eddystone*, which can send specific information to points of interest (e.g., for advertising, or to serve as an input to a recommendation system).

6.4 Driver behaviour profiling literature

This section highlights a literature review of data collection methodologies that have been used to collect driver behaviour information using smartphone sensors (Table 6.2), along with pre/post-processing procedures, algorithms used, features extraction and calculation (Table 6.3).

6.4.1 Summary of the main findings

6.4.1.1 Directions

Despite a large body of research, identifying precise driving behaviours using a smartphone-based sensing system is far from being a solved problem. Table 6.2 and Table 6.3 display a comprehensive analysis of the prior studies on smartphone-based sensors/OBD to evaluate driving patterns. The commentary that follows describes the key achievements and milestones that have taken place.

Table 6.2: Comprehensive Analysis of the Prior Studies on Driving Behaviours

#	Authors	# users	Duration	Scenario	Sampling rate	Vehicle	Sensors
1	Hong et al. (2014)	22	2 weeks/CD 32520 Min	Real	30 seconds	Cars of individuals were utilised	OBD2, IMU, 3D Acc, 3D Gyr, GPS, compass orientation, illumination, air pressure
2	Júnior et al. (2017)	2	13 Min /SD	Real	50 and 100 Hz	Honda Civic	3D Acc, Lin Acc, 3DGyr, magnetometer,
3	Arau´jo, et al. (2012)	-	-	Real			OBD2
4	Lee and Chung	10	-	Simulation		Simulated system	3DAcc, camera, ECG, PPG, in-vehicle temperature
5	Araujo et al. (2012)	-	66 Min/SD	Real	200s window	Volkswagen Sharan	OBD,
6	Bergasa et al.(2014)	12	400 Min/CD	Real	-	Renault Laguna	camera, microphone, the inertial sensors and the GPS.
7	Yu et al. (2016)	20	CD, 4 Months 60 to 80 KM per day.	Real	300Hz.	Cars of individuals were utilised	3DAcc, 3D orientation
8	Castignani *et al.*(2016)	10	Multiple trips/CD	Real	1 *Hz GPS,* 20 &50 for other sensors	Renault Twizy	linear Acc, Magnetometer, Gravity, GPS Fusion is done with fuzzy logic to obtain accurate results
9	Johnson, D.A. and Trivedi, M.M., (2011)	3	200driver events/CD	Real	25 Hz, Acc,Gyr	92 Pontiac Firebird 2001 Ford Escape 2008 Volkswagen Passat (Sedan instrumented)	Acc, GPS, rear cam, magnetometer
10	Eren et al. (2012)	15	CD	Real	-	-	Acc, Gyr and magnetometer.
11	Sing et al (2017)	-	CD	Real	200 hz	Honda Deluxe Motorbike Maruti Swift car	GPS, Acc, Gyr and magnetometer.
12	Oren et al. 2012	109	2-90 Min over 6 months-CD	Real	40 HZ	-	Acc, GPS
13	Omar Baghdadi 2013	109	40s before crash+ 20s after crash = 1 min	Real	--	100 cars	Acc, GPS, Radar

#	Authors	# users	Duration	Scenario	Sampling rate	Vehicle	Sensors
14	Assaf et al. 2016	30	2 weeks	Real	-	-	Acc, GPS, Camera
15	Chaovalit et al.	1	120 driving events/CD	Real	5Hz, 1Hz	Toyota Vigo	3D Acc, MAG, GPS
16	Bejani and Ghatee (2018)	27	7 minutes/SD	Real	10 Hz	Different cars	3D Acc, MAG, GPS

Legend: OBD2: Bluetooth-based (mostly) on-board diagnostic, IMU: inertial measurement unit, Acc: accelerometer, Gyr: gyroscope, Mob: mobile, SW: smartwatch, SD: same day, CD: Cross day, BN: Bayesian Network, SVM: Support Vector Machines, ANN: Artificial Neural Networks, RF: Random Forest

Table 6.3: Comprehensive Analysis of the Methods, Features and Classification Algorithms Used in the Prior Art

#	Data	Features	Aim	Class considered	Classifier	Performance (%)
1	1- Speed (GPS) 2-Speed change (Acc) 3-The lateral and longitudinal acceleration of the car. 4-fine-grained speed, engine RPM, and throttle position (OBD2)	1- Mobile features are: Max/avg/std of speed, speed change, longitudinal/lateral acceleration. 2- OBD2 features are: Max/avg/std of speed, speed change, engine RPM, engine RPM change, throttle position, throttle position change 3- IMU: Used to detect turn events based on its z-axis acceleration change	Driver Aggressive mode	-	Naive Bayes	91
2	Acceleration 3 axis (Acc), Force of the magnetic,	Mean, median, STD, and increase/decrease tendency	Driver Aggressive mode	Breaking, Acceleration Turning	ANN, SVM, RF, BN.	

#	Data	Features	Aim	Class considered	Classifier	Performance (%)
	Rotation. Acc and Gyr were selected as it shows the best performance.			Lane changes	RF performs better	
3	Speed, acceleration, altitude, throttle signal, instant engine fuel consumption, engine rotations	average speed, minimum and maximum	Driving conditions	Urban, Highway Combined	Special Equations	-
4	1- facial image (camera) 2-heart rate (ECG) 3-blood pressure (PPG) 4-speed (Acc) and temperature	1. Eye feature (e.g., pupil size) 2. changes in skin blood 3. interval between PPG peak and valley in a single cycle 4. speed	drowsiness detection.	Score 0.6-0.75, the driver is partially sleeping. Above 0.75 is sleeping	BN	96
5	1- speed, acceleration, altitude, throttle signal, instant engine fuel consumption, engine rotations	average, minimum and maximum, percentage of time that the vehicle is stopped	fuel efficiency	-	Personalised classifiers	
6	1- Image of lane markings on the road (rear camera) 2-speed (GPS) 3-Accelration (Acc) 4-clicking sound generated by the indicator (Mic)	1. Horizontal and vertical coordinate of the edge feature pixel in the image plane. 2. Initial curvature, 3. Velocity of the clothoidal curve 4.Road lane width, 5.Lateral displacement of the car with regard to the centre of the lane, 6. Angular displacement of the car with regard to the lane orientation.	Detection of some inattentive driving behaviours	Lane drifting, Lane Weaving Acceleration Braking Turning	Canny	82 at 92 Recall

#	Data	Features	Aim	Class considered	Classifier	Performance (%)
7	Acceleration and orientation	maximum, minimum, value range, mean, and standard deviation	Detecting Abnormal Driving Behaviours	Weaving, Swerving, Side slipping, Fast U-turn, Turning with a wide radius and Sudden braking	NN, SVM	97,95
8	Acceleration (Acc) Orientation Rate (Magnetic) Speed Variation (GPS)	Jerk (the rate of change of the Acc with respect to time) Acceleration Fusion of X,Y,Z Yaw, Pitch, Roll The average yaw rate and the jerk standard deviation	Identify Risky driving manoeuvres	Over-Speed Normal Acceleration Normal Braking Normal Steering Aggressive Acceleration Aggressive Braking Aggressive Steering	Fuzzy Logic + WeatherMap + day time	90
9	Acceleration (Acc) Rotation (Gyr)	SMA of Gyr_x	determining a driver's style. Aggressive or not Aggressive in active and passive mode (forensic)	Right turns (90) Left turns (90) U-turns (180) Aggressive right turns (90) Aggressive left turns (90) Aggressive U-turns (180) Swerve right (aggressive lane change) Serve left (aggressive lane change)	DTW k-NN	82
10	position, speed, acceleration, deceleration and deflection angle sensory information	Energy	Detect risky driving	Aggressive and Non-Aggressive	DTW and Bayesian +weather	93
11	Acc, Gyr, Gravity, GPS,	Rate of change of Acc.	Braking events Risky manoeuvres	Aggressive driving, Sudden braking	DTW	95

#	Data	Features	Aim	Class considered	Classifier	Performance (%)
12	Trip duration	Frequency of events (EF)	Detect undesirable events (Braking, acceleration, etc.)	Normal vs abnormal events	EM	NA
13	Acceleration	Jerk (rate of acc. change)	Detect rare events (near-crash, crash, critical brake …)	Sudden braking,	Savitzky Golay polynomial differentiation method	86
14	Acceleration	Jerk	Detect collisions	Collision – no collision	Questionnaire	
15	Position, speed (GPS) Acceleration (Acc)	Distance between samples	Determining a driver's style.	Sudden Acce, Sudden Brake, Sudden Left Turn, Sudden Right Turn	Symbolic Aggregate Approximation	50-67
16	Acceleration Position, speed,	variance of acceleration along X axis and P-feature. Average of GPS speed, Zero-Crossing Rate, Variance of accelerations, Average of abstract of accelerations, Maximum of acceleration, Minimum of acceleration		U-Turn, Turn, and Change-Lane	decision tree, SVM, multi-layer perceptron, k-NN	94,92, 92, 93

Depending on how the information is collected, approaches to profiling driving behaviour are mostly broken down in the literature into two directions:

- **Recognition of driving patterns and events**. This approach is based on the identification of pre-calculated manoeuvres or spatio-temporal driving patterns. Once the recognition of an event is done, a classification of aggressiveness (or any other behavioural indicator) can be performed. Although the implementation of such techniques achieved high accuracy, most studies are considering a limited range of events. Moreover, authors rarely consider the variants of the selected events, hence the accuracy of such system is completely based upon the quality of manoeuvres rather than the overall driving behavioural.
- **Multi-dimensional threshold measurement**. In this approach, the driving style would be predicted without collecting labelled data or predefined manoeuvres, the driver behaviour (e.g., aggressive or not aggressive) is identified based upon setting threshold. However, one of the key challenges is to capture the driver's data in a safe and trustable way. Moreover, the classification decision of abnormal driving behaviour could take long time, which puts a barrier to use such a method.

In both scenarios, it is essential that the driver receives a notification or warning when a bad driving style practice occurs. This could significantly beneficial to reduce the risk associated in the road, energy consumed, and less road congestion or traffic.

6.4.1.2 Challenges

Based on the current state of art, there are some challenges faced when implementing smartphone driver behaviour analysis. These include:

- Most previous studies have collected driver information by placing a smartphone in a fixed position (e.g., with an accessory on the dashboard, or in the pocket), which remains a necessary step when using accelerometric or gyroscopic data - but which can be constraining for the end user. One solution would be not to use such data or to get it through specific OBD-II readers.
- Although the use of smartphone sensors is a cost-effective strategy and user convenient, this would require complex computational processing and hence high demand upon the battery (which is one of the biggest weaknesses of these devices).
- Some studies (e.g., 4, 6, 9 in Table 6.3) utilised the smartphone's camera for analysing the facial expression of the driver. However, the performance of such system is affected by several factors such as surrounding illumination, image quality, and the distance between the face and camera. Moreover, the acceptance of this technology is usually low.
- It is highlighted (Al-Naffakh et al., 2018) that smartphone sensors suffer from accuracy issues due to different hardware specifications depending on the phone manufacturer. Hence, this could be resulted in inconsistent sampling rate of the collected information from these devices. Moreover, external factors such as road condition and vehicle could result in generating noisy sensor readings, which make the data collection scenario less accurate.
- Although the use of GPS information could be useful for analysing the driver behaviour, this would require complex computational processing and high demand upon the battery. Furthermore, the collected GPS information could be inconsistent due to several factors such as high-building, the vehicle in a tunnel, forest, and phone position as well as limited sampling rate (i.e., only 1Hz which is not sufficient to detect and classify certain manoeuvres accurately).

6.4.1.3 Data collection methodologies

The use of built-in smartphone sensors for gathering driving behaviour profiling data created a new domain for transparent and continuous data collection. However, as highlighted above, most of existing studies capture the driver's data by placing a smartphone in a fixed position, and this is not adaptable to all contexts as some drivers tend to put their mobile in different locations in the trouser pocket or on the hip. Moreover, in these studies, the volume of data per user is limited (specifically when it is captured on the same day, i.e., 7 to 66 Minutes) as illustrated in Table 6.2, and the majority of the experimental setup was based on data collected with a controlled environment (i.e., where all participants are asked to drive on a predefined route or using simulated implementation). Finally, in recent applications, the proposed systems have usually been designed for a specific purpose and situation, using only a small subset of the many types of sensor that are now available.

6.4.1.4 Data processing and machine learning approaches

As highlighted earlier, transforming the collected data into a form suitable for traditional machine learning classification algorithms is necessarily. Pre-processing provides a mechanism to remove unnecessary noise from the collected data, which might be resulted from phone position, road condition, vibrations from the vehicle, electromechanical components, and sudden phone movement. The literature showed that high, median or bandpass filter can be used to remove unwanted data.

Feature extraction is a key component of any detection system and needs to contain the user discriminative information necessary for classification. With respect to features, there have been several studies in literature that suggested the generation of statistical metrics such as the mean, median, and standard deviation of the temporal data collected (Table 6.3). While these features are easy to calculate and extract, it is essential to identify or select the most distinctive and unique feature subset to maximise the system performance and reduce the computation overhead. This can be achieved by adopting feature selection methods that take place after extraction and prior to classification. Feature selection is used to select feature subset from the entire extracted features through identifying the most optimal and remarkable features for the machine learning algorithms in order to reduce the dimensionality of input data.

Most of the research in this literature does not seem to be concerned about the number of features extracted, which could lead to excessive training time, poor model prediction and poor performance when implementing a real-time approach. Here, methods such as Principal Component Analysis and Independent Component Analysis can be used select the most optimal feature subset. Feedforward Multi-Layer Perceptron (FF MLP) neural network is a possible solution to improve the system accuracy and remove the redundant features. Nevertheless, plenty of data would be required to train the classifier in order to avoid the over-fitting.

6.4.1.5 Factors that have an impact on driver behaviour

Factors that have an impact on driver behaviour have been widely investigated in the scientific literature (references 1-7 in the tables below). Researchers usually distinguish among environmental and human factors. Table 6.4 summarises the factors that have been judged important by the authors since they would influence the driver's behaviour.

Table 6.4: Key Factors that Affect Driver Perception

Environmental Factors	Human Factors
Traffic	Age, Gender
Weather and session	Character
Road type and condition	Demographic Background
Visibility	Driving experience
	Decision making
	Familiarity with the vehicle
	Current body condition such as influence of alcohol drugs, distraction, fatigue, recklessness, stress, and mood

6.4.1.6 Possible solutions

This section describes possible solutions that could help address some of the key challenges mentioned in the previous section. In MODALES, we will explore new approaches, which include but are not limited to:

- The development of a **context-aware driving behaviour detection system**. As shown in Table 6.4, several factors can influence the driving pattern of individuals such as traffic, road type and condition. Nevertheless, several studies in this literature have not considered these factors during the design of their system (e.g., the impact the road type and environmental conditions was neglected in the classification phase and the authors mainly focused on the driver pattern only). For example, it is expected that the driver behaviour on a normal road is completely different for the same driver on a congested area, where shock waves are created due to an accumulation of inappropriate user behaviours - as it often happens on heavily congested cross-border areas. Driving context-aware systems would use the collected information in order to characterise the circumstances that surround a driving activity without explicit user interaction, thus allowing targeted and pertinent recommendations to be done.
- The use of **wireless network traces** to infer specific metrics that are energy-intensive or inaccurate, or to support the development of context-aware approaches described above.
- **AI Edge-based profiling techniques** that are partially or completely free of internet connectivity, and
- The use of smartphone data to **infer metrics** traditionally obtained via OBD to open up a much wider range of possibilities.

6.4.2 Related work

This section presents all the papers that were considered in order to draw the previous conclusions, through Table 6.2 and Table 6.3. The main ones are detailed below.

A context aware system was developed by Bejani and Ghatee (2018) to investigate the influence of the car types and traffic conditions on the driving style, and recognise risky manoeuvres and low acceleration patterns. The data collection methodology was divided into three stages (i.e., pre-manoeuvre, in-manoeuvre, and post manoeuvre). The raw acceleration, magnetometer, and GPS of the smartphone were captured at 10 Hz sampling rate from 27 taxi drivers using different car types and each driver participated in single session of seven minutes only. A set of features (e.g., average of GPS speed, zero crossing rate, variance, maximum, and minimum, of acceleration readings) were extracted and used as input to detect the manoeuvre type. Based on the magnetometer information, C4.5 decision tree and a radial basis function (RBF) algorithms were utilised to classify limited manoeuvre types (i.e., U-turn, turn, and change-lane).

Symbolic Aggregate Approximation algorithm was used by Chaovalit et al. (2013) to predict driving events such as sudden brake and acceleration by determining the similarity of training and testing samples using a Euclidean distance function (i.e., min - distance). The proposed method can also contribute to reduce the inconstancy of the collected acceleration signal, which might be caused during the driving in different road surfaces. To capture the driver's style characteristics, the smartphone sensors information was utilised (i.e., accelerometer, magnetometer, and GPS) at a sampling rate of 5 and 1Hz for the accelerometer and GPS respectively. Data was labelled into four different classes: sudden acceleration, sudden brake, sudden left turn, sudden right turn. Apart from the low accuracy of the proposed system that ranged from 50% to 67%, the evaluation of this study was based on very limited data that captured from only one driver (using short distance of 120 driving events).

Although the prior art utilised different smartphone sensors to effectively analyse behavioural patterns, the authors did not fully address which sensor can provide more consistent and reliable data for profiling driver behaviour. As a result, an extensive experimental work is required to investigate and identify the most appropriate data that should consider developing a reliable and robust system. With respect of the sampling rate, all the presented studies in Table 6.2 also only poorly considered the impact of different sampling rates on the system performance (Hoang et al., 2013).

7 Low-emission driving behaviour in relation to safety and fuel consumption

The ultimate goal of MODALES is to develop guidelines for drivers to reduce the emissions of air pollutants (e.g. NO_x, O_3, PM, PN) due to their significant exceedances found particularly in many European cities affected by specific environmental or industrial conditions. Courses on low-pollutant emission driving complement the existing ones on eco-driving or safety since common good practices such as regular servicing, adequate tyre-pressure, avoidance of harsh acceleration or braking and avoidance of long idling can be shared. Therefore, MODALES will make sure that the driver is clear about which driving practice should be used and when.

In this chapter, an in-depth review of fuel and safety related studies was carried out to identify key common factors (especially driving behaviours) which affect emissions, energy and safety.

7.1 Fuel consumption models

7.1.1 Virginia Tech Comprehensive Power-Based Fuel Consumption Model (VT-CPFM)

VT-CPFM is a microscopic fuel consumption model based on instantaneous vehicle power, developed by Rakha et al. to overcome the major shortcomings of most models (Abdelmegeed and Rakha, 2017).

$$FC(t) = \begin{cases} \alpha_0 + \alpha_1 P(t) + \alpha_2 P(t)^2 & P(t) \geq 0 \\ \alpha_0 & P(t) < 0 \end{cases} \quad \text{(Eq. 7-1)}$$

Where,

- $\alpha_0, \alpha_1, \alpha_2$ are the fitted coefficients using test data;
- $P(t)$ is the energy consumption by vehicle wheels.

Applications of the VT-CPFM model suggest various choices of vehicle parameters and different values for the quadratic parameters $\alpha_0, \alpha_1, \alpha_2$ giving the fuel consumption function. The energy term $P(t)$ is shown as follows,

$$P(t) = \frac{1}{3600\eta_d}\, v(t) \left\{ \frac{\rho}{25.92} C_D C_h A_f v(t)^2 + \frac{g\, M\, C_r}{1000} [c_1 v(t) + c_2] + g\, M\, G(t) + (1+\lambda)\, M \frac{dv}{dt} \right\} \quad \text{(Eq. 7-2)}$$

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 drag;
- C_r is rolling resistance factor;
- c_1 and c_2 are rolling parameters;
- η_d is driveline efficiency;
- λ is Rotl masses.

The advantages of the VT-CPFM model for this purpose are that it overcomes the bang-bang control problem of other models and that publicly available data can be used for model calibration. In addition, because the VT-CPFM model requires only eight coefficients and two primary inputs, speed and acceleration, it is easier to implement.

7.1.2 Fuel consumption model based on exhaust emissions

As the products of the fuel consumption are mainly include CO_2, H_2O, CO, and HC, the fuel consumption of the vehicle can be calculated based on the C (carbon) balance before and after fuel combustion (Song et al., 2009).

$$FR = \left(ER_{CO_2} \cdot \frac{12}{44} + ER_{CO} \cdot \frac{12}{28} + ER_{HC} \cdot \frac{12}{13}\right) \cdot \frac{1}{\%C} \qquad \text{(Eq. 7-3)}$$

Where,

- FR is fuel consumption rate (g/s);
- ER_{CO2}, ER_{CO}, and ER_{HC} are emission rate of CO_2, CO, and HC (g/s);
- %C is carbon percentage of gasoline (petrol) by weight, and its typical value is 86.4%.

The exhaust emission rate is tested using portable emission measurement system (PEMS) instruments.

7.1.3 Fuel consumption model based on engine energy output

This vehicle model (Cappiello et al., 2002) which only applies to petrol engines is similar to the VT-CPFM model, which is also based on the energy consumption by vehicles. However, the energy consumption in VT-CPFM model is the value consumed by wheels, however, it is for the engine power in this fuel consumption model. Consequently, this model includes the energy losses of the transmission system and engine friction loss. Meanwhile, the fuel consumption under idle conditions is also included.

$$FR = \emptyset \cdot \left(K \cdot N \cdot V + \frac{P}{\eta}\right) \quad if\ P > 0 \qquad \text{(Eq. 7-4)}$$

$$FR = K_{idle} \cdot N_{idle} \cdot V \quad if\ P = 0 \qquad \text{(Eq. 7-5)}$$

Where,

- Ø is fuel/air equivalence ratio, which is the ratio of stoichiometric air/fuel mass ratio (14.5) to the actual air/fuel ratio
- K: engine friction factor (kJ/revolution/liter)
- N: engine speed (revolution/s)
- V: engine displacement (litres)
- η: engine indicated efficiency
- K_{idle}: constant idle engine friction factor (kJ/revolution/liter)
- N_{idle}: constant idle engine speed (revolution/s)
- P: engine power output (kW)

When the engine power is zero, the fuel consumption rate is equal to a typically small constant value. Otherwise, fuel consumption is mainly dependent on engine speed and demanded power. The stoichiometric ratio corresponds to the mass of air needed to ideally oxidise a mass of fuel completely. Under higher power conditions, engines are typically designed to operate with a mixture rich in fuel ($\emptyset > 1$) in order to prevent the catalyst from overheating. This can have a significant effect on emissions. Enrichment often occurs during cold-starts to heat the engine and exhaust so that the catalyst can light-off sooner. During long deceleration events, the mixture can go lean ($\emptyset < 1$) because engines are often designed to shut off the fuel since power is not required.

The engine power is modelled as the general form,

$$P = \frac{P_{tract}}{\varepsilon} + P_{acc} \quad \text{(Eq. 7-6)}$$

Where,

- P_{tract} is total tractive power requirement at the wheels (kW)
- ε is vehicle drivetrain efficiency
- P_{acc} is engine power requirement for accessories, such as air conditioning

The values of K, N, and ε depend on vehicle speed and engine conditions

Positive tractive power is given in following equation,

$$P_{tract} = A \cdot v + B \cdot v^2 + C \cdot v^3 + M \cdot a + M \cdot g \cdot v \cdot sin\theta \quad \text{(Eq. 7-7)}$$

Where,

- v is vehicle speed (m/s)
- a is vehicle acceleration (m/s^2)
- A is rolling resistance term (kw/m/s)
- B is speed-correction to rolling resistance term ($kW/(m/s)^2$)
- C is air drag resistance term ($kW/(m/s)^3$)
- M is vehicle mass (kg)
- g is gravitational constant (9.81 m/s^2)
- θ is road grade (degrees)

7.2 Driving safety model analysis

The safety of driving significantly depends on driving behaviours, traffic conditions, and road parameters. This part shows the traffic accident models related driving behaviours.

7.2.1 Injury crash model based on the vehicle speed

In the accident model (Kloeden et al., 2001; Kloeden et al., 2001), the injury crash rate is considered as the functions of speed and the difference between vehicle speed and average traffic speed, as indicated in following equations. The difference of individual vehicle speed and the average traffic speed is taken as an important factor. It means that the speed consistency with traffic average speed can effectively decrease the occurrence of injury crash rates.

Urban roads with speed limit of 60 km/h

$$I_r = \exp(0.113337 * \Delta v + 0.0028272\, v^2) \quad \text{(Eq. 7-8)}$$

Rural roads with speed limits of 80-120 km/h

$$I_r = \exp(0.07039 * \Delta v + 0.0008617\, v^2) \quad \text{(Eq. 7-9)}$$

Where,

- I_r is injury crash rate;
- Δv is difference between individual vehicle speed and average traffic speed;
- v is vehicle speed.

7.2.2 Accident model based on the speed limit and vehicle speed

The injury crash model (Baruya, 1998a; Baruya, 1998b) is established using the reported data from Sweden, Netherland and the UK, which includes 171 road links, with speed limits in the range of 70~110 km/h. In this accident model, the proportion of speed limit offenders is linked with the frequency of injury crashes. It is obvious that higher speed limit infractions are directly linked to increased crashes and injury rates.

$$A_r = (C_{road})\bar{v}^{-2.492} o_{v_{limit}}^{0.114} \quad \text{(Eq. 7-10)}$$

$$C_{road} = 5.663 fl^{0.748} l^{0.847} e^{(0.038j - 0.056w + 0.023v_{limit})} e^{0.023v_{limit}} \quad \text{(Eq. 7-11)}$$

Where,

- A_r is frequency of injury crashes
- $\bar{v}$ is average speed
- w is width of the road lanes
- fl is traffic flow
- l is length of the road section
- j is the number of junctions per road section
- v_{limit} is speed limit
- is proportion speed limit offenders (driving behaviours related)

As a summary of the accident models, only the speed related driving behaviour are linked with the accidents. Sudden deceleration, unreasonable lane change, and disobeying traffic light signals also increase traffic accidents. However, these important factors are neglected in these accident models in the author's opinion.

7.3 Exhaust emission model

In Chapter 3, the exhaust emission models have been reviewed in detail. However, some important KPIs are not included in the emission models, such as gearshift strategies, and frequency of stops. The KPIs related to low emission driving are summarised, as shown in Table 7.1.

Table 7.1: Driver behaviours KPIs related to exhaust emissions

KPIs	Unit
Vehicle speed distribution	%
Average speed	km/h
Average driving speed without stops	km/h
% of distance in speed interval 50~70 km/h	%
Acceleration distribution	%
Average acceleration	m/s^2
% of time in acceleration	%
% of distance in acceleration	%
Deceleration distribution	%
Average deceleration	m/s^2
% of time in deceleration	%
% of distance in deceleration	%
Frequency of stops	n.
Average stop durations	S
Gear upshift speed	km/h
Gear downshift speed	km/h
Frequency of gear shift	n.
Engine speed when shifting gear up	rpm

7.4 KPIs of driving behaviours for exhaust emissions, energy consumption and safety

Table 7.2 briefly shows the correlations of driving behaviour KPIs with exhaust emissions, energy consumption and safety. As can be seen, all the KPIs relating to the exhaust emissions also have a strong relation to energy consumption. The KPIs related to exhaust emissions and energy consumption are related to engine operation conditions, which dominates the emission formation and fuel consumption in the combustion process simultaneously. In addition, some relation between emissions and energy consumption is clear, such as high in-cylinder temperature contributes to improving the brake thermal efficiency and decrease the HC and CO emissions, while causing high formation rates of NO_x and particles. Vehicle speed distribution, acceleration distribution, and deceleration distribution are relevant to exhaust emission, energy consumption and safety. Safety should have a priority when considering the driving behaviours for optimising exhaust emissions and energy consumption.

Table 7.2: KPIs for driving behaviours

KPIs for driving behaviours	Emission	Energy	Safety
Vehicle speed distribution	X √	X √	X √
Average speed	X √	X √	
Average driving speed without stops	X	X	
% of distance in speed interval 50~70 km/h	X	X	
Acceleration distribution	X √	X √	X
Average acceleration	X	X	
% of time in acceleration	X	X	
% of distance in acceleration	X	X	
Deceleration distribution	X	X	X
Average deceleration	X	X	
% of time in deceleration	X	X	
% of distance in deceleration	X	X	
Frequency of stops	X	X	
Average stop durations	X	X	
Gear upshift speed	X	X	
Gear downshift speed	X	X	
Frequency of gear shift	X	X	
Engine speed when shifting gear up	X	X	
Frequency of improper lane change			X
Distance from other vehicles			X
Numbers of breaking traffic regulations per distance			X √
Numbers of distraction per distance during driving			X
Headways			X
Drunk driving			X
Excessive speed			X √
Fatigue driving			X
Driving in an opposite direction			X
Infrequency use of safety belt			X
Participation in car races			X
Speed difference with traffic speed			X √

X: it is confirmed that KPIs are related to emissions/energy/safety; √: there are equations indicating the detailed relations

7.5 Importance ranking of KPIs for different driving purposes

For various driving purposes, for example low emission driving, eco-driving, and safe driving, different driving modes are required. This makes an importance ranking necessary for driving behaviour KPIs in terms of exhaust emissions, energy consumption and safety, as shown in Table 7.3. As we know, the exhaust emissions and energy consumption are closely related to each other, which leads to a similar ranking tendency for most of the driving behaviour KPIs. For the energy consumption, acceleration related KPIs (e.g. acceleration/ deceleration distribution, average acceleration/ deceleration, % of time in acceleration/ deceleration, and % of distance in acceleration/ deceleration) are the most important. Vehicle speed distribution and average speed are less important for CO and HC emissions, however, they are the most important for PM and NO_x emission.

Table 7.3: Importance ranking for KPIs of exhaust emissions and energy consumption

KPIs for Driving behaviours	Energy consumption	Emissions			
		CO	HC	NOx	PM
Vehicle speed distribution	XXX	XX	XX	XXXX	XXXX
Average speed	XXX	XX	XX	XXXX	XXXX
Average driving speed without stops	X	X	X	XXXX	XXXX
% of distance in speed interval 50~70 km/h	XX	XX	XX	XXX	XXX
Acceleration distribution	XXXX	XXXX	XXXX	XXXX	XXXX
Average acceleration	XXXX	XXXX	XXXX	XXXX	XXXX
% of time in acceleration	XXXX	XXXX	XXXX	XXXX	XXXX
% of distance in acceleration	XXXX	XXXX	XXXX	XXXX	XXXX
Deceleration distribution	XXXX	XXXX	XXXX	XXXX	XXXX
Average deceleration	XXXX	XXXX	XXXX	XXXX	XXXX
% of time in deceleration	XXXX	XXX	XXXX	XXXX	XXXX
% of distance in deceleration	XXXX	XXX	XXXX	XXXX	XXXX
Frequency of stops	XXX	XXX	XXX	XXX	XXX
Average stop durations	X	X	X	X	X
Gear upshift speed	XX	XX	XX	XX	XX
Gear downshift speed	XX	XX	XX	XX	XX
Frequency of gear shift	XX	XX	XX	XX	XX
Average engine speed when shifting gear up	XX	XX	XX	XX	XX

XXXX: very important; XXX: important; XX: less important; X: slightly important

For the safety driving, most of the “very important” KPIs are focused on the driver itself, such as contravening traffic regulations, drunk driving, driving while fatigued and driving in the wrong direction, as presented in Table 7.4. Only excessive speed and vehicle speed distributions are related to vehicle operational driving.

Table 7.4: Importance ranking for KPIs of safety

KPIs for Driving behaviours	Importance to safety
Vehicle speed distribution	XXXX
Acceleration distribution	X
Deceleration distribution	XX
Frequency of improper lane change	XX
Distance from other vehicles	XX
Numbers of breaking traffic regulations per distance	XXXX
Numbers of distraction per distance during driving	XXX
Drunk driving	XXXX
Excessive speed	XXXX
Driving while fatigued	XXX
Driving in the wrong direction	XXXX
Infrequent use of safety belt	XX
Participation in car races	XXX
Speed difference with traffic speed	XXX

XXXX: very important; XXX: important; XX: less important; X: slightly important

8 Low-emission driving requirements

This chapter is a summary of low emission/fuel reduction existing projects and programmes found in the literature. The size of the literature is extremely large, and the authors has selected the most recent one in order the results to reflect the effects of modern vehicle technologies. The literature study aimed to provide information that could specify the following research items:

- How "low consumption /emission driving" is perceived by the drivers in different countries;
- in-depth review of project findings and distinguish the key factors between eco driving and low emission driving;
- Requirements categorisation taking into account the vehicle and driver profile: e.g. vehicle type, driver experience, professional or normal user, gender, age, etc;
- Mapping of eco-driving and low emission characteristics and check the areas were requirements and driving techniques coincide in both;
- Definition of the term "low emission driving".

8.1 Perception of low-emission driving in different countries

The aim of this section is to provide insights for understating what people already know of green-driving, what they think of it, and how these variables relate to demographic factors and environmental attitudes.

McIlroy & Stanton (2017) posed the following research questions during their research which was joint-funded by the UK's Engineering and Physical Sciences Research Council (EPSRC) and Jaguar Land Rover PLC:

- *Q1. What perceptions do people have of eco-driving and its effects?*
- *Q2. What do people know of eco-driving (i.e. of the specific behaviours)?*
- *Q3. Are more pro-environmental individuals more knowledgeable of the means for eco-driving?*
- *Q4. Do more pro-environmental individuals report performing eco-driving behaviours to a greater extent than less pro-environmental individuals?*
- *Q5. Do people with greater knowledge of eco-driving also report performing it to a greater extent?*
- *Q6. How does knowledge of, and propensity to perform eco-driving behaviours vary with age and gender?*
- *Q7. Do those with higher levels of general education also have more knowledge of eco-driving behaviours?*

An online survey of 321 respondents revealed that the majority of people are aware of eco-driving and have a positive attitude towards it. Although the types of eco-driving tips offered by respondents, and their potential effect on fuel consumption, were in line with those found in the popular and academic literature, knowledge of specific fuel saving behaviours was generally low. Relationships were found between environmental attitudes and knowledge of, and propensity to perform eco-driving behaviours; however, these relationships were weak, indicating that neither pro-environmental attitudes nor knowledge of eco-driving behaviours is strongly indicative of actual eco-driving performance. Males were found to be more knowledgeable of the means for driving in a fuel-efficient manner than females; however, no effect was found for either age or level of general education.

A survey of 350 respondents from UK and CZ (Harvey et al., 2013) investigated attitudes towards saving fuel. The focus groups' findings showed that the environment is a lower priority than comfort and convenience, and that saving money was less important than saving time. The attitude survey showed that price, convenience, attitudes and eco-driving are not conceptually linked together, that convenience is rated as more important than saving money from fuel efficiency and that although the environment is of concern, it is not a high enough priority to increase fuel efficiency.

An interview-based study took place in Serbia in 2015, where 113 professional drivers have responded (Veličković et al., 2015). The study aimed at investigating the level of eco-driving implementation by companies. 75% of drivers answered that their company did not implement any of the measures. However, 50% said that implementation of eco-driver recognition and rewarding system is highly desirable. The investment into the air drag reduction aids additionally indicate that the company care about environmental impact. Around 30%of vehicles were not equipped with air drag reduction aids at all. Roof deflectors were on 97% and side extenders on 39% of vehicles equipped with any aid. When it comes to tyre pressure checking, research results show that 35% of drivers perform frequent checks and around 40% do it occasionally. In few cases, another person in company was responsible for vehicle operational maintenance, so drivers were not obligated to check tyre pressure. The two thirds of the light commercial vehicle (LCV) drivers shift gear between 2000 and 2500 rpm. Drivers of vehicles with load capacity more than 3.5 tons (middle and heavy commercial vehicles – MCV and HCV) mostly shifts between 1250 and 1500 rpm. When maintaining a steady speed, drivers act different: 40%tend to maintain speed at low rpm, other 40% maintain a certain rpm (the most at 1250, but there were answers up to 3000 rpm) and 20% maintain desired speed regardless amount of rpm.

Czechowski et al. (2018) presented differences in perception of eco-driving principles in two random and nation-wide surveys in Poland that one carried out in 2015 and the other in 2017. Initial conclusions showed a major increase (49.4% to 53.2%) of eco-driving awareness among respondents in 2017 when compared to 2015. Their model shown suggested that the probability of eco-driving awareness decreases with each year of age. The probability of the decrease in awareness grew with each subsequent age category by 38%. The research also showed that women are less aware of eco-driving - by about 112% than men. While the respondents who use less fuel are more aware by about 127%. The results suggested that men were more aware of eco-driving in 2015, but it was not significant, and it became significant in 2017. At the same time, the awareness first of all in the case of men improved, while in the case of women it remained on the same level.

Table 8.1: Driver's perception towards low emissions / fuel consumption driving

A/A	Country	Drivers	Study type	Results	Ref.
1	UK	321	Survey	• Males more knowledgeable than females • no effect found for either age or level of general education • neither pro-environmental attitudes nor knowledge of eco-driving behaviours is strongly indicative of actual eco-driving performance	McIlroy & Stanton (2017)
2	UK & CZ	350	Survey	• Environment is a lower priority than comfort and convenience • Saving money was less important than saving time	Harvey et al. (2013)
3	Serbia	113 Professionals	Survey	• 75% of drivers' companies did not implement any of the eco- measures • 50% believe that implementation of eco-driver recognition and rewarding system is highly desirable	Veličković et al. (2015)
4	Poland	1000	Survey	• Probability of eco-driving awareness decreases with each year of age • Women are less aware of eco-driving (by about 112%) than men • The awareness of men improved, while of women remained the same within a period of two years	Czechowski et al. (2018)

8.2 Key factors of low-emission driving

In the previous Chapters, some key factors of low-emission driving were reviewed with reference to vehicle emissions from exhaust, brake and tyre. This section provides a systematic review of key factors which represent the characteristics of low-emission driving to help map eco-driving and low-emission characteristics, as well as categorise the low-emission requirements.

Automobiles are significant contributors of gaseous emissions, deteriorating urban air quality (Smit et al., 2017). According to the United National Framework Convention on Climate Change (UNFCCC) data[2], by 2030, the transportation sector will account for 40% of all new investment in carbon reduction efforts worldwide, the third highest of all sectors considered. The last decades a big effort is undertaken to improve fuel economy and reduce emissions of on-road vehicles including more stringent automotive emission standards (e.g. Euro 6/VI standards[3]), new engine and vehicle technologies (e.g. engine downsizing and hybrid/ electric vehicles, Zhang et al. 2018; Huang et al.,

[2]UNFCC, 2007. Investment and Financial Flows to Address Climate Change, http://unfccc.int/files/cooperation_and_support/financial_mechanism/application/pdf/background_paper.pdf

[3] European Commission. Amending regulation (EC) No 7152007 of the European Parliament and of the Council and Commission regulation (EC) No 6922008 as regards emissions from light passenger and commercial vehicles (Euro 6). Off J Eur Union 2012; 142:16–24.

2015), better fuel quality and renewable fuels (e.g. higher octane rating petrol and bio-fuels, Zhen and Wang, 2015). However, an important factor which is often overlooked and may improve vehicle fuel economy and emissions is the driving style. The investment for new vehicle technologies and fuels is usually significant and long-term, and an improvement of a few percentages may be considered significant. It was estimated that the potential efficiency improvements of advanced engine and vehicle technologies were only about 4–10% and 2–8% respectively (Gallus et al., 2017). However, the implementation of a different low emissions driving style is relatively low-cost and immediate.

The aim of the current section is to review the literature and analyse the parameters that affects the emissions of vehicles and to present different driving patterns for emission reduction.

8.2.1 Light and heavy duty engines

The emissions and fuel consumption of heavy-duty engines is a hot topic the last decades as every year, bus and truck companies consume millions of litres of fuel, and their fuel costs often exceed millions of US dollars (Lai, 2015). These companies have an obvious interest in reducing their fuel consumption and thus emissions. Such companies have adopted a number of fuel use reduction strategies, including vehicle maintenance, vehicle replacement and driver behaviour management. The latter is mainly implemented through training, which can improve drivers' knowledge of alternative driving and encourage them to adopt better behaviours. Similar is the effect of light-duty engines on air pollution worldwide. In general, there are variety of factors that affects the emissions and fuel consumption during the driving such as:

- Driving speed
- Acceleration/deceleration
- Route
- Idling
- Grade/terrain
- Other secondary factors

To that aim various adaptation systems have been implemented or they are under development by research groups targeting the improvement of emissions and fuel consumption of vehicles during driving. A comprehensive review for each parameter will be presented below.

Driving speed:

In case of **heavy-duty** engines, experiments have shown that given the same route, different driving profiles (speed and gear applied) are implemented by different truck drivers, resulting in a large variation in fuel consumption and thus emissions (Chaozhe et al., 2016). This implies that optimising the driving profile has a large potential for saving fuel and as a result to reduce emissions. Recent developments in information and communication technologies present opportunities to solve this problem. There are many researches that investigate and develop various mathematical models on optimising the speed profile and gear changes during driving. A mathematical framework to optimise the speed profile and select the optimal gears for heavy-duty vehicles traveling on highways while varying parameters (road elevation, headwind, desired terminal time, and traffic information) was developed by Chaozhe et al. (2016). Schwarzkopf and Leipnik (1977), ended to a necessary condition for optimality using Pontryagin's maximum principle (PMP) while taking into account road elevation. Furthermore, in other studies (Chang and Morlok, 2015; Froberg et all., 2006), the solutions were derived analytically for simplified models. In general, constant speed is the optimal speed profile for fuel consumption and thus emissions under various road conditions (Chang and Morlok, 2005; Lee and Son, 2011). According to the research of Chen et al. (2007), the vehicle emission rates vary significantly with factors like speed and acceleration, their results have shown that low speed has a negative effect on fuel economy and vehicle emissions. Therefore, strengthening traffic management will not only improve traffic capacity but also have a positive effect on reducing vehicle emissions. The U.S. Bureau of Transportation Statistics (US BTS) reported that bus fuel consumption had been continually increasing from 827 million gallons/year to 2059 million gallons/year between 1960 and 2012. Consequently, improving bus fuel efficiency is of value to reduce energy consumption and CO_2 production from the transportation perspective. Wang et al. (2016) developed a model for city buses and conclude that the optimum fuel economy cruise speeds for city buses range between 40 and 50 km/h which is lower than that for light duty vehicles (60– 80 km/h). The CO_2, CO, HC, NO_x, PM emissions and FC factors all decreased with bus speed increased. The results show that low-speed operations of bus results in higher emission and FC factors. As a result, bus drivers should avoid low-speed operations to reduce bus per kilometre emissions and FC (Wang et al., 2011).

As far as **light-duty** engines is concerned, according to a research that was made from the University of Michigan (Saltsman, 2014), Transportation Research Institute where the fuel consumption rates were studied from a naturalistic driving data set employing a fleet of identical passenger vehicles with petrol engines and automatic transmissions the fuel consumption rates vary considerably with speed. In this study, one hundred and seventeen drivers travelled a total of over 342,000 kilometres (213,000 miles), unsupervised, using one of the experiment's instrumented test vehicles as their own (Honda Accord V6 2006-2007 model). A substantial variation in the overall fuel consumption rate was observed. Their results have shown that the higher speed of 119 km/h results in a higher fuel consumption rate than that observed at 98 km/h. In general, the fuel consumption is well linked with engine emissions which shows that at higher travel speed higher engine emissions are produced. Similar results were also observed by El-Shawarby et. al. (2005) who found that vehicle fuel-consumption rates per-unit distance are optimum in the range of 60–90 km/h with the use of a gasoline (petrol) Ford Crown Victoria vehicle. Decrease or increase in vehicle cruise speeds outside this optimum range results in considerable increases in vehicle fuel-consumption rates as well as in NO_x, HC, CO, and CO_2 emissions. Wang et. al. (2008), after testing several car vehicles at various routes found that fuel consumption per unit distance is optimum at speeds between 50 and 70 km/h, while too high or too low a speed can both lead to a high fuel consumption rate in L/100 km. According to EEA (2011), cutting speed can significantly reduce emissions, particularly reducing NO_x and particulate matter (PM) output from diesel vehicles. The safety gains from slower driving are also indisputable. Based on a simulation, cutting motorway speed limits from 120 to 110 km/h could deliver fuel savings for current technology light-duty vehicles (e.g. passenger cars) of 12–18 %, assuming smooth driving and 100 % compliance with speed limits. However, relaxing these assumptions to a more realistic setting implies a saving of just 2–3 %. In summary, whereas heavy goods vehicles speed limits in motorways are in line with the optimum speed in terms of energy and CO_2 reductions per vehicle-km (80–90 km/h), decreasing car passenger speed limits in motorways could lead to substantial benefits. At lower speeds, vehicles are spending a greater time on the roads and therefore have a high fuel/distance value. At higher speeds, the engine needs to work harder to overcome aerodynamic resistance, and therefore the emissions are higher. In between these extremes, the fuel consumption and emissions are minimised, generally around 60 km/h-70 km/h, depending on the vehicle type. As a result, in order to minimise overall fuel consumption and emissions while traveling down the road, it is best to maintain a steady-state velocity at these mid-range speeds (Xia et al., 2013).

Table 8.2: Studies investigating the effect of cruise speed on fuel consumption (FC) and emissions

A/A	vehicle	Duration	Drivers	Tests	Results	Suggestions	Ref.
Heavy-duty vehicles							
1	9 trucks	186 km	NA	On road	CO, THC, and NOx vary with speed. Low speed negatively affects FC and emissions	Strengthening traffic management will have a positive effect on emissions.	Chen et al. (2007)
2	Model for city buses	NA	NA	Sim/tion Model	Improving bus fuel efficiency is of value to reduce energy consumption and CO_2 production	The optimum fuel economy cruise speeds range between 40 and 50 km/h	Wang et al. (2016)
3	6 buses (2 Euro III, 2 Euro IV diesel and 2 compressed natural gas	3 routes (arterials, residential, Freeways)	Various drivers	On road	CO_2, CO, HC, NO_x, PM emissions and FC factors all decreased, with bus speed increased	Drivers should avoid low-speed operations to reduce bus per kilometre emissions and FC	Wang et al. (2011)
Light-duty vehicles							
1	16 cars Honda Accord (2006-2007) petrol	36-49 Days	117	On road	The higher speed of 119 km/h results in a higher FC rate than that observed at 98 km/h.	Keep constant low speed	Leblanc et al. (2010)
2	Ford Crown Victoria 1999 4.6L V8 petrol	80 tests at specified route	NA	On road	FC rate increases with the engine load from a speed of 56 km/h through the highest measured cruise speed of 104 km/h.	vehicle FC rates per-unit distance are optimum in the range of 60–90km/h.	El-Shawarby et al. (2005)
3	Tier 1 emissions certified vehicle	Various patterns	NA	Sim/tion Model	At higher speeds, the engine needs to work harder to overcome aerodynamic resistance, and therefore the emissions are higher	FC and emissions are minimised, generally around 60 km/h, depending on the vehicle type	Xia et al. (2013)
4	Two diesel vehicles (Rover Freelander)	Various city routes	Professional driver	On road	Strong influence of average speed on CO_2 emissions and FC	Less critical influence for a car equipped with the Start/Stop system	Fonseca et al. (2011)
5	10 petrol vehicles (1.6L-2.0L)	3 test per day	NA	On-road	Too high or too low a speed can both lead to a high FC rate	The FC rate per unit distance appears to be optimum in the speed range of 50–70 km/h.	Wang et al. (2008)
6	Diesel and petrol (1.4L, Euro 4)	NA	NA	Sim/tion model	Motorway speed significantly affects FC and emissions	Cutting speed limits from 120 to 110 km/h could deliver fuel savings of 12–18%	EEA (2011)

Acceleration/deceleration:

Another factor that influence engine emissions and fuel consumption is the rate of acceleration and deceleration during the driving. In case of **heavy-duty** engines, according to Chen et. al. (2007), who tested 9 trucks with on road measurements, within a period of 0–6 s, the fuel consumption of the engine changes from 1 L/h in idle condition to 6 L/h, which is three times the amount used in normal running conditions. After the vehicle starts to move, the fuel consumption continues to increase until it reaches 10 L/h. It can be seen that more fuel needs to be provided to the vehicle during the ‘‘stop-go’’ periods. Traffic signals and congestion conditions cause these ‘‘stop-go’’ driving patterns and lead to higher fuel consumption. Results show that frequent acceleration have a negative effect on fuel economy and vehicle emissions. Therefore, strengthening traffic management will not only improve traffic capacity but also have a positive effect on reducing vehicle emissions. According to Wang et. al. (2011), the CO_2, CO, HC, NO_x, PM emissions and FC factors all increased as bus acceleration increased. It can be seen that acceleration, especially sharp acceleration, increases emission and FC factors significantly although the effect of deceleration is of less significance. From deceleration to cruise speed, and to acceleration, emission and FC factors increase rapidly as acceleration increases. The analysis reveals that the low-speed or high-acceleration operations lead to higher emission and FC levels. As a result, buses should avoid operating at low speeds or high accelerations to improve their emission and FC levels (Wang et al., 2011).

Similar results were also observed for **light-duty** vehicles. Fuel consumption and emissions are directly related to the acceleration/deceleration patterns of the vehicles travelling on the arterial and the idling at traffic signals (Xia et al., 2013). When travelling on a roadway where there are specific points where traffic is controlled (traffic lights), specific constraints emerge in time and space; as a result, it has been found that hard accelerations that quickly get a vehicle up to a target speed and then have a steady cruise to reach a specific location at a specific time are less fuel-consuming compared to a velocity profile that takes a longer period of time of acceleration to reach the same point of time and space. Similarly, it is beneficial to decelerate quickly, and then hold a steady-state cruise speed when reaching a traffic signal just as it is turning green (Xia et al., 2013).

Compared to normal driving, severe driving caused an elevation of 20–40% for CO_2 and 50–255% for NO_x emissions, depending on the driver and the vehicle (Gallus et al., 2017). In contrast, there was no distinct separation of the driving style for CO and HC emissions. It is reasonable to assume that for CO and HC emissions other parameters than driving style were more important, e.g. ambient temperature or the cold start. CO and HC showed completely different results clearly suggesting that the temperature has a more pronounced impact on these emissions than the driving style (Gallus et al., 2017). Fonseca et al. (2010) calculated a performance index in order to characterise the driving style along an urban route. For a group of Euro-2 to Euro-5 Diesel vehicles, they found an average CO_2 increase related to aggressive driving of around 40%. Considering a Euro-5 Diesel vehicle, NO_x emissions increased for 50% comparing severe to normal driving, which was in-line with the results of Gallus et al. (2017).

According to El-Shawarby et. al. (2005), if vehicle fuel-consumption and emission rates are only considered while the vehicle is accelerating, then as the aggressiveness of the acceleration manoeuvre increases, the mobile-source emissions decrease. The reduction in vehicle fuel-consumption and emission rates is caused by the reduction in the distance and time that are required to execute the acceleration manoeuvre as the acceleration aggressiveness increases. The results, however, demonstrate that if the emissions are gathered over a sufficiently long fixed distance, then the conclusions are reversed (i.e., as the level of acceleration increases, the mobile-source emissions increase). This conclusion is caused by the fact that high levels of acceleration result in a rich fuel-to-air ratio operation, which is required to prevent engine knocking, thus bypassing the catalytic converter and increasing vehicle emissions. This bypassing of the catalytic converter continues even after the aggressive event is completed, causing increases in vehicle emissions. Similar results were found by Wang et. al. (2008), acceleration significantly increases fuel consumption, although the impact of deceleration is much less noticeable.

The relations between the period of strong acceleration and increasing values of NO_x and HC have been also observed by Ericsson, 2001. Deceleration also affects fuel consumption. Johansson et al. (2003) show that it is important to decelerate slowly to decrease fuel consumption. The definition of aggressive acceleration based on fuel consumption and emissions shows that acceleration leads to an increase in fuel consumption and emissions. This means that aggressive acceleration causes excess fuel consumption and emissions. The aggressive acceleration and start are the main driving behaviours that lead to a sharp increase of the fuel consumption and CO_2 emissions. The magnitude of acceleration and its impacts on fuel consumption are different in a starting vehicle and a driving vehicle. When the vehicle accelerates from a stationary state, additional traction is necessary to overcome the inertia and weight of the vehicle. In the case of aggressive start, the average increment fuel consumption is over 10 times than that of normal start when starting acceleration is less than 1.105 m/s^2 and the average increment of aggressive acceleration is over 4 times than that of normal acceleration when acceleration value is less than 1.4705 m/s^2. According to Fonseca et. al. (2011), aggressive driving (about 3 km/h/s) can result in an increase of more than 76 g/km of CO_2 emissions in the vehicle with start/stop (S/S) system turned on and almost 92 g/km in the vehicle equipped with S/S system turned off. In general, high acceleration rates but rather low, constant, average speeds are found to result in optimal vehicle operation, factors that are important in enhancing low emissions-driving (Mensing et al., 2013).

Table 8.3: Studies investigating the effect of acceleration/deceleration on fuel consumption (FC) and emissions

A/A	Vehicle	Duration	Drivers	Tests	Results	Suggestions	Ref.
Heavy-duty vehicles							
1	9 trucks	186 km	NA	On road	frequent accelerations have a negative effect on FC and vehicle emissions	Strengthening traffic management will improve vehicle emissions.	Chen et al. (2007)
2	6 buses (2 Euro III, 2 Euro IV diesel, 2 compressed natural gas	3 routes (arterials, residential, Freeways)	Various drivers	On road	The CO_2, CO, HC, NOx, PM emissions and FC factors all increased as bus acceleration increased	Buses should avoid operating at high accelerations to improve their emission and FC levels	Wang et al. (2011)
Light-duty vehicles							
1	Renault Clio 1.5L diesel	Sim/tion route	NA	Sim/tion model	High acceleration rates but rather low, constant, average speeds are found to result in optimal vehicle operation	A theoretical improvement of fuel economy of 34% is found for a free flow urban setting	Mensing et al. (2013)
2	Ford Crown Victoria 1999 4.6L petrol	80 tests at specified route	NA	On road	The reduction in FC and emissions is caused by the reduction in the distance and time that are required to execute the acceleration maneuver as the acceleration aggressiveness increases	The aggressiveness of acceleration and deceleration is correlated to the distance and travel time	El-Shawarby et al. (2005)
3	10 petrol vehicles (1.6L-2.0L)	3 test per day	NA	On road	FC rates increase significantly when the vehicles are accelerated and change little during deceleration	FC rate per unit distance appears to be optimum in the speed range of 50–70 km/h.	Wang et al. (2008)
4	4 Renault Kangoo 1.6 L Petrol	Various daily routes	20	On road	Aggressive acceleration increases FC	Smooth acceleration improves FC and thus emissions	Larsson and Ericsson (2009)
5	2 diesel vehicles (euro 5 and 6)	86 km route (urban, rural and motorway parts)	3	On road	Compared to normal driving, severe driving caused an elevation of 20–40% for CO_2 and 50–255% for NO_x emissions. No distinct separation of the driving style for CO and HC emission	Normal driving is suggested	Chang and Morlok (2005)

A/A	Vehicle	Duration	Drivers	Tests	Results	Suggestions	Ref.
6	2 diesel vehicles (Rover Freelander2)	City routes	Professional driver	On road	Aggressive driving (~3 km/h/s) can result in an increase of more than 76 g/km of CO_2 in the vehicle with S/S system turned on and almost 92 g/km in the vehicle equipped with S/S system turned off	Start/Stop (S/S) system improve emissions and FC	Fonseca et al. (2011)
7	Liquefied Petroleum Gas (LPG) car 2L	27 tests	NA	On road	The magnitude of acceleration and its impacts on FC are different in a starting vehicle and a driving vehicle	The aggressive acceleration and start lead to a sharp increase of the FC and CO_2 emissions	Eunjin and Eungcheol (2017)
8	Tier 1 emissions certified vehicle	NA	Model	Sim/tion model	FC and emissions are directly related to the acceleration/deceleration patterns of the vehicles traveling on the arterial and the idling at traffic signals.	Hard accelerations up to a target speed and steady cruise to reach lead to lower FC compared to a longer acceleration to reach the same point of time and space. It is beneficial to decelerate quickly, and then hold a steady-state cruise speed when reaching a traffic signal	Xia et al. (2013)

Route:

Environmental impact and economic factors impose the need for reducing the amount of energy spent by a vehicle in order to travel from a source to a destination point. Minimising the consumed fuel leads not only to financial savings but also to simultaneous reductions in the released emissions, as their volume is proportional to the vehicles consumption rate (Ma et al., 2012). It has been found that route choice can greatly affect vehicle fuel efficiency and emissions. Thus, finding an optimal route that is most environmentally friendly is formulated as ''eco-routing'' problems and different solution methods have been proposed. By following the environmentally friendly paths, vehicles are expected to use less gas or make less emissions. Although there have been many methods to find the optimal paths in terms of travel distance or travel time, it has been shown that a time or distance minimising route does not always minimise fuel consumption or emissions. A recent study has shown that, CO_2 emissions may increase by 20% in local streets over secondary streets because of the higher frequency of stops (Rueger, 2008). Motorists typically select routes that minimise their travel time or generalised cost. This may entail travelling on longer but faster routes. This raises questions concerning whether travelling along a longer but faster route results in energy and/or air quality improvements. The results from a recent study (Ahn and Rakha, 2008) have shown significant improvements to air quality and energy savings when motorists utilised the longer time arterial route. The problem to consider environmentally related costs is much more complicated than those to use time or distance as costs, as vehicle fuel consumption and emissions depend on many factors. Because vehicle behaviours are highly dependent on traffic situation at intersections, vehicle trajectories are estimated using traffic information at intersections, including traffic signal and vehicle arrival information. Then, vehicle trajectories are used as inputs to well-developed microscopic vehicle emission models, like CMEM and VT-Micro, to calculate corresponding vehicle emissions (Sun and Liu, 2015).

Most research related to the vehicle routing problem (VRP) aims to minimise total travel time or travel distance not considering fuel consumption and thus emissions. A proposed method from Kuo (2010), provides a 24.6% improvement in fuel consumption over the method based on minimising transportation time and a 22.7% improvement over the method based on minimising transportation distances. Recent literature shows that selecting different travel routes between the same origin and destination can result in different vehicle emissions and fuel consumption. Ecological route (eco-route) planning is one such strategy that provides the least CO_2 emission and fuel consumption routes for vehicles (Yao and Song, 2013). The results show that the proposed eco-route algorithm significantly reduces fuel consumption and has good environmental performance. When average speed is about 48 km/hr, the greatest effectiveness reduction is achieved and about 8% amount of CO_2 emissions can be reduced for light-duty vehicles (Yao and Song, 2013).

It is found that the average reduction in CO_2 emissions achieved by the eco-friendly path reaches a maximum of around 11% when the travel time buffer is set to around 10% (Zeng et al., 2016). In some cases, a shortest distance or shortest duration route will also have the minimum fuel consumption and emissions. However, there are several cases where this may not be true, particularly with high levels of congestion and in areas with significant road grades. For example, comparing the results of a driving experiment performed in Japan (Kono et al., 2008), the fuel consumption of the ecological route is 9% lower than that of the time priority route, while its travel time is 9% longer. In another experiment performed between the Los Angeles Airport and the Los Angeles centre (Boriboonsomsin et al., 2012), the least fuel consumption route is compared against the shortest duration route. According to this comparison, the least fuel consumption route is 25%

more energy efficient and 8% slower than the shortest duration route. Likewise, the results of a field trial performed in the Northern Virginia area (Ahn and Rakha, 2008) demonstrate that significant improvements in energy consumption (18–23%) and air quality (4–5% reduction in NO_x and 20% reduction in CO_2) can be achieved when motorists utilise a slower and 30% longer arterial route instead of a faster highway route. A shortest distance route may have a driver travel through heavily congested conditions, resulting in higher fuel consumed and emissions (Boriboonsomsin et al., 2012). On the other hand, there may be cases where a shortest duration route results in longer distances travelled, albeit on less congested roadways. Travel on a route at very high speeds for longer distance generally results in higher fuel consumption and emissions compared with a more direct route at moderate speeds (Boriboonsomsin et al., 2012). An exploratory study in Sweden (Ericsson et al., 2006) found that 46% of the trips were not made on the most fuel-efficient route. These trips could have saved fuel by an average of 8% through a fuel-optimised navigation system (Ericsson et al., 2006).

Table 8.4: Studies investigating the effect of route on fuel consumption (FC) and emissions

A/A	Vehicle	Duration	Drivers	Tests	Results	Suggestions	Ref.
Heavy-duty vehicles							
1	Truck	120 km route	NA	Sim/tion model & on road	The choice of route strongly affects the fuel consumption and emissions	Selection of eco-route instead of shortest route lead to lower FC	Hellstrom et al. (2009)
2	Light-duty petrol, mid- and heavy-duty diesel	NA	Sim/tion model	Sim/tion model based on real data	The faster highway route choice is not always the optimal route from an environmental and energy consumption perspective	The proposed eco-route algorithm significantly reduces FC and has good environmental performance	Yao and Song (2013)
Light-duty vehicles							
1	2 4x4 diesel vehicles (Rover)	City routes	Professional driver	On road	CO_2 emissions increase by 20% in local streets over secondary streets because of the higher frequency of stops	Avoid routes with many lights and traffic	Fonseca et al. (2011)
2	Electric vehicle	2 routes, an energy efficient route and a fastest route	NA	On road	Following the fastest path towards the destination is not always the best choice from an environmental and energy consumption perspective	Average energy savings of 20.7% when using energy friendly route (1.45% longer,10% more time) compared to fastest route	Masikos et al. (2015)
3	2 diesels (euro 5 and 6)	4 routes	3 drivers	On road	If the route involved much more hilly sections (expressed by a larger cumulated altitude gain), the NO_x emissions are above the regression line	Flat routes lead to lower emissions and FC	Gallus et al. (2017)
4	3 cars (Volvo petrol, VW petrol, Skoda Diesel)	Various routes	NA	On road	46% of the trips were not made on the most fuel-efficient route	An average, 8.2% fuel saving by using a fuel-optimised navigation system	Ericsson et al. (2006)
5	Common vehicle	Various routes	NA	Sim/tion model	Most research related to the vehicle routing problem (VRP) aims to minimise total travel time or travel distance not considering	Eco route provides 24.6% and 22.7% improvement in FC compared to the fastest route and to the shortest	Kuo (2010)

A/A	Vehicle	Duration	Drivers	Tests	Results	Suggestions	Ref.
					FC and emissions	respectively	
6	Common vehicles	In city routes	NA	On road	Routing approaches usually provide the optimal path based on distance, travel time and on-time arrival probability. Few of them consider vehicle emissions	Average reduction in CO_2 emissions achieved by the eco-friendly path reaches a maximum of around 11%	Zeng et al. (2016)
7	Common vehicle	highway or arterial routes	NA	On road	The faster highway route choice is not always the best from an environmental and FC perspective	Significant improvements to air quality and energy savings were observed when motorists utilised the longer time arterial route.	Ahn and Rakha (2008)
8	Audi A8 vehicle	Various routes	NA	On road	Selecting different travel routes between the same origin–destination lead in significant differences in FC and emissions	The least FC route is 25% more energy efficient and 8% slower than the shortest duration route.	Boriboonsomsin et al. (2012)

Idling:

Idling refers to situations in which a vehicle's engine is running while the vehicle is stopped. Although there are a variety of settings in which individuals may idle a vehicle, this behaviour can be broadly categorised in to three domains (Carrico et al., 2009):

i. idling to warm the engine
ii. idling while waiting for something unrelated to traffic (e.g., waiting for a passenger in a drive-thru); and
iii. idling while in traffic (e.g. at stop lights; in traffic jams).

In order to maintain cab comfort, truck drivers have to idle their engine to obtain the required power for accessories, such as the air conditioner, heater, television, refrigerator, and lights. This idling of the engine has a major impact on its fuel consumption and exhaust emission. Idling emissions can be as high as 86.4 g/h (for HC), 16,500 g/h (for CO_2), 5130 g/h (for CO), 4 g/h (for PM), and 375 g/h (for NO_x), respectively (Rahman et al., 2013). Idling fuel consumption rate can be as high as 1.85 gallons/h or 7 litres/h. When the duration of idling is longer than 10 seconds the engine consumes more fuel compared with restarting it. The fuel consumed during 5 miles (8 km) of driving is equivalent to just 10 minutes idling. 10 minutes of idling per day will consume more than 27 US gallons (102 litres) of fuel per year.

Similar findings were observed also in case of light-duty vehicles. Carrico et al. (2009) tried to quantify the emissions and fuel use associated with idling at US. The results suggest that idling accounts for over 93 MMt of CO_2 and 10.6 billion US gallons (40.1 billion litres) of petrol a year, equalling 1.6% of all US emissions. Results indicate that the average individual idled for over 16 min a day and believed that a vehicle can be idled for at least 3.6 min before it is better to turn it off. Mahler and Vahidi (2014) proposed an optimal velocity-planning algorithm to minimise the idling time behind red lights and maximise the chance of going through green lights based on probabilistic traffic-signal timing models. The model showed a 61% increase in fuel economy in a motivating case study (ideal and best condition), but 16% for fixed-time signals and 6% for actuated signals compared with the un-informed drivers. In general, idling should be minimised because every vehicle achieves zero fuel efficiency when idling. Eliminating unnecessary idling of personal vehicles would be the same as taking 5 million vehicles off the road in terms of saving fuel and reducing emissions (Huang et al., 2018).

Table 8.5: Studies investigating the effect of idling on fuel consumption (FC) and emissions

A/A	vehicle	Dur.	Drivers	Tests	Results	Suggestions	Ref.
1	Personal vehicles	NA	1300	On road	Idling accounts for over 93 MMt of CO_2 and 10.6 billion gallons (40.1 billion litres) of petrol a year, equalling 1.6% of all US emissions	A reduction in mean idling times ranging from 1.2 to 4.5 min would prevent between 7 and 26 million tons of CO_2 from entering the atmosphere each year, and reduce fuel consumption by 660 million to 2.3 billion gallons (2.5–8.7 billion litres) a year	Rahman et al. (2013)

Grade/terrain:

Another important factor that strongly influence fuel consumption and real-world emissions of a vehicle is the road grade (Zhang and Frey, 2006). On the predominately flat route, the road gradient has poor correlation with instantaneous NO_x emissions; however, on the hilly route, particularly when the force from inertia is kept low (i.e. timid driving), the road gradient correlates well with instantaneous CO_2 and NO_x emissions (Prakash and Bodisco, 2019). Increased emissions at higher road grades could be explained by more frequent high engine load points. According to Zhang and Frey (2006), when the road grade is varied from 0% to 6%, and speed is varied from 0 km/hr to 120 km/hr, for a given speed, larger positive road grades lead to higher average emission rates. For example, the estimated average NO_x emission rate for a road grade of 6% is approximately a factor of two greater than for 0% road grade. According to Boriboonsomsin et al. (2009), 5% higher total mass leads to an increase in fuel consumption of 5–20% at 1–6% road grade, respectively. On another study (Gallus et al., 2017), PEMS trips over four different routes were conducted in order to investigate the impact of route characteristics on on-road NO_x emissions. As soon as the route involved much more hilly sections as expressed by a larger cumulated altitude gain, the NO_x emissions were clearly above the regression line. Similar findings were also observed by the same authors (Gallus et al., 2017), NO_x emissions also showed a clear correlation with road grade, the strongest was observed regarding motorway data and lowest regarding the urban data sets. This was primarily due to the formation of NO_x under high engine temperature operation during high speed driving on the motorway, which was supported by large road grade sections. Furthermore, the slope and the type of street affect emissions and fuel consumption of vehicles. An increase in the street gradient of only 1% can cause an increase in CO_2 emissions of approximately 30 g/km when maintaining the same speed profile (Fonseca et al., 2011).

Table 8.6: Studies investigating the effect of grade/terrain on fuel consumption (FC) and emissions

A/A	Vehicle	Dur.	Drivers	Tests	Results	Ref.
1	2 4x4 diesel vehicles (Rover Freelander2)	City routes	Professional driver	On road	An increase in the street gradient of only 1% can cause an increase in CO_2 emissions of approximately 30 g/km when maintaining the same speed profile	Fonseca et al. (2011)
2	Tier 1 light duty petrol vehicle 3.5 L	Various road grades	NA	Sim/tion model	Average emissions increased with the road grade	Zhang and Frey (2006)
3	2 Diesel vehicles (Euro-5 and Euro-6)	4 routes	NA	On road	Larger emissions at higher road grades could be explained by more frequent high engine load points. The step from 0 to 5% road grade led to a CO_2 increase of 65–81% and a NO_x increase of 85–115%.	Gallus et al. (2017)
4	2009 Toyota Hilux Double Cab	1 hilly route and 1 flat route	NA	On road	The road gradient correlates well with instantaneous CO_2 and NO_x emissions	Prakash and Bodisco (2019)
5	Light-duty vehicles	Flat route and hilly route	NA	On road	The vehicle fuel economy of the flat route is superior to that of the hilly routes by approximately 15% to 20%.	Boriboonsomsin and Barth (2009)

Secondary factors:

In previous paragraphs the most important factors that strongly influence the fuel consumption as well as the emissions of a vehicle during driving were deeply analysed. Furthermore, there are some other factors not so important which however influence the emissions and fuel consumption of a vehicle. For example, air conditioning system uses extra fuel and eco-driving principles suggest using it conservatively. According to a research by Huff et al. (2013), measurements have shown that a small passenger car consumed more fuel with maximum cooling than with windows-down when cruising speed was between 64 km/h and 114 km/h, but at 129 km/h fuel consumption with windows-down overtook air conditioner due to the increased aerodynamic drag. Moreover, the use of other extra facilities of the car such as heating seat, light adapter etc. could lead to increase in fuel consumption and thus to higher exhaust emissions. Conservative use of these features is recommended Sanguinetti et al., 2017). Additional factors that influencing the fuel consumption and emissions are the tyre pressure, the weight and the aerodynamic drag. According to Alam et al. (2014), 45 kg of extra weight on a small vehicle lead to an increase of fuel consumption at about 1-2 %. It is suggested to remove the useless weight from the car during driving. As far as tyre pressure is concerned, improper tyre air pressure can lead to an increase of fuel consumption at about 1-2 %. Aerodynamic drag of the vehicle also plays an important role in fuel consumption and thus in exhaust emissions. It has been found that, additional exterior parts in a vehicle could increase the fuel consumption by up to 20% at high driving speeds[4,5].

Another important factor that strongly influences the emission formation during the driving is the cold start operation of the vehicle. The analysis of vehicle cold start emissions has become an issue of utmost importance since the cold phase occurs mainly in urban context, where most of the population lives. To that aim, Faria et al. (2018) have investigated the impacts of cold start in urban context using naturalistic driving data and also performed an assessment of the influence of ambient temperature on the percentage of time spent on cold start operation. Their results have shown that, during cold start, energy consumption is 110% higher than during hot conditions while emissions are up to 910% higher. Moreover, a higher increase on both energy consumption and emissions was found for petrol vehicles than for diesel vehicles. In addition, during cold start operation, CO emissions show an increase, both for petrol (910%) and for diesel (~300%) vehicles due to the relative enrichment of the fuel mixture and higher thermal losses both in cylinder walls and catalytic converters. As far as HC emissions is concerned, a high variation was observed especially for petrol vehicles (2700%), which is due to the high efficiency of the catalyst when it is warm, leading to almost insignificant emissions during the hot phase. Variations between cold and hot operation were also observed in NO_x emissions, for petrol vehicles the higher variation is explained by the efficiency of the exhaust aftertreatment systems when the vehicle achieves its optimal conditions. An important role for cold start operation is also the ambient air temperature. In countries with lower ambient temperature and colder climate the percentage of time spent on cold start is higher than for countries with higher ambient temperatures. For example, measurements by Faria et al. (2018) have shown that from 0 °C to 29 °C, the percentage of time spent on cold start decreases significantly from circa 80% to <50%. This variation occurs independently of the vehicle fuel type (diesel or petrol). Cold start impacts on a street level are highly dependent on the percentage of time that vehicles are on cold start conditions. It is important to note that the engine warms faster when is working on higher loads and speeds, as a result the selection of the route is an important factor for the time spent in cold operation mode. It is noticeable that for local streets (particularly in the city centre) the percentage of time spent in cold start conditions is higher than for those streets that are in the external ring of the city. In order to improve emissions, it is wider for the driver to use a road with less traffic and lights if this is possible. Another factor is the parking place. Parking the car in the shade in hot weather and in a warm place in cold weather could save fuel from the engine warm-up and usage of the air conditioner and thus could lead to lower emissions.

[4] Australian Department of the Environment, 10 top tips for fuel efficient driving. https://www.environment.gov.au/settlements/transport/fuelguide/tips.html

[5] USDoE, Driving more efficiently. http://www.fueleconomy.gov/feg/driveHabits. jsp

Table 8.7: Studies of the effect of secondary car factors on fuel consumption (FC) and emissions

A/A	Factor	Results	Ref.
1	Air conditioning	A small passenger car consumed more fuel with maximum cooling than with windows-down when cruising speed was between 64 km/h and 114 km/h, but at 129 km/h fuel consumption with windows-down overtook air conditioner due to the increased aerodynamic drag	Huff et al. (2013)
2	Extra facilities (heating seat, light adaptor, headlights, entertainment system etc.)	These features lead to increase in fuel consumption and thus to higher exhaust emissions. Conservative use of these features is recommended	Sanguinetti et al. (2017)
3	Tyre pressure	Improper tyre air pressure can lead to an increase of fuel consumption at about 1-2 %	Sivak and Schoettle (2012)
4	Weight	45 kg of extra weight on a small vehicle lead to an increase of fuel consumption at about 1-2 %.	Alam and McNabola (2014) Huang et al. (2018)
5	Aerodynamic drag	Additional exterior parts in a vehicle could increase the fuel consumption by up to 20% at high driving speeds	4, 5
6	Cold start operation	During cold start, energy consumption is 110% higher than during hot conditions while emissions are up to 910% higher	Faria et al. (2018)
7	Parking place	Parking the car in the shade in hot weather and in a warm place in cold weather could save fuel from the engine warm-up and usage of the air conditioner and thus could lead to lower emissions	Huang et al. (2018)

8.2.2 Vehicle systems for low emission/fuel driving

As it was already discussed previously, there are various factors that affect the fuel consumption and emissions of a vehicle during driving. To that aim many researches groups study and develop various adaptation systems to improve the engine fuel efficiency and to reduce the emissions of a vehicle during driving. Below there is a short presentation of the most important adaptation systems that have been reported in the literature.

Adaptive Cruise Control (ACC): Both positive and negative effects of ACC systems on capacity have been discussed in the literature. By avoiding congestion, ACC systems are reported to have ecological and environmental benefits (Unal et al., 2003), with the relative savings in travel time three times higher than that in fuel consumption/emissions. According to Wang et al. (2014) total CO_2 emissions of the eco-driving strategy at free flow conditions are much lower than that of the efficient-driving strategy, because of the lower flow in the eco-driving platoon. However, in the ring-road scenario where the demand is not fixed, the total CO_2 emissions of the eco-driving platoon at moderate congested conditions is higher compared to the efficient-driving platoon, because in this case the benefits on average spatial CO_2 emission rate is diluted by the higher flow it produces.

Predictive Cruise Control (PCC): PCC systems are offered as an option by all major manufacturers and the technology has seen an accelerated market adoption since 2012 when PCC was first introduced commercially. The current new sales penetration of PCC in the truck market in the EU is 20%[6]. Scania introduced Active Prediction in 2012, which is an advanced cruise control system that uses GPS to obtain the location of the vehicle and use the topographical information for the road ahead. This system is a rule-based controller which mimics the driving style of experienced long haulage truck drivers. Fuel savings of up to 3% with minimal time loss are reported, compared to highway or motorway driving with normal cruise control. Volvo has introduced predictive cruise control technology named I-See in 2013. I-See uses GPRS/3G technology to download data on the route topography in the travel direction. While in cruise, the I-See system constantly monitors factors such as road grade, speed, weight and engine load to help maintain the most efficient drive possible. DAF offers Predictive Cruise Control available on its XF series trucks since 2015. Anticipating impending changes in the gradient, PCC may overrule the set cruise control speed, change the shift strategy of AS Tronic gearboxes or induce EcoRoll actions in order to save fuel. The fuel saving potential is given as about 1.5% under normal driving circumstances and about 4% on hilly road segments.

Advisor Accelerator (AA): The effect of acceleration on emission and fuel consumption was presented in more details in previous paragraphs. However, no obvious conclusion about on exactly how drivers should accelerate to reduce fuel consumption was found. According to instructions for eco-driving (Johansson et al., 1999), drivers should accelerate quickly and steadily to the desired speed and change to a higher gear as soon as possible during acceleration. In another study, where the driving of 30 families was logged daily for two weeks in city of Vasteras, Sweden, the results showed that rapid acceleration (>1.5 m/s^2) resulted in a significant increase in the emission of HC, NO_x and CO_2 and fuel consumption (Ericsson, 2001). For this reason, an advisor accelerator (AA) system was developed (Larsson and Ericsson, 2009). AA is a driver support tool, that was tested by Larsson et al. (2009) on light duty vehicles, increases resistance in the accelerator pedal when the driver tries to accelerate too hard, however, it is possible for the driver to override the resistance whenever necessary. In general, no significant reduction in fuel consumption or emissions was found when AA was activated, which shows that emissions and fuel consumption are depended by various other factors prior to acceleration.

Look-ahead control system: A look-ahead control model was developed by Hellstrom et. al. (2009). The look-ahead control mainly differs from conventional cruise control near significant downhills and up hills where the look-ahead control in general slows down or gains speed prior to the hill. Slowing down prior to downhills is intuitively saving fuel. There is, however, no challenge in saving fuel by travelling slower, so if the vehicle is left to slow down at some point, the lost time must thus be gained at another point.

Haptic in-car interfaces: There is a growing body of research that presents the potential benefits of providing driving-related information via haptic in-car interfaces. The effects of providing vibrotactile feedback via the accelerator pedal to facilitate eco-driving was examined by Birrell et. al. (2013). A stimulus was triggered when the driver exceeded a 50% throttle threshold, past which is deemed excessive for economical driving. Results showed significant decreases in mean acceleration values,

[6] optiTruck. (2019). D7.4: Business Scenarios and Technology Roll-out. Project deliverable, EU Horizon 2020, Green Vehicle programme, August 2019.

and maximum and excess throttle use when the haptic pedal was active as compared to a baseline condition.

Start/stop (S/S) Technology: The ''start/stop'' (S/S) technology is an easy and low-cost solution, in which the internal combustion engine is automatically powered off when the car is stopped and restarted upon driver's demand or when needed. Thus, it eliminates fuel consumption during idling, as in the case of stops at traffic lights or jams, which can account for up to 10% of total consumption (Rueger, 2008). Two four-wheel-drive diesel vehicles with on-board exhaust emission and vehicle activity measurement systems were tested in two urban driving circuits representative of downtown Madrid. The vehicles had similar turbocharged and intercooled diesel engines fulfilling the same Euro 4 emissions regulation; but one had an improved engine incorporating start/stop technology. CO_2 emission reduction of more than 20% for the car equipped with the start/stop system was obtained. Fonseca et. al. (2011), have investigate the influence of start/stop technology by using two Rover Freelander vehicles one with and one without start/stop technology. Their results have shown that CO_2 emission reduction of more than 20% for the car equipped with the start/stop system was obtained. Regardless of the variability in driving style, the grade and type of streets, traffic congestion, and the engine operating temperature, the car equipped with the start/stop system has intrinsically a lower CO_2 emission factor. Bishop et al. (2007) performed chassis dynamometer tests to determine the fuel economy improvement of a start/stop system, noting a 5.3% reduction in fuel consumption in the city FTP75 test cycle. In general, from the literature it is observed that the start/stop system can improve the fuel economy of a vehicle and thus can lead to lower exhaust emissions.

Automatic longitudinal control system: Automatic longitudinal control of vehicles is an automobile technology that has been implemented for many years. Connected eco-driving has the potential to extend the capability of an automatic longitudinal control by minimising the energy consumption and emissions of the vehicle. Jin et al. (2016) proposed an alternative algorithm that can reduce the energy consumption by about 4% compared to the existing algorithm if the travel time and arrival speed at are the same.

Table 8.8: Studies of the effect of adaptation systems on fuel consumption (FC) and emissions

A/A	System	Vehicle	Drivers	Tests	Results	Ref.
1	ACC (Adaptive Cruise control	Passenger vehicle	NA	Simulation	At free flow conditions CO_2 emissions are much lower than at moderate congested conditions	Wang et al. (2014)
2	PCC (Predictive Cruise Control)	Trucks	NA	Real-life testing	Fuel savings of up to 3% (Scania). Fuel saving of about 1.5% under normal driving circumstances and about 4% on hilly road segments (DAF)	6
3	AA (Acceleration Advisor)	Renault Kangoo 1.6 L Petrol	20 drivers, 4 similar cars	On-road	No significant reduction in FC or emissions was found with AA	Ericsson E. (2001)
4	Velocity planning system	light-duty Tier 1 emissions certified vehicle	NA	Simulation	Results of velocity planning algorithms show approximately 12% fuel economy improvement and 13% emission reductions in individual vehicles over a standard baseline case without the velocity planning	Xia et al. (2013)
5	A look-ahead control model	Truck	NA	Simulation model & On road Truck	The look-ahead control mainly differs from conventional cruise control near significant downhills and up hills where the look-ahead control in general slows down or gains speed prior to the hill. Slowing down prior to downhills is intuitively saving fuel.	Hellstrom et al. (2009)
6	Haptic feedback at accelerator pedal	Driving simulator of Jaguar S-Type	12 drivers	Driving simulator of Jaguar S-Type car	Results from this study suggest that the use of a vibrating, haptic pedal to warn drivers when they exceed a 50% threshold had some positive effects on acceleration and throttle parameters associated with eco-driving.	Birrell et al. (2013)
7	Start/stop (S/S) system	2 4x4 diesel vehicles (Rover Freelander)	Professional driver	On road	CO_2 emission reduction of more than 20% for the car equipped with the start/stop system was obtained	Fonseca et al. (2011)
8	Start/stop system	Hybrid electric vehicle (HEV)	NA	Chassis dynamometer	5.3% reduction in FC in the city test cycle with the use of start/stop system	Bishop et al. (2007)
9	Automatic longitudinal control system	Petrol fuel vehicle	NA	Simulation	Compared to the existing algorithm the proposed algorithm can reduce the energy consumption by about 4% in the scenario tested if the trip travel time and the arrival speed at the intersection are the same	Jin et al. (2016)

8.2.3 In-vehicle assisting systems

Driving Alert Traffic Signals System: Vehicle fuel consumption and CO_2 emissions can be lowered by improving traffic operations through the use of various intelligent transportation system (ITS) technologies (Li et al., 2009). An advanced driving alert system for traffic signals was investigated by Li et. al. (2009), savings on fuel consumption can be as much as 8% and the reduction of CO_2 emissions can be around 7% for each vehicle when traffic is in medium congestion.

Fuel efficiency tool: Van der Vort et al. (2001) presented a prototype fuel-efficiency tool which supports an energy-saving driving style through advice to the driver on when to change gear and when to accelerate. The tool includes a normative model that back-calculates the minimal fuel consumption for manoeuvres carried out. If actual fuel consumption deviates from this optimum, the support tool presents advice to the driver on how to change his behaviour. To take account of the temporal nature of the driving task, advice is generated at two levels tactical and strategic. The logic of the tool takes into account both the tactical and strategic aspects of driving. Evaluation in a driving simulator showed an overall potential in reduction of fuel consumption of 16%.

Eco routing navigation system: Navigation tools and trip planning services have introduced a vehicle routing option that is designed to minimise vehicle fuel consumption and emission levels in response to rising energy costs and increased environmental concerns. Such a routing option is referred to as eco-routing. Routing approaches usually provide the optimal path based on distance, travel time and on-time arrival probability. Few of them consider vehicle emissions. Intuitively, one may think that the shortest path or fastest path would also be the eco-friendliest path. However, a shortest path may take a driver through a heavy congested area, resulting in high vehicle emissions. On the other hand, there may be cases where a fastest path results in longer travel distance, albeit on less congested roadways. However, traveling on a path at a higher speed over a longer distance will also result in higher vehicle emission compared with a shorter path. A study of Zeng et al. (2016) proposes a vehicle dynamics-based CO_2 emission model and an eco-routing approach to address the problem of finding the eco-friendliest path in terms of minimum CO_2 emissions constrained by a travel time budget. It was found that the average reduction in CO_2 emissions achieved by the eco-friendly path reaches a maximum of around 11% when the travel time buffer is set to around 10% (Zeng et al., 2016). According to Ahn et al. (2013), eco-routing systems can reduce network-wide fuel consumption and emission levels in most cases; the fuel savings over the networks range between 3.3% and 9.3% when compared to typical travel time minimisation routing strategies. The results from the application of an eco-routing system on an electric vehicle have shown that the energy efficient routes were achieved an average energy saving of 20.7%, although they are on average 1.45% longer in distance and 10.26% longer in travel time than the corresponding fastest path routes (Masikos et al., 2015). On another study, it was found that the proposed, from an eco-routing system, route with the least fuel consumption, is 25% more energy efficient and 8% slower than the shortest duration route (Ahn and Rakha, 2008). According to Bandeira et al. (2014), different methodologies may produce very different absolute results with impact on a qualitative indication of eco-routes i.e. different optimal paths can be provided in accordance with the method for estimating emissions.

Table 8.9: Studies of the effect of in-vehicle assisting systems on fuel consumption (FC) and emissions

A/A	System	Vehicle	Drivers	Tests	Results	Ref.
1	Advanced driving alert system for traffic signals	2 simulated vehicles	NA	Simulation model	Savings on fuel consumption can be as much as 8% and the reduction of CO_2 emissions can be around 7% for each vehicle	Li et al. (2009)
2	Eco-driving and eco-routing mechanisms	Electric vehicle	NA	On road	Average energy savings of 20.7% when using energy friendly route (1.45% longer,10% more time) compared to fastest route	Masikos et al. (2015)
3	Eco-routing system	400 simulated vehicles	software	Simulation model	Savings in fuel consumption levels in the range of 15 percent were observed	Rakha et al. (2012)
4	Eco-routing system	Audi A8 vehicle	NA	On road	The least fuel consumption route is 25% more energy efficient and 8% slower than the shortest duration route	Boriboonsomsin et al. (2012)
5	Eco-routing system	Diesel vehicles (Citroen, Skoda), petrol vehicles (VW, Nissan, Mitsubishi)	3 drivers	On road measurements-simulation tests	Different methodologies may produce very different absolute results with impact on a qualitative indication of eco-routes i.e. different optimal paths can be provided in accordance with the method for estimating emissions.	Bandeira et al. (2014)
6	Eco-routing system	Simulated vehicles	NA	Simulation	Eco-routing systems can reduce network-wide FC and emission levels in most cases; the fuel savings over the networks range between 3.3% and 9.3% when compared to typical travel time minimisation routing strategies	Ahn and Rakha (2013)
7	Prototype fuel-efficiency support tool	Common vehicle simulator	88 male drivers	Simulation	Evaluation in a driving simulator showed an overall potential in reduction of fuel consumption of 16%.	Van der Voort et al. (2010)

8.2.4 Alternative fuel/energy vehicles low energy driving

CNG fuel: Generally speaking, the use of CNG (compressed natural gas) as an alternative to diesel fuel in buses has not only avoided the diesel FC, but also significantly reduced the NO_x and PM emissions (though there are studies which show that gas buses emit both PM and NOx to similar or even higher levels than Euro VI buses). The average NO_x and PM emissions emitted from CNG buses are very lower, relative to all the diesel buses. They are reduced by 72.0% and 82.3% respectively, compared with Euro IV diesel buses. The results show that the use of CNG in buses significantly contributes to reduce conventional diesel fuel consumption and emissions, and thus meet more stringent emission standards (Wang et al., 2011).

Electric Vehicles: Even in the case of zero emission vehicles, like Fully Electric Vehicles (FEVs), reducing the energy consumption contributes into limiting both the travel cost as well as the environmental impact coming from the generation (in power stations) and transfer of the energy required for vehicle recharging (Masikos et al., 2015).

Table 8.10: Effects of low energy driving when using AF vehicles

A/A	System	Vehicle	Drivers	Tests	Results	Ref.
1	Alternative fuel CNG	6 buses (2 Euro III diesel, 2 Euro IV diesel and 2 CNG)	Various drivers	On road	The use of CNG as an alternative to diesel fuel in buses has not only avoided the diesel FC, but also significantly reduced the NO_x and PM emissions.	Wang et al. (2011)

8.2.5 Infrastructure related systems for green driving

Variable speed limit / controlled speed zones: *Variable Speed Limit Sign* (VSLS) Systems enable speed limits to be changed dynamically in response to traffic conditions. *Average speed control* (also called 'section control' or 'point-to-point' control) is a relatively new speed enforcement technique. Average speed control systems measure the average speed over a road section (usually 2 - 5 km). The vehicle is identified when entering the enforcement section, and again when leaving it. The average speed can be calculated based on the time interval between these two points.

Based on simulation using COPERT 4 (EEA, 2019), cutting motorway speed limits from 120 to 110 km/h could deliver fuel savings for current technology passenger cars of 12–18 %, assuming smooth driving and 100% compliance with speed limits. However, relaxing these assumptions to a more realistic setting implies a saving of 2–3 %. Cutting speed can also significantly reduce emissions of other pollutants, particularly reducing NOx and particulate matter (PM) output from diesel vehicles. The benefits of reducing average speed from 100 km/h to 90 km/h range from 25 % (petrol/gasoline CO) to 5% (diesel PM). However, there is the rise in diesel CO and petrol NOx emissions at decreasing average speeds, which is largely due to the operation of after-treatment devices. The diesel oxidation catalyst operates more efficiently at high speed due to the higher temperature, therefore oxidising carbon monoxide more effectively. For petrol engines, increasing speed up to approximately 115 km/h leads to lower NOx emissions, although emissions increase again above that speed.

Green wave: Kiers and Visser (2017) have studied the effect of a green wave that was calculated by using three different models (VISSIM, HBEFA and Car2). Nitrogen dioxide and particulate matter have decreased more than 50%. Others, like carbon monoxide, carbon dioxides, sulphur dioxide and fuel consumption had smaller decreases. The reduction of CO_2 was found to be 178.824,88 kg when comparing the current green wave with the static program. Thus, a green wave has quite a large impact on the emissions when it is changed from a stop-and-go situation into a homogenised green wave situation. Unal et al. (2003) performed onboard air pollutant emission measurements along a signalised arterial road in North Carolina, US, using four different drivers and eight gasoline (petrol) fuelled light-duty vehicles, before and after the coordination of traffic signals. They found that, depending on the type of vehicle and the level of congestion, the implementation of traffic signal coordination yielded reductions in HC, NO and CO emissions per unit of distance between 10 and 20 %. Zhang et al. (2009) used a portable emission measurement system to compare the NOx, HC and CO emissions of a single vehicle, when driven along two different roads in Bejing, China, one with and one without coordinated traffic signals (both carried similar traffic flow and composition). It was found that the emission of HC and CO per unit of distance was lower along the road with coordinated signals, by resp. 50 % and 30 %, but the emission of NOx per unit of distance was higher by 10 %. A detailed analysis of the driving cycles showed that NOx emission increased slightly with increasing average vehicle speed, while HC and CO emissions decreased with increasing average vehicle speed.

Table 8.11: Effect of infrastructure systems to low emission

A/A	System	Country	Drivers	Study type	Results	Ref.
1	Speed limit	NA	NA	Simulation Pas. cars	A saving of 2–3 % from 120 to 110 km/h. From 100 km/h to 90 km/h, gain from 25 % (petrol CO) to 5% (diesel PM). There is a rise in diesel CO and petrol NOx emissions at decreasing average speeds	EEA (2019)
2	Green wave	NA	NA	Simulation	Nitrogen dioxide and particulate matter decreased more than 50%. Carbon monoxide, carbon dioxides, sulphur dioxide and fuel consumption had smaller decreases	Kiers and Visser (2017)
3	Green wave	US	4 drivers and 8 LDV	Real-life	Reductions in HC, NO and CO emissions per unit of distance between 10 and 20 %	Unal et al. (2003)
4	Green wave	China	1 driver and 1 vehicle	Real-life	HC and CO per unit of distance were lower by resp. 50 % and 30 %, but NOx per unit of distance was higher by 10 %	Zhang et al. (2009)

8.2.6 Green driving training schemes

Numerous eco-driving training programmes have taken place in the framework of projects, enterprise social responsibility schemes and strategic goals for achieving economic – environmental targets. Those programmes were carried out by EU - funded projects, public transport management bodies, research institutes, organisations or transport operators of all kinds (both for freight and passenger transport) and are showing clear and immediate results. International organisations like OECD’s ITF and IRU have promoted eco-driving training for professional drivers as a sustainable and economical way of driving[7,8]. Eco-driving is a quick, efficient and low-cost measure with a benefits/cost ratio that is larger than one and payback time of even less than a year in the EU ECOEFFECT project. The first attempts to calculate the impact of eco-driving can be found in 1999 by Johansson et al. (1999) calculating an approximate 10.9% fuel consumption decrease. Eco-driving includes training on the optimisation of gear changing, avoidance of idling and rapid acceleration – deceleration and reducing of unnecessary weight carried (Kojima & Ryan, 2010). The OECD reviewed 21 different eco-driving programmes internationally and found that the effect of eco-driving results to a 16,8% average decrease in fuel consumption in the short-term and 6,9% in the mid-term (Kojima & Ryan, 2010).

In the literature review conducted and as shown in Table 8.12, both professional and non-professional drivers were included (the identified groups had a range of 6 drivers minimum to 2 million drivers – in that case both directly and indirectly involved). Related to the geographical coverage, the review included mainly EU member states, but also the United States and others. The types of vehicles examined were mainly HDVs and buses but also LCVs and the trainings took place from 1999 to 2015. The most important results to focus on are the fuel savings achieved resulting to at least 1% in some cases related to driving in highways - where the driving behaviour cannot change significantly - to 20% or even 25% in some limited cases[16]. In most cases, fuel economy of approximately 10% was achieved, however, it is not safe to conclude to an average due to the difference in vehicles, participants' numbers and approaches. It is of great importance to note that differences were found in the short and medium term fuel savings and driving behaviour 6 months after the training in some cases declined and in other cases increased[15]. In economic terms, the investment of a training has an estimated payback time of 5 months up to two years[10,17,18] and the annual fuel savings were valued to 1.323€ and 3.500€[10,18].

[7] ECO-Driving Fuel Efficiency Training, (2018). https://www.itf-oecd.org/eco-driving-fuel-efficiency-training
[8] Eco-driving – IRU. https://www.iru.org/iru-academy/programmes/eco-driving

Table 8.12: Effect of training programmes to low emission

A/A	Project - company	Type of vehicle	Duration	Drivers	Tests	Results
1	TREATISE[9]	All types	2005-2007	1722	AT, BE, FI, GR, NL, ES, etc. (8 countries)	95,000 tonnes CO_2 achieved and 1.011.000 tonnes CO_2 savings forecasted. Results from several large-scale field tests show all devices mentioned save about 5% fuel. Combined with driving style training the benefits are significantly higher.
2	ECOEFFECT[10]	All types	2011-2013	2500	PO, RO, CZ	5%-9% reduction in fuel consumption - CO_2 emissions by more than 1.000 tonnes and saved 480.000€ in fuel - ROI of 1.323€ per driver per year - Payback in 5 months.
3	CIVITAS eco-driving[11]	Buses	2010	274	Tallinn bus company	Reduced by 3,9% on average for participants of the training - number of accidents was reduced by 22% - The driving style index was improved by 7,3% in average - drivers awareness on the environment was improved by 29% - B/C ratio 1,567.
4	Kesko Logistics eco-driving[12]	Trucks	2012	Not specified	FI & 100 other countries	Average fuel cost saving of 10 to 15 % after one-day eco-driving course.
5	Comparative effects of eco-driving initiatives aimed at urban bus drivers – Results from a field trial[13]	Buses	2013	Not specified	Not specified	Examined two programs to develop and maintain ecological bus driving behaviour. A 6.8% fuel saving and large decreases in instances of harsh deceleration and speeding were found. Drivers reported gains in theoretical knowledge, but found it difficult to put that knowledge into practice. Contextual factors were found to limit drivers' to eco-driving.
6	Eco-driving: pilot evaluation of driving behaviour changes among U.S. drivers[14]	LCVs equipped with eco-driving	2010	23 light commercial vehicle drivers	South California, USA	This study evaluated how an on-board eco-driving device that provides instantaneous fuel economy feedback affects driving behaviours, and consequently fuel economy, of gasoline-engine vehicle drivers in the U.S. under real-world driving conditions. The results from 23 samples of drivers in Southern

[9] TREATISE EU-funded project (2007). https://ec.europa.eu/energy/intelligent/projects/sites/iee-projects/files/projects/documents/treatise_teatrise_report_en
[10] ECOEFFECT EU-funded project (2013). //ec.europa.eu/energy/intelligent/projects/en/projects/ecoeffect
[11] CIVITAS eco-driving training for bus drivers (2010). https://civitas.eu/measure/eco-driving-training-bus-drivers
[12] Kesko Logistics eco-driving (2010). https://www.resourceefficient.eu/en/good-practice/kesko-logistics-trains-drivers-eco-driving
[13] Strömberg, H.K.; Karlsson, I.M. (2013). Comparative effects of eco-driving initiatives aimed at urban bus drivers–Results from a field trial. Transp. Res. Part D Transp. Environ. 22, 28–33. V
[14] K. Boriboonsomsin, A. Vu, and M. Barth, (2010). Eco-driving: pilot evaluation of driving behavior changes among us drivers, University of California Transportation Center

A/A	Project - company	Type of vehicle	Duration	Drivers	Tests	Results
		device				California show that on average the fuel economy on city streets improves by 6% while the fuel economy on highways improves by 1%.
7	Bus eco-driving training[15]	Buses	2015	29	Several places	Fuel economy for the treatment group improved significantly immediately after the eco-driving training (11.6%) and this improvement was even larger six months after the training (16.9%).
8	A summary of previous eco-driving training programmes[16]	All types	1999-2015	Not specified	Nine eco-driving training programmes	Fuel economy of 9.88% on average ranging from 1% to 25%. The review included nine eco-driving training programmes.
9	STIB-MIVB Brussels public transport company[17]	Buses – public transport	2013	Not specified	Brussels	5% fuel savings were achieved which would result to 750.000€ in savings if deployed on the whole bus fleet. Payback time of investing in eco-driving equipment and training was estimated to be around two years.
10	BIELEFELD (MOBIEL)[18]	Buses – public transport	2013	6	Bielefeld, DE	This eco-driving program allowed moBiel to reduce its fuel consumption by 10% (252,000 liters), resulting in a 3.500€ cost saving per bus every year. The investment cost reached 1.800€ per training and payback was achieved in approximately 6 months.
11	ECODRIVEN[19]	All types	2006-2010	Directly and indirectly up to 2.000.000	UK, FR, NL, BE, FI, AT, PL, CZ, GR	Savings immediately post-training are often in the region of 15-20% with long-term savings after training of approximately 10%. Explored the potential of short-duration (snack) training courses, with good results. Reached over 20 million licensed drivers in 9 EU countries and Resulted in 1 million tonnes CO_2 emission avoidance from 2006 until 2010.

[15] Sullman, Mark & Dorn, Lisa & Niemi, Pirita. (2015). Eco-driving training of professional bus drivers – Does it work? Transportation Research Part C, 58. 749–759.

[16] Wang, Yang & Boggio Marzet, Alessandra. (2018). Evaluation of Eco-Driving Training for Fuel Efficiency and Emissions Reduction According to Road Type. Sustainability. 10. 3891. 10.3390/su10113891.

[17] Bus eco-driving in Brussels – STIB (2014). https://www.stib-mivb.be/irj/go/km/docs/resource/tickettokyoto/en/cases/bus-eco-driving-brussels-stib.html

[18] Bus eco-driving in Bielefeld – MOBIEL (2014). https://www.stib-mivb.be/irj/go/km/docs/resource/tickettokyoto/en/cases/bus-eco-driving-bielefeld-mobiel.html

[19] ECODRIVEN EU-funded project, (2008). Retrieved from: https://ec.europa.eu/energy/intelligent/projects/en/projects/ecodriven

8.2.7 Incentives schemes promoting eco-driving

Taking into consideration the lower impact on fuel savings from eco-driving training programmes in the mid-term to long-term, there has been noticed a trend in such companies to promote eco-driving by rewarding drivers on the savings achieved. Similar approach has been followed by insurance promotion schemes mainly by achieving safer driving behaviour – which many times has similar effects to the eco-driving approach. Companies motivate employees and specifically drivers with monetary or non-monetary rewards. A 7.6% improvement in fuel efficiency was achieved in the first month after the introduction of a reward system. During the fourth to sixth month fuel efficiency showed an improvement of 10% related to the baseline. There was no decline of the benefit over time and the money saved from fuel reduction was much more than the rewards offered (Lai, 2015). Incentives (mainly financial) are used to encourage eco-driving. Examples of incentives are awards for fuel-efficient public drivers or eco-driving based insurance for private drivers. Schall and Mohnen (2017) investigated the effects of monetary and tangible non-monetary incentives on eco-driving in a Germany logistics company. The results showed an average reduction of 5% in fuel consumption due to non-monetary incentive and 3.5% due to monetary incentive. The majority of drivers showed a very good knowledge of the eco-driving methods (Lai, 2015; Liimatainen, 2011).

Table 8.13: Effects of incentives schemes to green driving

A/A	Scheme	Type of vehicle	Duration	Drivers	Type of reward	Results	Ref.
Companies reward systems							
1	The effects of eco-driving motivation, knowledge and reward intervention on fuel efficiency	Bus	2012 – one year	116	Monetary	The average fuel efficiency of all of the buses in the experimental group company changed from 3.3 km/l to 3.62 km/l after the intervention of the reward system. The estimated amount of total fuel saved was 645,706 litres, and the total cost saved was US$ 732,000. The eco-driving reward system had significant benefits to the bus company when compared to the amount of monetary rewards given (US$ 108,000) and should be more widely adopted within the industry.	Lai (2015)
2	Utilisation of Fuel Consumption Data in an Eco-driving Incentive System for	Bus	2007-2009	309 on average each month	Monetary and non-monetary	Drivers (70%) stated that an incentive system based on monitoring fuel consumption would affect their driving behaviour, and 60% thought that fuel consumption could be measured and compared	Liimatainen (2011)

A/A	Scheme	Type of vehicle	Duration	Drivers	Type of reward	Results	Ref.
	Heavy-Duty Vehicle Drivers					fairly among drivers. Incentive systems have the potential to maintain these results in the long term and to even further decrease costs. The incentive system is expected to have a payback period of two years.	
3	Incentivising energy-efficient behaviour at work: An empirical investigation using a natural field experiment on eco-driving	LCVs	6 months	Not specified	Monetary and non-monetary	Results show an average reduction of fuel consumption of 5% due to a tangible non-monetary reward and suggest only a small reduction of the average fuel consumption in the equivalent monetary reward treatment. We find indications that more emphasis on the fun of achieving a higher fuel efficiency, a more emotional response to non-monetary incentives, and a higher frequency of thinking and talking about non-monetary incentives might play a role in the stronger effect of the tangible non-monetary reward.	Schall and Mohnen (2017)
Insurance schemes							
1	OnStar Smart Driver	All	-	-	Discount on insurance costs	OnStar Smart Driver is a connected to the vehicle application which calculates a score based on parameters as: hard braking, distance driven, time of day (such as late-night driving) and speed	[20]
2	Snapshot app by	All	-	-	Calculation of	Snapshot calculates how and how much drivers use	[21]

[20] Discover the Advantages of Being an OnStar Smart Driver. Retrieved from: https://www.onstar.com/us/en/smart_driver/

[21] Snapshot application by Progressive. Retrieved from: https://www.progressive.com/auto/discounts/snapshot/

A/A	Scheme	Type of vehicle	Duration	Drivers	Type of reward	Results	Ref.
	Progressive				insurance costs	their cars instead of just traditional factors. Drivers save money by limiting hard brakes and accelerations, avoiding late night driving, driving less overall and staying off their phones.	
3	myDrive app by Intact insurance	LCVs	-	-	Discount on insurance costs	A discount is calculated based on the driving behaviour. By avoiding distractions and risky behaviour on the road, savings could reach up to 25%.	Xia et al. (2013)

In addition to the reward systems companies introduce to achieve better fuel efficiency, insurance companies have started to introduce applications that can give scores to the driving style followed and provide discounts of up to 25%[22] to the drivers that follow a non-aggressive driving style. This can be achieved by taking into consideration practices as late night driving, speeding and other distractions and risky behaviours. The insurance schemes for rewards of the safe driving style follows similar practices to the eco-driving by discouraging practices as: hard braking, speeding, accelerating, etc.

8.2.8 Identifying low emission factor through the use of simulation tools

Literature Overview for Microscopic Emission Models and Simulation System: In many research papers, macroscopic models based on average travel speed have been the most common methodology used for estimating vehicle emissions. These macroscopic models entail enormous simplifications on the accuracy of physical processes involved in pollutant emissions. An important drawback of this methodology is that it calculates emissions per kilometre for vehicle trajectories using primarily the average speed. Although the overall trip speed is an important factor influencing emissions, instantaneous speed fluctuation plays a greater part. For the same average speed, one can observe widely different instantaneous speed and acceleration profiles, each resulting in very different fuel consumption and emission levels. For the compilation of emission inventories of large areas and over long time periods, this microscopic effect may be ignored and the results from the macroscopic models may give reasonably good estimates. Models taking traffic dynamics partially into account by partitioning the traffic situations in several have been less widely used. For smaller scale and real-time applications, however, one needs to develop models that take into account vehicle operation conditions. This is especially the case when the policy to be evaluated is real-time

[22] Introducing my Drive. Retrieved from Intact insurance company, Canada: https://www.intact.ca/qc/en/personal-insurance/vehicle/car/mydrive.html

driving assistance and results in changes in driving behaviour such as those mentioned above. In order to effectively measure the behavioural changes on exhaust emission, it is crucial that the models fully incorporate the new technology employed by the policy measures, the behavioural responses of the drivers and the real-time vehicle operations. Joumard et al. (1995) correlated their emission measures with vehicle speeds and the product of speed and acceleration. They showed that the emission rates increased not only with increasing speed, but also with increasing acceleration. Currently, significant effort is being devoted to the development of models that can account for speed fluctuations and allow instantaneous emission modelling, such as the Comprehensive Modal Emission Model developed at the University of California (An et al., 1997; Barth et al., 2000) and many others around the world (e.g. Rakha et al., 2004; Pelkmans et al., 2004; Cornelis et al., 2005; El-Sgawarby et al., 2005).

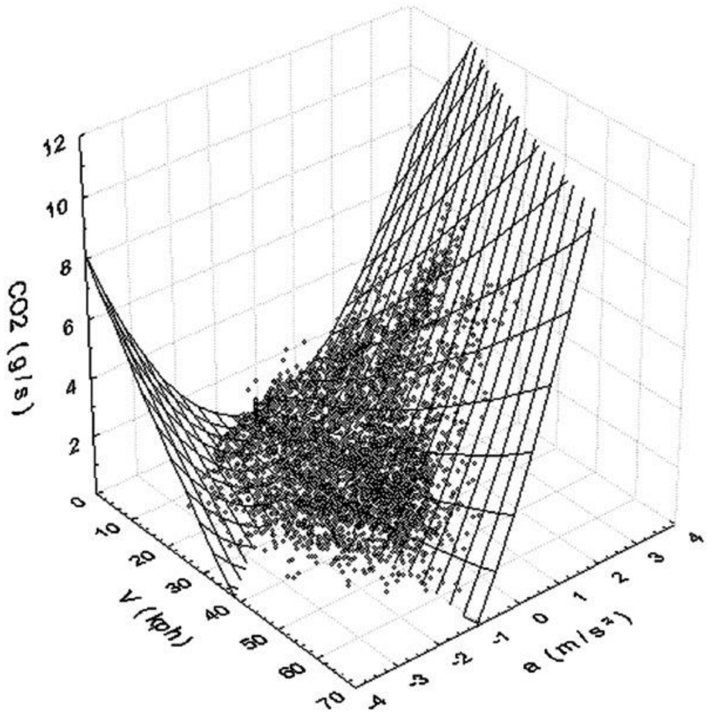


Figure 8.1: CO2 emission as a function of speed and acceleration (the surface) versus measurements (points) for a EURO-3 diesel car (Skoda Octavia)

In parallel, recent years have seen a tremendous interest in the transport field in the use of microsimulation techniques to model traffic on road networks through which to represent the real-time, behaviourally-based policy measures (e.g. Ben-Akiva et al., 1997; Hu and Mahmassani, 1997; Liu et al., 2006). Traffic microsimulation models are based on the explicit representation of the individual driver behaviour and individual vehicles' real-time space-time trajectories. They offer detailed vehicle operation and instantaneous speed and acceleration of vehicles required by the microscopic emission models. In below discussion, we present individual main parameters affecting the emissions which are namely the instantaneous acceleration and the speed of the vehicle. Furthermore, we introduce the vehicle simulation environment and present similar emission results for the simulated truck with respect to variations in instantaneous acceleration and speed of the truck.

Acceleration: For most passenger vehicles, the maximum acceleration rate ranges from about 3.6 to 2.1 m/s2 as vehicles start from rest, depending upon their weight–power ratio. Normal acceleration rates for passenger cars are significantly lower than the maximum acceleration rates and are typically estimated at about 1.1 m/s^2. Data collected by the Oak Ridge National Laboratory (ORNL) for 1300–1600 individual vehicle data points and the predicted emission by Ahn et al. are shown in above figure. This illustrates that both instantaneous speed and acceleration significantly affect the emission. Vehicle acceleration becomes the most influential factor for CO and hydrocarbon (HC) emission levels, especially at high speeds. The minor variations in speed and throttle position, which have been found to result in significant emission increases relative to true steady state operation, have also been reported in the recent work of the EPA.

Average speed: Predicted emission levels as functions of average vehicle speed are shown in below figure. Based on the predictions presented by Ahn et al. (2013), emission levels are generally high under low-speed congested driving conditions and fall at intermediate speeds in low-density traffic conditions. All emission levels increase with increasing vehicle speed.

In below figures, effect of acceleration and average speed are depicted (Samuel et.al, 2002). Simulation will be run to check the results presented in the figures.

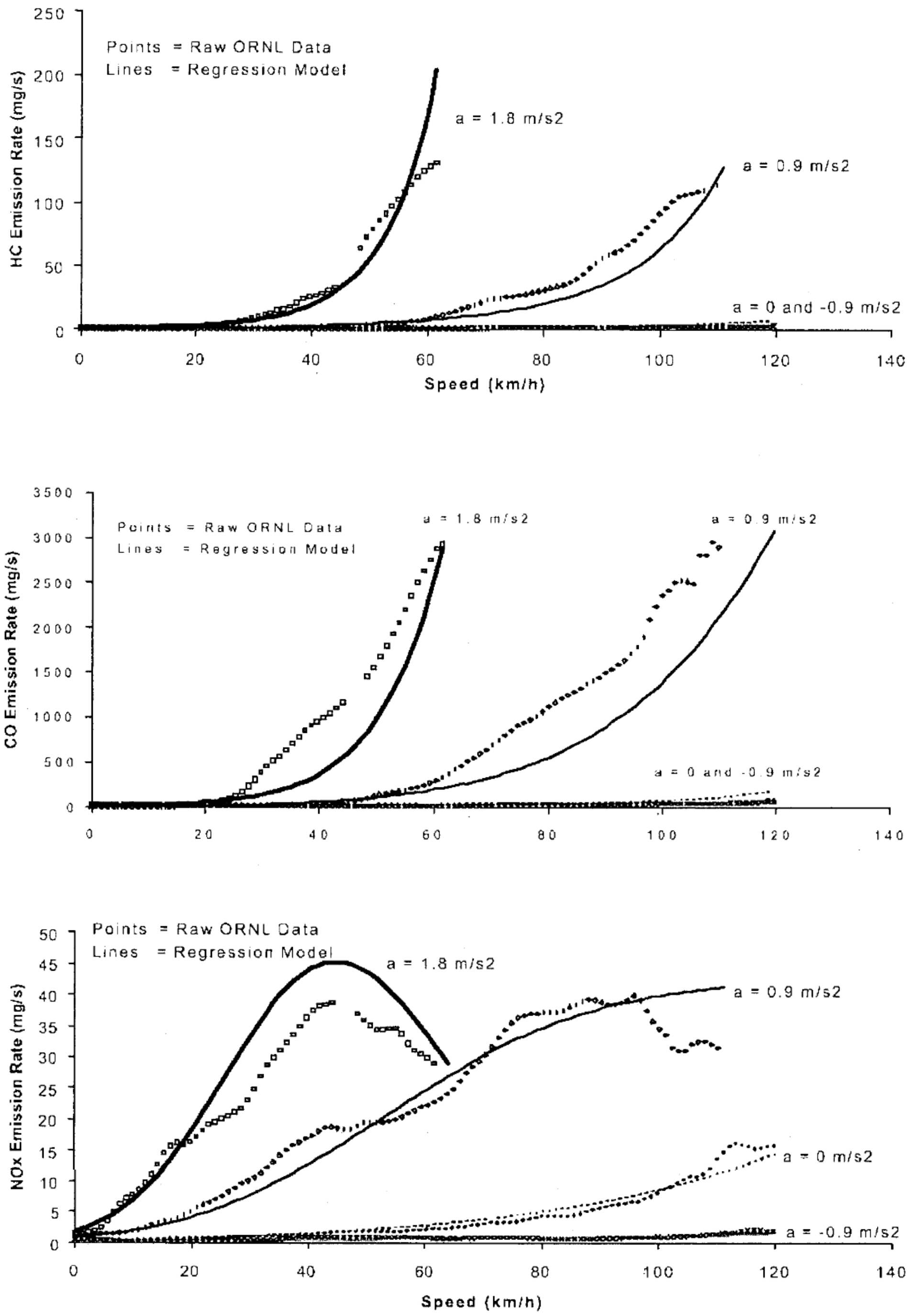


Figure 8.2: Vehicle emission as a function of vehicle speed and acceleration

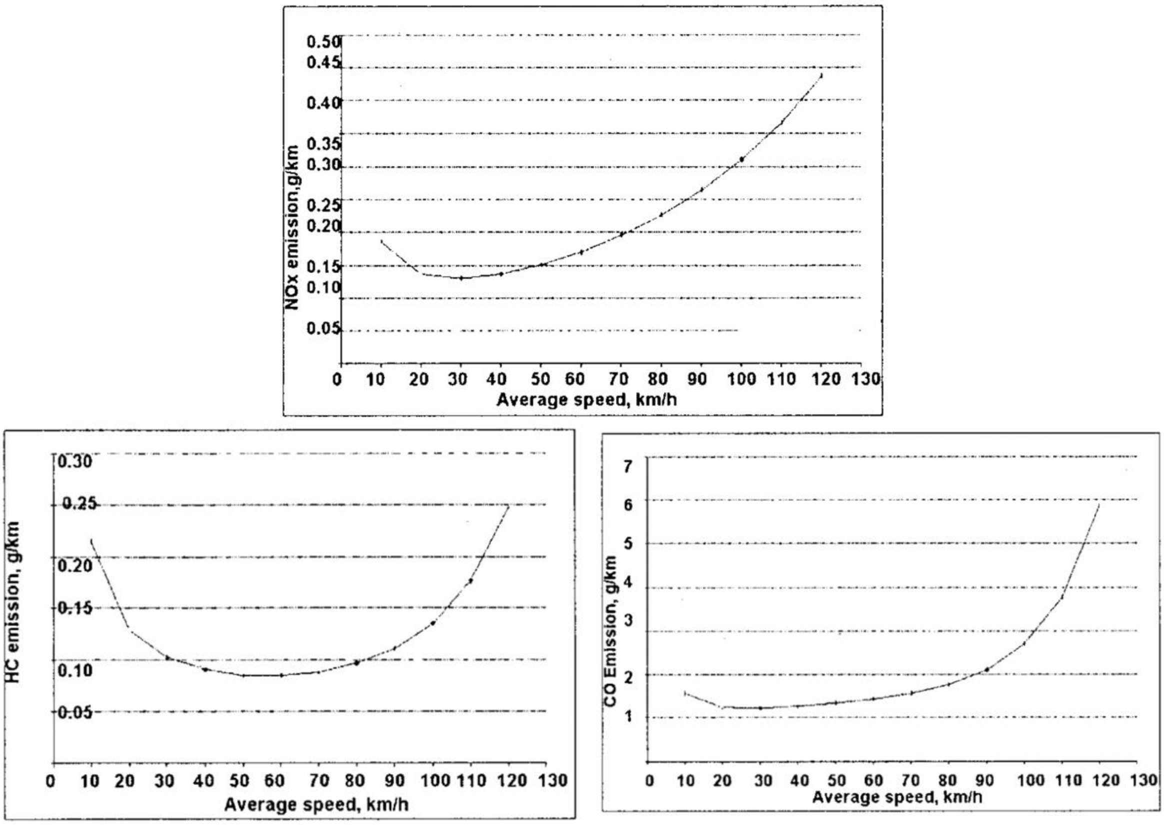


Figure 8.3: The effect of average speed on vehicle emission.

Simulation System: The simulation system plays a key role in developing control algorithms and strategies for reducing the fuel consumption and emissions of the truck and to accomplish the objectives that are set forth within the scope of the optiTruck project. A representative schema of the overall system and sub-systems are as shown in the below figures.

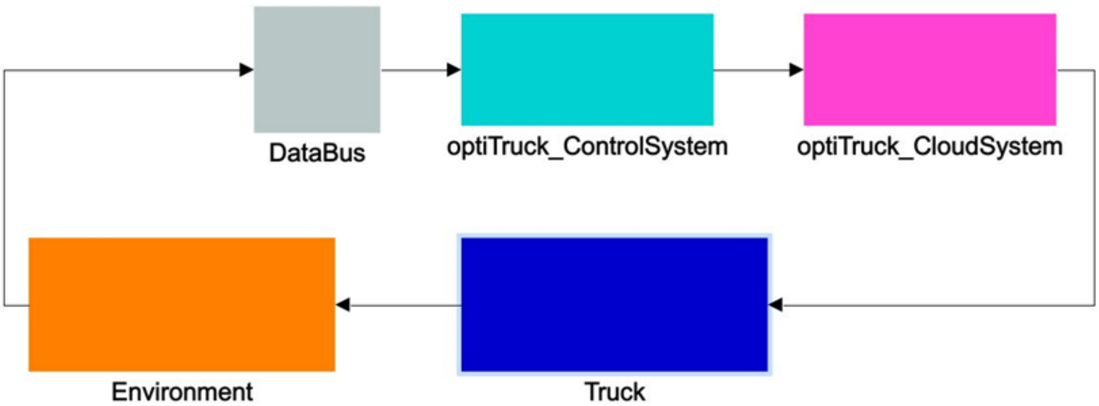


Figure 8.4: Overall Representation of the Vehicle Simulator Environment

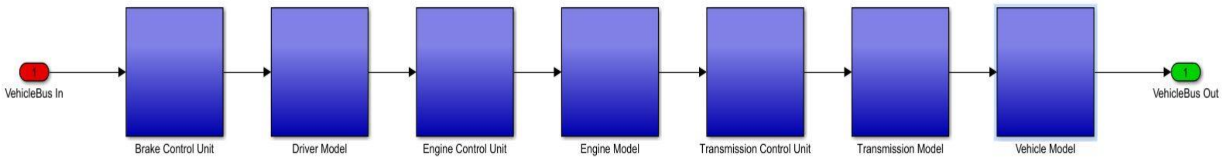


Figure 8.5: System Level Separation of the functionalities

On board system has many different functions, below these functions are listed,

a) Engine simulation
b) Transmission simulation
c) Emission estimator
d) Engine operating point estimator
e) Fuel consumption estimator
f) Energy systems simulation
g) Auxiliary systems simulation
h) Longitudinal Vehicle model
i) Radar and camera simulation

For engine and transmission system simulations and related function estimators main systems are GT-SUITE, AVL CRUISE, AVL BOOST, AVL FIRE and RICARDO IGNITE. The systems have got similar capabilities. For example, GT-SUITE can simulate engine performance, exhaust aftertreatment, cooling systems and thermal management, air conditioning and waste heat recovery, transmission simulation, auxiliaries simulation and fuel consumption calculations.

As seen, most of the functions listed above can be simulated through GT-SUITE. It is important that specific subroutines can be added to GT-SUITE by using programming languages such as C and Matlab. Longitudinal vehicle model and radar and camera simulation exist in most of the vehicle simulations systems. TRUCKMAKER has a built-in predictive cruise control system with radar. However, such systems are to be ready also for specific subroutine interfaces and insertion and be compatible with Matlab and C programming languages.

Below simulation results obtained for NOx as a function of speed and velocity are shown. The results are similar to the ones shown on the literature. For HC and CO the results are similar. The objective will be to fine tune the simulation system results for different vehicle types with the PEM results obtained and run several scenarios including road topographic conditions to derive the effect of microscopic driving on emissions and find optimised driving conditions for best conditions of emissions which affect human health.

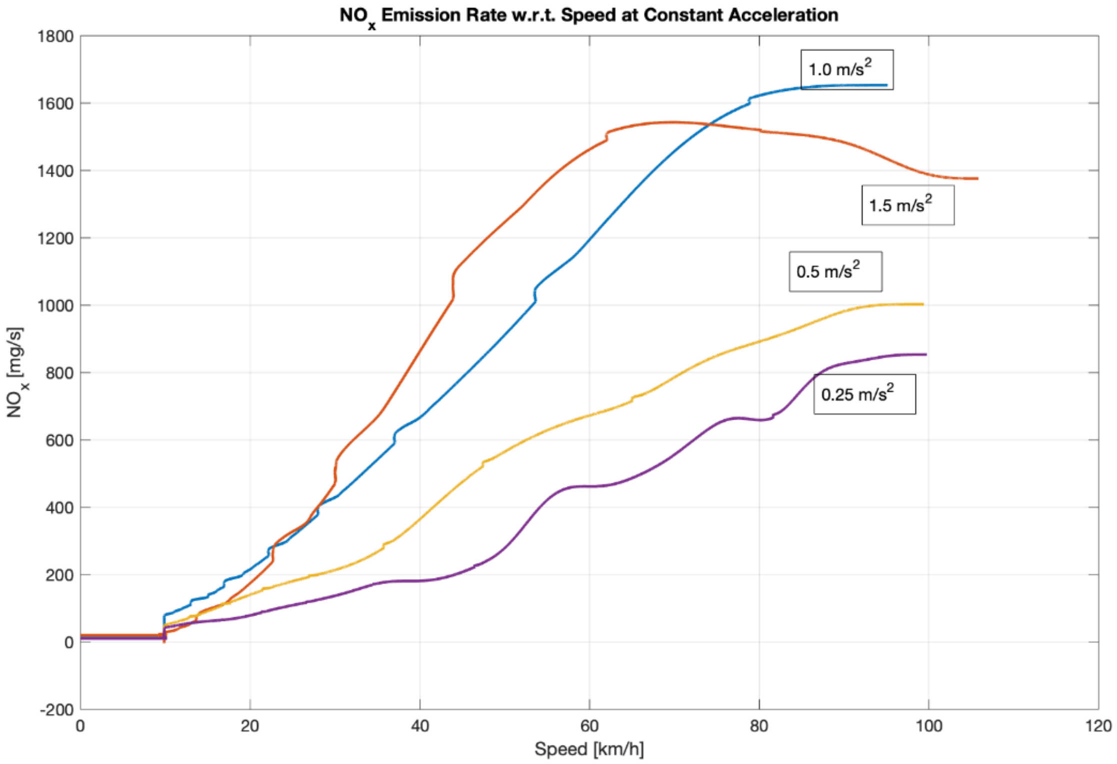


Figure 8.6: NOx Emission rate with respect vehicle speed at constant acceleration operation

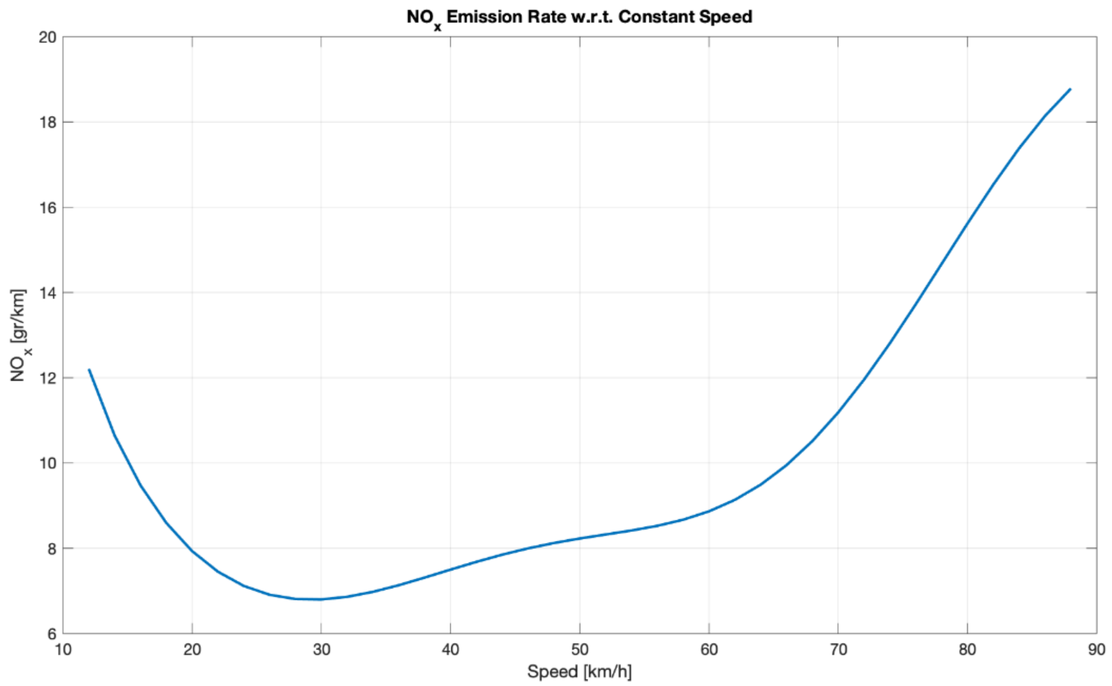


Figure 8.7: NOx Emission with respect constant vehicle acceleration

Macroscopic modelling is used to estimate fleet emissions on large geographical scales (e.g. at regional level or nationwide). This type of models uses the average speed as the main traffic parameter to determine emissions and therefore can only provide a long-term average measure of traffic emission. Microscopic models, on the other hand, are able to estimate the instantaneous emissions, often on a second-by-second basis and are therefore more suited to evaluate the environmental impact of real-time transport policies. Unlike macroscopic models, microscopic models are also able to adequately capture the effects of driving style and vehicle dynamics on emissions. Vehicle dynamics play a very important role when studying the impacts of speed and safety related traffic measures on vehicle emissions and fuel consumption.

8.3 Mapping of the characteristics of low-emission driving vs eco-driving

In response to the negative impacts of global warming, many countries are adopting policies to reduce greenhouse gas emissions and fuel consumption. The fuel efficiency of the transportation sector has become a key issue in such actions. The strategies for carbon emission reductions in the transportation sector are summarised into four main categories according to U.S. Department of Transportation (2010)[23]:

- reduced carbon-intensive travel activity (e.g., changes in urban design and land utilisation patterns);
- improved transportation system efficiency (e.g., increasing the use of public transportation);
- increased vehicle fuel economy (e.g., popularising **eco-driving** practices); and
- development of the use of low-carbon fuels (e.g., promoting the use of electric vehicles).

From the above categories, the implementation of an eco-driving style is relatively low-cost and immediate. In passenger vehicles, an important amount of energy is often wasted. An immediately applicable way to reduce fuel consumption for passenger vehicles is to adapt the use of the vehicle to the system functionality. Vehicle efficiency is not constant over its operating range but depends on the losses of each component in the drive train. It is therefore strongly dependent on vehicle velocity and acceleration. A driver can reduce energy needed to perform a trip by his utilisation of the vehicle. The behaviour of a driver that minimises fuel consumption is often referred to as **eco-driving** (Mensing et al., 2014).

Eco-driving has attracted considerable research interest the last decade since it is a technique for increasing energy efficiency and is also a relatively low-cost and immediate measure to reduce fuel consumption significantly (Gense, 2000; Huang et al., 2018). There are various definitions on eco-driving in the literature. In general, eco-driving consists of a variety of driving techniques including not driving too fast; not accelerating too quickly; shifting gears earlier to maintain a lower engine speed; keeping a steady speed; and ensuring that vehicles are well-maintained (Barth and Boriboonsomsin, 2009; Lai, 2015). Furthermore, the choice of the most appropriate driving route is also considered as another important eco-driving factor (Pampel et al., 2015). As a result, a general definition for eco-driving is that: *eco-driving is a set of behaviours that drivers can practice to reduce fuel consumption*.

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[23] U.S. Department of Transportation. (2010). Transportation's Role in Reducing U.S. Greenhouse Gas Emissions. http://ntl.bts.gov/lib/32000/32700/32779/ DOT_Climate_Change_Report_-_April_2010_-_Volume_1_and_2.pdf

From a simplified perspective, it could be argued that the more aggressively a vehicle is driven the more fuel it will use and therefore the more emissions it will produce. In general, an increase in driver aggressiveness causes an elevation of 20–40% for CO_2 and 50–255% for NO_x emissions, depending on the driver and the vehicle, while CO and HC are not significant influenced (Gallus et al., 2017; Gonzalez et al., 2010). Another observation is that, the composition variations of the exhaust emissions are dependent on the technology of the vehicle, the mileage and the mass/performance ratio as well as the drivers' mood. More specifically, the biggest increases with aggressive driving profile were observed on newer petrol vehicles' carbon monoxide (CO), unburned hydrocarbon (HC) and nitrogen oxides (NO_x) emissions, while, carbon dioxide (CO_2) showed the smallest increase (Tzirakis et al., 2007).

Another factor that defines the eco-driving is the vehicle speed, where it was found that the optimal fuel economy zone for passenger light duty vehicles was in the range of 40 km/h-110 km/h (Gao et al., 2019). Furthermore, very important is also the road gradient profiles as it strongly influences fuel consumption and emissions. Larger emissions and higher fuel consumption at higher road grades could be explained by more frequent high engine load points, the step from 0 to 5% road grade can lead to a CO_2 increase of 65–81% and a NO_x increase of 85–115% (Gallus et al., 2017).

The cold start operation of the vehicle is also a parameter that influence eco-driving. During cold start, energy consumption is 110% higher than during hot conditions while emissions are up to 910% higher (Faria et al., 2018). Moreover, a higher increase on both energy consumption and emissions was found for petrol vehicles than for diesel vehicles. An important role for cold start operation is also the ambient air temperature. In countries with lower ambient temperature and colder climate the percentage of time spent on cold start is higher than for countries with higher ambient temperatures. For example, measurements (Faria et al., 2018) have shown that from 0 °C to 29 °C, the percentage of time spent on cold start decreases significantly from circa 80% to <50%. This variation occurs independently of the vehicle fuel type (diesel or petrol). Cold start impacts on a street level are highly dependent on the percentage of time that vehicles are on cold start conditions. It is important to note that the engine warm faster when is working on higher loads and speeds, as a result the selection of the route is an important factor for the time spend in cold operation mode. It is noticeable that for more local streets (particularly in the city centre) the percentage of time spent in cold start conditions is higher than for those streets that are in the external ring of the city. In order to improve fuel consumption and emissions, it is wider for the driver to use a road with less traffic and lights if this is possible.

According to the literature, due to the reduction in fuel consumption and therefore CO_2 emission eco-driving is generally considered to be an environmentally friendly behaviour of drivers. However, due to growing fuel prices, for most drivers the interests are in the reduction of cost. Many studies on energy and/or fuel-efficient driving can be found in literature (van der Voort et al., 2010; Larsson and Ericsson, 2009; Fiat, 2012), as well as studies on CO_2 reduced driving (Martin et al., 2013). From the above analysis, it is observed that eco-driving is strongly related to low emissions driving, which was presented in a previous section. The major difference of the two driving styles is that "**eco-driving**" is focused mainly on *reducing fuel consumption* and thus CO_2 emissions while "**low emissions driving**" is focused on *reducing exhaust emissions*.

8.4 Categorisation of the low-emission requirements

From the current analysis, it was observed that there are many factors during driving that strongly influence the fuel consumption and exhaust emissions of a vehicle either light or heavy duty. However, most of these factors are related with the driver's behaviour. It was found that normal driving is more energy and emissions friendly compared to aggressive driving. In addition, the choice of the most emissions friendly route could help in fuel savings and exhaust emissions. Furthermore, the decision of a lower cruising speed also could help on fuel savings. As a result, if someone would like to give a definition to the term "Low emissions driving", he could say that it is the ***driving in which lower emissions are achieved due to the driver's technique***. It is more than obvious that there is a pattern on how a driver should behave to follow a low emission driving profile. These techniques are, the choice of the most appropriate route and a mild driving profile. A mild driving profile is characterised by not driving too fast, not accelerating too quickly, shifting gears sooner to keep the engine speed lower, maintaining steady speeds, anticipating traffic flow when accelerating and slowing down and keeping the vehicle in good maintenance. The latest years, some new advanced technologies have also been developed called as adaptation systems which help the driver to follow this low emission driving profile. Advices on how a driver can achieve a low emissions driving are summarised in Chapter 9.7 below.

9 Conclusions

A state-of-the-art literature review of driving behaviour variability and vehicle emissions has been thoroughly carried out. The low-emission driving requirements which will be used in WP3 (to plan and execute real-world tests and lab experiments of vehicle emissions from engines, brakes and tyres) and in WP5 (to develop guidelines and tools for low-emission training)) have been analysed in great detail. The overall finding is that there are an enormous number of studies carried out to monitor, analyse and model the relationship between driving behaviour and air pollutants emitted from road vehicles. Key findings from this review and recommendations and guidelines for new driving behaviour data to be collected in this project are summarised as follows.

9.1 On variability of driving behaviour

9.1.1 Summary of driving behaviour variability

The main factors related to driving behaviour variability have been reviewed from NDSs (Naturalistic Driving Studies), large-scale FOTs (Field Operational Tests) and other published materials. The driving behaviours are structured by the factor categories, such as vehicle types, time of the day, road types, countries, weather, gender, ages, and driving experience. The main conclusions are as the follows:

- Private cars have the highest mean vehicle speed and speed variations compared to other types of vehicles, meanwhile they have the highest mean acceleration and deceleration in all speed ranges. The mean vehicle speed and speed deviations are low for trucks.
- At the daytime (especially 2 pm), vehicle speed is low which can cause a high exhaust emission factor compared to other time; meanwhile, speed deviations are quite high which indicates the frequent deceleration and acceleration.
- High speed situations mainly happen at highway, and low speed focuses on collector and arterial roads; the speed changes over different road types are quite different if training and eco-driving technologies are used.
- Vehicle speed distributions and acceleration distributions are different for various countries, which can be caused by the joint effects from weather, road characters, traffic conditions, and so on.
- Terrible weather conditions tend to decrease the mean vehicle speed, and lead to a higher percentage of time in deceleration and acceleration.
- Female drivers tend to drive slower than male drivers.
- Young drivers have a higher driving speed than older drivers; meanwhile old drivers drive gently with low speed deviations.
- Greater experience produces significantly smaller speed deviations; however, the effect of driving experience on mean vehicle speed is still in debate.

9.1.2 Recommendations and guidelines for new driving behaviour data

Driving behaviour variability is affected by many factors which need to be considered when the road test is planning. Table 9.1 shows the level of influence of the factors in relation to driving variability. The recommendations are as the follows:

- Vehicle types: three vehicle categories (passenger car, light duty vehicle, and heavy duty vehicle) are recommended to be included when planning real road tests. Three vehicles for each category are suggested.

- Time of the day: The real road tests are recommended to be conducted at daytimes, especially for the rush hours.
- Road types: both urban roads and motorway are recommended for future road tests. At least three road sections for each road category should be taken.
- Countries: it has a low priority, such that it can be dependent on the requirements and availability of the project.
- Weather: weather conditions have a medium priority, and the safety of the tests should be covered, so clear weather is recommended.
- Gender: real road tests should include an equal number between male and female drivers.
- Ages: ages will cause a significant variability of driving behaviours during real world tests, such that ages of the drivers should cover the hole ranges (18~70 years)
- Driving experience: suggest 10 drivers for each driving experience level (new drivers, average experienced drivers, and experienced drivers) for real road tests.

Table 9.1: Priorities of the factors should be included in the real road tests

Factors	Vehicle type	Time of the day	Road types	Countries	Weather	Gender	Ages	Driving experience
Priority	Medium	High	High	Low	Medium	High	High	High

9.2 On exhaust emissions

9.2.1 Summary of key factors influencing exhaust emissions

Several emission monitoring approaches have been introduced, such as portable emission tests, remote sensors, and chassis dynamometer. In addition, various emission models that are widely used have been reviewed. The emission models can be divided into four categories:

(1) Professional software-based model, which needs the vehicle specific parameters and tested engine maps, such as fuel consumption map and exhaust emission maps.
(2) Regression models, where the coefficients of the emission equations are fitted using the real test data, but they have some limitations under special situations such as cold start, fuel cut-off if aggressive deceleration.
(3) Inventory model, where the emission factors can be looked up or indirectly calculated from the database, as long as the related situations are provided (e.g. vehicle type, road situation, fuel type and so on).
(4) Energy consumption-based model, where the exhaust emissions are estimated based on the fuel consumption of the engines. This kind of model is slightly weak because it has an assumption that there are clear and unique equations between fuel consumption and exhaust emissions. In reality, the fuel consumption and exhaust emissions are not consistent for most situations.

Based on the reviewed exhaust emission database, the preliminary meta-analysis of the vehicle emissions is conducted to uncover exhaust emission disciplines and distributions for all types of vehicles, and preliminary results are presented. As a summary, the key factors influencing exhaust emissions are presented in Table 9.2.

Table 9.2: Key factors influencing exhaust emissions

Driving behaviour related factors	Non-driving behaviour related factors
Vehicle speed distribution Average speed Average driving speed without stops % of distance in speed interval 50~70 km/h Acceleration distribution Average acceleration % of time in acceleration % of distance in acceleration Deceleration distribution Average deceleration % of time in deceleration % of distance in deceleration Frequency of stops Average stop durations Gear upshift speed Gear downshift speed Frequency of gear shift Average engine speed when shifting gear up	Vehicle type Engine technology Vehicle ages Fuel types Loading mass After-treatment system Cold start conditions Road types Regions Traffic conditions Weather

9.2.2 Recommendations and guidelines for new exhaust emissions data

Recommendations for the new exhaust emission data are shown in the following:

1) In order to investigate the low emission driving behaviours for a given vehicle, driver and route, the effect of warm up process on exhaust emissions should be clear. Such that, the records of coolant and lubricating oil temperature during real road tests are necessary to figure out the warm up difference for various driving behaviours. Two Euro-6 compliant passenger cars (one diesel vehicle and one petrol vehicle) are suggested to conduct three real road tests for each vehicle, with recording the temperature histories of coolant, lubricating oil, after-treatment.
2) Altitude shows a significant effect on the driving behaviours and exhaust emissions, which may be caused by low fresh air density, but it is still unknown. Real road emission tests under this type of roads, whose altitude is higher than 1500 m (at least), should be done for one Euro-6 compliant diesel vehicle and one petrol vehicle.
3) After-treatment performance over different conditions should be tested under real roads, in order to figure out the situations where the after-treatment is failure of emission reductions. It will provide guidelines for retrofit technology. Because the after-treatment efficiency is low for urban driving even after long time running. One Euro-6 compliant diesel vehicle and one petrol vehicle under urban driving situations are recommended.
4) In the MODALES project, particle number is an important KPI to be assessed. However, the relations between driving behaviours and particle number emissions are few to date, meanwhile the equations between them is still unknown. Number emissions of particles from one Euro-6 compliant diesel vehicle and one gasoline direct injection (GDI) vehicle are recommended to be used to conduct real-world tests over both urban road and motorway.

5) In the meta-analysis section, it is difficult to normalise exhaust emissions due to the external (road, drivers, weather and so on) and internal (vehicle itself) factors influencing exhaust emissions. So, two passenger cars (one petrol-fuelled and the other diesel), one van, one truck are recommended to test the vehicle emissions under the same urban road and motorway (at least three sections for each road categories).

9.3 On emissions from brake wear

9.3.1 Summary of key factors related to brake emissions

Non-exhaust sources (e.g. brake, tyre, road surface) contribute significantly to road traffic-related PM emissions. Brake wear has been recognised as one of the most important sources of NEE. The difficulties associated with the study of brake wear particles include:

- Physical-chemical characteristics of brake wear particles are different;
- Generation mechanism and rate vary;
- A wide variety of sampling methodologies and measurement techniques are used.

The wear rate (or emission factor) of brake depends on road conditions, driving behaviour, traffic intensity, etc., which can partly explain the wide range of values observed. There are functional relations that predict the quantity of brake wear emitted per distance driven, under typical driving, in particular braking, conditions. On the other hand, a set of standardised measurement and sampling procedures are needed. Inter-laboratory correlation exercise can be carried out to evaluate the repeatability and reproducibility of the tests carried out by different researchers.

Road dust resuspension was advised not to be examined – due to the fact that re-suspended dust derives from multiple sources, some of which are not traffic related (i.e. industry, natural sources). There is a general problem in distinguishing brake wear particles from those arising from resuspension of deposited brake dust from the road in real traffic environment. Laboratory testing that enables the wear debris to be collected without significant particle loss to the surrounding is believed to more reliable than on-road testing.

Regenerative braking does not rely on frictional wear of brake materials, thus vehicles using regenerative braking, e.g. electric vehicles, should have lower brake wear emissions. However, tyre and road wear emissions increase with vehicle mass (so is brake wear), which has implications for any vehicle with a powertrain that is heavier (e.g. due to additional battery and hardware mass) than conventional fuel-powered vehicle it replaces. The net reduction of brake wear emissions and potential increases in tyre and road wear emissions from electric vehicles remains unquantified. Further experimental studies are recommended.

To conclude, the high variability of the brake emission factors reported in the literature is mainly ascribable to the different brake cycles used during the emission measurement. Furthermore, the driving parameters that influence the brake emission factors are summarised in Table 9.3 with the estimation of their importance on the measured emissions.

Table 9.3: Parameters influencing the brake emission factors

Parameter	Influence on the Brake Emission Factor
Disc temperature	High
Initial brake speed	High
Average deceleration	High
Braking time	Medium
Use of the engine brake torque	Medium
Average acceleration	Low
Traffic situation	Unknown
Distance with other vehicles	Unknown

The disc temperature, the initial brake speed and the deceleration level play the most important roles in the brake emission factors. Typically, the higher their value the higher the brake emission factor will be. The use of the engine brake torque by the drivers influence in a significant way the emissions because it is strongly related to the initial brake speed and to the disc temperature. Acceleration of the vehicle also contributes to the variation of the brake emission factors though to a limited extent. I In fact, the particles, which have been generated by previous braking actions, could be expelled from the pad-disc system due to the variation in the centrifugal force generated by an increase in the rotational speed of the brake disc. The traffic situation and the distance to other vehicles have hardly been investigated in the literature and their influence on the brake emission factors is still not clear.

From the literature survey conducted in this chapter, the influence of different measurement methods is found as the main source of variability in the brake emission factors. This leads to the fact that selection of the correct brake sequence for testing the brake emissions is fundamental to the measurement of real-world emission factors. The study of the most representative brake cycle, that has been carried out by the Particle Measurement Programme (PMP) by UNECE informal Working Group, highlighted that the average European braking behaviour is characterised by mild braking actions at slow vehicle speeds and with limited vehicle decelerations. As a general consideration, the general guidelines for decreasing the brake emission factors should be a defensive and conservative driving style characterised by the use of engine brake torque to limit the initial brake speed and the temperature of the braking system.

9.3.2 Recommendations and guidelines for new laboratory data

The high variability of brake emission factors reported in the literature leads to the need of defining a novel testing procedure that could guarantee a better measurement of the actual emissions from the brake wear. The work of the PMP – Informal working group about the non-exhaust emissions made first steps of developing a new experimental setup to characterise the emissions of brake materials with brake dynamometers.

Thanks to the efforts of several industrial and academic partners, a novel cycle has been developed and proposed for the measurement of brake wear emission. This cycle, described in section 4.6, has been named WLTP-Brake. Furthermore, a novel procedure considers this WLTP-Brake cycle as the reference cycle for brake emission measurements. This testing procedure provides a definition of reference brakes, used in proving-ground measurements, and equivalent brakes (i.e. equivalent to the reference ones) to be used for the dynamometer testing. At present, the data collected from on road-tests with instrumented vehicles are based on internal combustion engine (ICE) vehicles equipped with standard brake rotors, i.e. made of cast iron and standard brake pads, such as NAO, low-met or low-steel friction materials. According to the definition of equivalent brake, the disc dimensions will not differ by more than 8 mm in the outer diameter and 4 mm in thickness, compared with the reference brake used for the on-road tests. These requirements about the reference and equivalent brakes are fundamental to ensure the reproducibility of disc temperature profile during the test that, as extensively reported in the literature, is one of the parameters with the highest influence on the brake emissions. In addition to the considerations above, the testing protocol defines some fundamental guidelines for the correct implementation of the tests:

- The inertia used to simulate the vehicle mass must be adjusted to take into account the vehicle parasitic losses (due to the aerodynamic drag, internal friction of the components and the friction between the tyres and the road);
- A disc temperature metrics to be referred to during the tests, this metrics have been defined on the basis of road-tests with instrumented vehicles.

According to the most recent guidelines from the PMP group (Steven, 2016), the brake enclosure of the brake dynamometer must satisfy the following requirements:

- It must be made of a conductive grounded material, to avoid losses of the emitted particles due to electrostatic forces;
- The inner walls of the chamber must be smooth;
- The cross-sectional changes inside the enclosure must be small and gradual;
- The calliper fixtures must be positioned in the upper part of the brake disc.

As for the brake enclosure, and the inlet airflow, which are used to cool down the brake during tests and to bring the particles to the sampling instruments, must meet some requirements:

- Filtered, through a high efficiency filter (HEPA H13 or equivalent);
- Conditioned at 20±2°C and 50±5% RH.

All these requirements and guidelines must be adhered to provide reliable and reproducible data of brake wear emissions.

During these brake dynamometer tests, several parameters are going to be monitored and measured, the most important ones are summarised in Table 9.3 and Table 9.4.

Table 9.4: Measured parameters during brake-dynamometer tests

Parameter	Description
Disc mass loss	Measured in [g], it is the total amount of material lost by the disc from the beginning to the end of the test
Pad mass loss	Measured in [g], it is the total amount of material lost by the pads from the beginning to the end of the test
Temperature of the disc	Real-time temperature of the brake disc
Particle number concentration (PN10)	Real time concentration of particles, measured in [#/cm^3], during the test
Particulate matter mass (PM10)	Particulate matter mass in [mg] collected on different substrate, according to the aerodynamic diameter of the particles
Vehicle simulated speed	Real-time simulated vehicle speed, in [km/h], measured during the entire cycle
Simulated vehicle deceleration	Deceleration of the vehicle, in [m/s^2], that is simulated during the braking actions
Brake pressure	Pressure of the brake fluid, in [MPa], during each braking action
Brake torque	Real-time brake torque, in [N m], measured during each braking action

In order to fulfil the aim of the MODALES project and to explore the braking behaviours that are not considered by the WLTP-Brake "standard" cycle, some tests with two variants of this cycle need to be performed. The reason behind this is the need for a better relation between brake emissions and braking conditions. By testing the brake system in harsher and milder conditions with respect to the "standard" cycle and relating the measured emissions to the modified testing parameters, some fundamental principles can be found. The information can be used in the development of guidelines for the modification of the driver behaviours in order to reduce the emissions from the brake wear.

9.4 On emissions from tyre wear

9.4.1 Summary of key factors related to tyre emissions

The main conclusions drawn from the present literature study can be summarised below:

- Available data indicate exhaust and non-exhaust sources contribute almost equally to total traffic-related emissions. Among non-exhaust sources, tyre and road wear particles can contribute from 5% to 30 % by mass to non-exhaust traffic-related emissions. Tyre wear particles represents between 1%-8.5 % by mass to PM10 emissions. Among tyre wear particles, only up to 10% are PM.
- Given the variety of factors that influence the generation of tyre wear particles, any future efforts at reducing this source would need to consider not only the characteristics of the tyre, but also the vehicle to which it is mounted, the manner in which the vehicle is operated and the pavement on which the vehicle is driven.
- As varied sampling and analysis methodologies have produced non-comparable and in some cases even contradictory results, a single methodology should be developed to produce reliable and comparable results.
- The most important chemical constituents of tyre wear are comprised of both coarse and fine particle fractions. Despite the fact that some research regarding organic constituents of

wear particles has been conducted, there is very limited information regarding organic composition of tyre wear particles.

- The available information on tyre wear particles requires collation, and the methodologies currently employed to measure and model emissions should be summarised in order to provide general recommendations for model development.
- Tyre wear involves mechanical processes, thermos-mechanical and thermochemical processes. These processes result in different size distribution of tyre wear particles. Size distribution is extremely critical parameters, because the airborne particles generated from tyre wear seriously harm the environment and human health and are likely to become one of the restricted non-exhaust emissions. More detailed information regarding size distribution of tyre wear particles can be found in the literature (Gustafsson et al. 2008b, Harrison et al. 2012, Kim &Lee 2018, Kreider et al. 2009, Kreider et al. 2010, Kumar et al. 2013, Park et al. 2018, Sjödin et al. 2010)

9.4.2 Recommendations and guidelines for new driving data for tyre emissions

Since the MODALES project is focused on the link between particle emissions and driving behaviour, we propose to set up a classification (Table 9.5) of these influencing factors which could be a method for the driver to reduce his tyre emissions.

This classification sort in term of influence domain for the driver:

- Methods that driver could activate **before driving**
- Methods that driver could activate **during driving**
- Methods that driver could activate **outside a driving phase**

Each factor is linked to a physical parameter which can be measured and ranked in term of knowledge maturity. Since it is difficult to study all these factors in an experiment, we propose to focus on the more important parameters in the work package 3.3 (WP3.3).

Table 9.5: Driving behaviour influencing factors on wear rate classification

Influence domain	Controlled parameter	Physical parameter impacted	Knowledge maturity (0..2)*	Studied in WP3.3	Potential impact (1..3)**
Before driving (preparation)	Trip duration	Tyre thermal state --> tyre wear impact	2	x	2
	Route choice (grading)	Torque applied at the wheel	2	x	2
	Route choice (type of road)	Road roughness (µ)	1		2
	Load repartition	Tyre load repartition	2		1
During driving	Longitudinal acceleration	Ax	2	x	3
	Lateral acceleration	Ay	2	x	3
	Average speed	< V >	2	x	3
Outside a driving phase	Inflation pressure	P	1		2
	Permutations	/	0		1

*0: no scientific publication available | 1: one scientific publication available | 2: few scientific publications available

**1: Moderate impact on tyre wear | 2: Intermediate impact on tyre wear | 3: Strong impact on tyre wear.

9.5 On driving profiles based on smartphones

Many mobile apps have already been developed for helping drivers to reduce their emissions, both through academic or industrial projects. However, to the best of our knowledge, existing applications do not provide the level of user experience anticipated in MODALES. Figure 9-1 presents a few popular of these apps and classifies them according to two fundamental differentiating criteria.

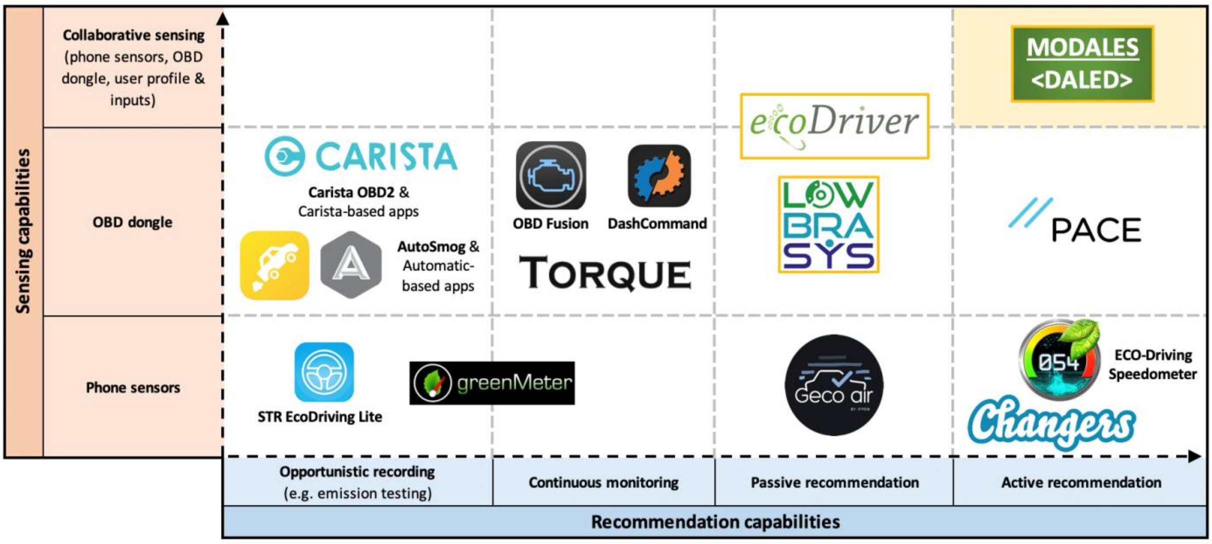

Figure 9-1: Preliminary competitive matrix of the apps (to be further developed in WP5)

The data collected by the app is an essential element for understanding the relationship between a user's behaviour and emissions produced by his/her vehicle. Many apps focus on using the phone's built-in sensors, such as *greenMeter* (accelerometer) or *Geco air* (GPS). This can result in easily obtainable estimates that do not require any additional equipment, although they are usually limited in terms of analysis and accuracy. Other more advanced apps use data provided exclusively by an ODB dongle (e.g. *PACE*), or even combine these two data sources (e.g. *ecoDriver*). MODALES is opting for a fully modular and collaborative sensing system. Users are free to use the data sources they require – the most important factor to consider is the personal preferences the app needs in order to build a representative driver profile, and thereby recommend relevant targeted actions. New models, to be created, will consider all these data inputs. More importantly, unlike existing solutions, our efforts will be aimed at developing an exclusively local application, one that is not based on online services, which are rarely adapted to real-time assistance.

On the other hand, the level of recommendation given to the user is also a fundamental factor for changing driving habits as effectively as possible. While most apps generally provide only a measuring or monitoring service, some of the more advanced ones offer relevant and precise recommendations, but they do so only after the trip is over, or in an extremely simplified way during the trip. MODALES, will create an individually tailored learning strategy that interacts with them safely and actively while they are driving and uses gamification techniques to provide proactive follow-up strategies.

An important aspect is that DALED does not seek to reinvent concepts already widely exploited by past projects or applications, but rather to use the knowledge accumulated by all these components in order to go further in the solutions offered to the end-users. Thus, we will take advantage, from the specifications to the implementation of our prototype, of the resources already available and the results of projects such as *Lowbrasys* or *ecoDriver*, which are among the most advanced prototypes to date, and in which MODALES partners have participated.

This study is only a preliminary view of applications that compete with MODALES and that meet the challenges associated with driving profile identification. It will be completed and further developed in the framework of the project's innovation management task and WP5.

9.6 On low-emissions, safety and fuel consumption

9.6.1 Summary

Driving behaviours are closely related to exhaust emissions, fuel consumption and driving safety. Detailed analysis of the equations between driving behaviours and exhaust emissions/fuel consumption/driving safety uncovers how these factors are related. KPIs related to vehicle speed, acceleration and deceleration are the key factors influencing exhaust emissions and fuel consumption. Vehicle speed profiles are the main target to optimise for eco-driving and low emission driving. For the safe driving, numbers of traffic regulation infractions per distance, numbers of distraction per distance, drunk driving, excessive speed and driving in the wrong direction are the most important factors.

9.6.2 Recommendations for new driving behaviour data

Low emission driving, eco-driving and safety driving have different requirements for the driving behaviours. As shown in the above tables, the overlaps of the driving behaviour among low emission driving, eco-driving, and safety driving are vehicle speed, acceleration and deceleration. For the acceleration and deceleration, low emission driving, eco-driving and safety driving have the same requirements that the acceleration and deceleration should be low. Low emission driving and eco-driving care about the absolute vehicle speed. However, safety driving is more dependent on the difference between the individual speed and traffic average speed, which is related the traffic conditions and road types. So, different requirements should be put forward based on the road types and traffic situations. The requirements for the low emission driving (especially for NOx and PM emissions) and eco-driving sometimes have the trade-off phenomenon in terms of vehicle speed. Such that balance should be made between low emission driving and eco-driving. Additionally, during the engine cold start conditions, low emission driving should have a priority requirement due to the failure of after-treatment at low temperature situations. After the engine is fully warmed up, aftertreatment has an excellent performance such that the exhaust emissions are quite low no matter the vehicle speed. Such that, eco-driving should have a high priority for the vehicle speed requirements under this situation.

9.7 On low-emission driving requirements

Table 9.6 presents the parameters that characterised both eco-driving and low emissions driving and give a comparison between these two driving styles. From the Table, both driving styles are characterised by similar driving techniques which makes them almost similar. As a result, if a driver adapts these driving techniques can achieve lower fuel consumption and lower emissions.

Table 9.6: Parameters that characterise the "eco-driving" and the "low-emission driving"

Parameters	Eco-Driving	Low-emission driving
Target		
Fuel consumption reduction	√	
Exhaust emissions reduction (CO_2)	√	
Exhaust emissions reduction (pollutant emissions, e.g. NOx)		√
Brake emissions		√
Tyre emissions		√
Driving profile		
Maintain a steady speed (low RPM)	√	√
Drive at low engine speeds in the highest gear possible	√	√
Shift up gears early	√	√
Release the throttle early and coast the vehicle with a gear engaged in order to stop or decelerate	√	√
Reduce idling time (stop the engine, even at shorter stops)	√	√
Do not drive too fast	√	√
Do not accelerate too quickly	√	√
Route selection		
Prefer flat roads	√	*
Avoid roads with traffic	√	*
Avoid roads with many lights	√	*
Vehicle maintenance		
Check tyre pressures frequently at least once a month and before driving at high speed	√	√
Consider any extra energy used (e.g., air conditioning)	√	*
Reduce vehicle weight (avoid carrying unnecessary things)	√	*
Improve aerodynamic drag (avoid adding exterior parts in the vehicle like roof bags etc.)	√	*

* = potentially relevant but outside the scope of MODALES

Recommendations for low-emission driving are summarised in the following table.

Table 9.7: Requirements for low emissions driving

A/A	Factor	Tips/Advices
1	Acceleration/Deceleration	Normal or mild driving is preferable (avoiding aggressive accelerations and decelerations)
2	Speed	Keeping constant speed: • for light vehicles at about 80-90 km/h • for buses 40-50 km/h • for trucks 75-80 km/h
3	Idling	Avoid unnecessary idling, turned off the engine for a waiting time more than 1 min
4	Gears	Shifting gears sooner to keep the engine speed lower
5	Route choice	Avoid routes with many lights and much traffic. Select eco friendly routes instead of shorter distance or less time routes
6	Grade-terrain	Select flat routes instead of hilly roads
7	Tyre pressure	Keep your tyres in good condition with air pressure at the manufacturer recommended values
8	Weight	Avoid carrying extra un-necessary weight in the vehicle
9	Aerodynamic	Avoid using exterior parts like large blunt roof cargo boxes etc.
10	Parking place	Prefer parking the car in the shade in hot weather and in a warm place in cold weather
11	Cold start	Avoid idling and driving off gently for about 10 s to warm up the engine
12	System adaptations	If the vehicle equipment includes eco systems, it is recommended to turned them on (for example, start/stop, eco routing navigation system, accelerator adaptor etc.)

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10.7 In Chapter 8

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Adapting driver behaviour
for lower emissions

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