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Optimisation of driving-parameters and emissions of a diesel-vehicle using principal component analysis (PCA)

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Abstract

Light-duty diesel vehicles contribute significantly to urban air pollution. Laboratory-based standard driving test cycles do not take into account external driving factors, which greatly impact the vehicle emissions compared to the real-world driving emission (RDE) measurements. This results in higher emission levels obtained by RDE tests, compared to the standard approaches. In the current study, an RDE measurement campaign has been conducted in Brisbane city traffic using a portable emission measurement system (PEMS). Thirty drivers with a wide variety of driving experiences participated using a Hyundai iLoad van in a custom test route. RDEs and driving parameters were recorded during each trip. Principal component analysis (PCA) was applied to investigate the relationship between driving dynamics and vehicle emissions. Also, the impact of different trips, driving time, and driving experience on driving behaviour and emissions. Route familiarity, traffic density, and driving experience have a strong impact on driving behaviour and emissions. The driver's response to changing traffic, unknown routes, and vehicles significantly vary among different drivers which results in a high volume of transient events (frequent acceleration and deceleration). Transient events are very common in city driving which has a strong correlation to vehicle emissions.

Keywords

Real driving emissions (RDE); Portable emission measurement systems (PEMS); Air quality; Principal component analysis (PCA).

Introduction

Urban air quality degradation is a serious public health concern as half of the world's population lives in urban areas. Road transport is a major source of air pollution in urban areas and has adverse effects on human health and the environment [1]. Several studies reported that on-road emissions are a major cause of cardiovascular and pulmonary diseases [2,3]. In recent years, an increasing number of deaths and hospital admissions have been reported due to exposure to air pollution, mainly affecting children and the elderly population. In Australia on-road emissions causes around 900 to 4,500 premature deaths yearly by cardiovascular and respiratory diseases [4]. In cities having a high population density, a small increase in air pollution can have a serious impact, such as a region with 5 million population, an increase in $PM_{2.5}$ of 10 μm/m^3 contributes on average one premature death per day [5]. To reduce air pollution, regulatory authorities continuously impose stricter emission legislation. For example, the EU commission reduced the NOx emission limits of diesel cars from 500 mg/km to 80 mg/km. This is implemented in the last 15 years (EURO 3 to EURO 6), however, the reduction is lower than the expected [6]. Until EURO 5 regulation, the vehicle emission certification procedure was laboratory-based using chassis-dynamometer testing where the vehicle was tested in a specific drive cycle such as the New European Driving Cycle (NEDC). During the test, the vehicle is run at different operating conditions, and the exhaust emissions are sampled using different gas analysers to measure the pollutants in the exhaust stream. Engine emissions are influenced by both engine internal factors such as engine operating conditions, driving parameters, exhaust after-treatment systems, and external factors including ambient air and temperature. These factors cannot be completely replicated in a test bench setup. Some transient cycles may be the representations of on-road measurements, however, vehicles vary depending on types, uses, and so many other factors. Also, one single cycle may not represent real road driving emissions. On-road studies can play an important role in minimising the shortcomings of existing emission testing models. Vehicle driving parameters such as speed, acceleration, deceleration, stopping, and gear shifting have a significant impact on vehicle emissions [7]. Moreover, in many cases, real driving emission testing found much higher values than that of the test bench [8,9]. For these reasons, the revised version of the Euro 6 emission standard Real Driving Emission (RDE) test is mandatory.

It is important to understand the influence of different driving dynamics on vehicle emissions as on-road emissions significantly change based on these parameters. There are multivariate statistical tools capable of providing powerful insights into vehicle emissions [10,11]. The current study aims to investigate the impact of driving time, driving experience, and trip number on driving behaviour and vehicle emissions. In addition, the relationship between driving dynamics and emissions, which will contribute to the development of driving dynamics-based emission models will also be explored. A multivariate statistical analysis method will be implemented to explore the relationship between the variables.

Real Driving Emission measurement campaign

The measurements were conducted in August 2019 in Brisbane city. A Hyundai iLoad 2017 diesel van was used to measure emissions and relevant driving parameters during the real-time driving cycles. The test vehicle specifications are given in table 1. This specific vehicle was chosen for the measurement as it is a popular model in the Australian market mostly used by couriers and tradespeople in urban areas. Figure 1 shows the map of the test route. The designated driving route is approximately 12.5 km in length and mostly covers city traffic with a portion of the motorway. The test route starts and ends at O-block, Queensland University of Technology (QUT) city campus. The route includes the usual city driving features such as inner-city highway, residential area, school and hospital zone, CBD (central business district), etc. To assess the real-world emissions and driving behaviour by the general users, thirty participant drivers were selected from a wide range of variation in terms of age, driving experience, profession, gender, and nationality. Each driver completed two trips on the designated route in order to evaluate the impact of familiarity with the vehicle and route on emissions and driving behaviour.

Figure 1. The test route for real driving emission measurement.

Emission standard	EURO 5b
Engine Capacity	2.5 L
No of Cylinders	4
Maximum torque	441Nm
Maximum power	125 kW
Odometer reading	14xxx km

Table 1. The Hyundai iLoad 2017 diesel van specifications.

Experimental Setup

A portable emission measurement system (PEMS) was used to measure vehicle emissions, engine parameters, and speed-related parameters. Four sensors were installed in the vehicle exhaust line which is connected to the PEMS data acquisition system to measure the gaseous emissions (NOx and CO_2) and exhaust temperature and pressure. The PEMS also measured the engine parameters through the vehicle onboard diagnostic port (OBDII). Instantaneous vehicle speed and position were recorded by the PEMS GPS device. The vehicle speed and acceleration-based driving dynamics parameters were calculated using the procedure developed by Barlow [12].

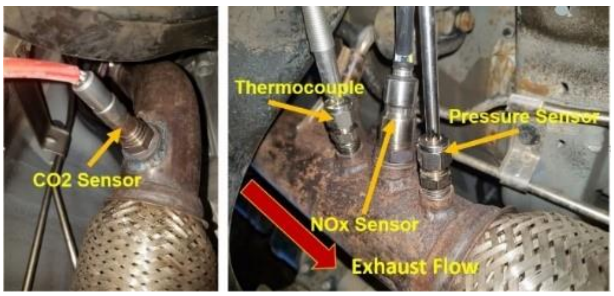

Figure 2. The installed sensors in the tested vehicle exhaust line.

Principal component analysis

The current study implemented principal component analysis (PCA) as a statistical tool to (a) perform the dimensional reduction among several driving dynamics and emission parameters, (b) explore the relationship between the driving dynamics and emissions and (c) investigate the impact of independent variables such as trip number, year of experience and driving time on driving behaviour and emissions. PCA is a commonly used multivariate data analysis method used on dimension reduction of data by identifying the principal direction without a significant loss of information [13]. PCA uses an orthogonal transformation algorithm that removes redundant variables and creates some new variables called principal components. These new variables are linearly uncorrelated and conserve the original information as much as possible. The primary purpose of implementing PCA in a data set is to: (a) identify a specific pattern, (b) dimensional reduction, and (c) specify the correlated variables. PCA uses a matrix factorization technique named singular value decomposition (SVD) to calculate the principal components of a dataset. Using SVD in a PCA analysis is advantageous as it is numerically robust, and it provides an overview of the working principle of PCA on both algebraic and graphical results. The algorithm performs to find the SVD of matrix X. The SVD results in orthogonal matrices (U and VT) which arise from left and right singular vectors as well as a square matrix (D) which contains the singular values as given by:

$$X= UDV^T \qquad (1)$$

The X can be further decomposed into loadings (P) and scores (T) matrix via:

$$X= (UD)V^T =TP^T \qquad (2)$$

The loading matrix interprets the influence of the dependent variables to a specific PC. The high magnitude of a specific variable in a PC indicates a strong influence of such variables in the resulting PC. The scores matrix presents the new co-ordinate space of the data found by PCA. In the current study, the number of dependent variables obtained from experimental measurement is quite large compared to the number of test conditions (independent variables). In such a case PCA is a useful technique for dimensional reduction and pattern recognition of the data set. The PCA was performed using RStudio version 3.4.2 in cooperation with FactoMineR and psych packages.

Results and discussion

A total of sixty trips were performed by thirty participant drivers in the designated route using the same test vehicle. Engine parameters, emissions, and driving dynamics parameters were recorded during each trip. The trips can be classified based on the trip number, driving period, and driving experience of the drivers to assess their influence on driving behaviour and emissions. Scores plots are presented in Figures 3, 4, and 5 based on the above-mentioned classifications. Figure 3 shows a clear difference in driving pattern between the first and second trips. PC 1 and PC 2 denotes principal component 1 and 2, respectively. In trip 1 the route and vehicle were unfamiliar to the drivers. In trip 2 the number of drivers clustered together is higher than trip 1 hence the drivers showed a similar pattern due to the increase of certainty with the route and better control over the vehicle. Figure 4 shows the effects of traffic density on the driving pattern. It can be seen that during the off-peak time, the majority of the drivers followed a similar pattern due to a reduction in the external interruptions on the route. On the other hand, peak time has a significant impact on driving style, leading to a lack of correlation between drivers. Peak time traffic conditions affect driving dynamics such as accelerating, braking, cornering, and taking traffic lights and speed bumps varied driver to driver. All these parameters have a great impact on emissions. Figure 5 shows the variation of driving patterns based on the driving experience. Years of driving experiences have a significant impact on driving style. It is seen that the drivers with low experience had shown a scattered distribution than the experienced drivers. Though driving behaviour not only depends on driving experience but also the other parameters such as traffic condition, familiarity with the route, and vehicle. The impact of driving experience on driving style could be further investigated as driving aggressiveness increases vehicle emissions.

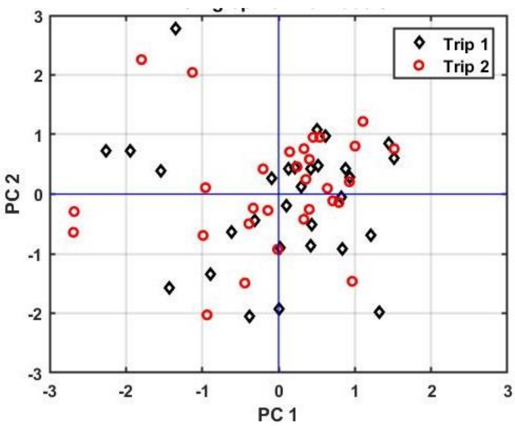

Figure 3. Scores plot all drivers based on the trip number.

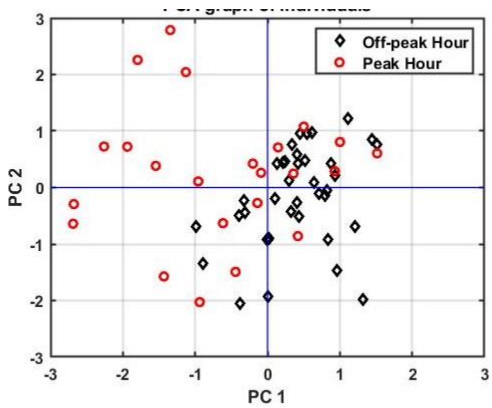

Figure 4. Scores plot all drivers based on driving time.

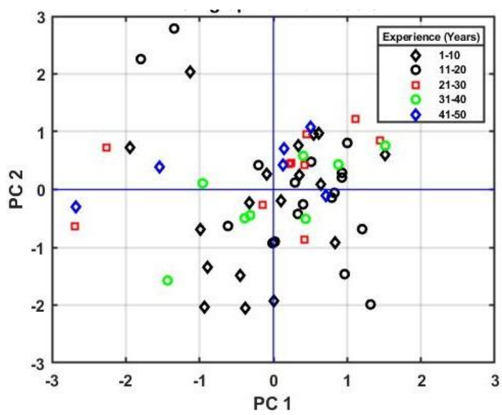

Figure 5. Scores plot all drivers based on the driving experience.

Figure 6 shows the factor loading diagram of the measured variables and the resulting principal components. The black line denotes the positive correlation and red line for anti-correlation among the variables. The absolute values of the factor loadings denote the strength of the correlation. The first PC is mostly dominated by time and speed-based parameters (DT: driving time, decT: deceleration time, AT: acceleration time, TT: total time, BrT: braking time, avgSpd: average speed, RCS: relative cubic speed, maxSpd: maximum speed, StT: stop time) while the second PC is influenced by the engine and emission parameters. Driving behaviour related parameters are dominant in the current analysis having comparatively strong correlation factors than the engine and emissions parameters that can be seen from the factor loading diagram in figure 6.

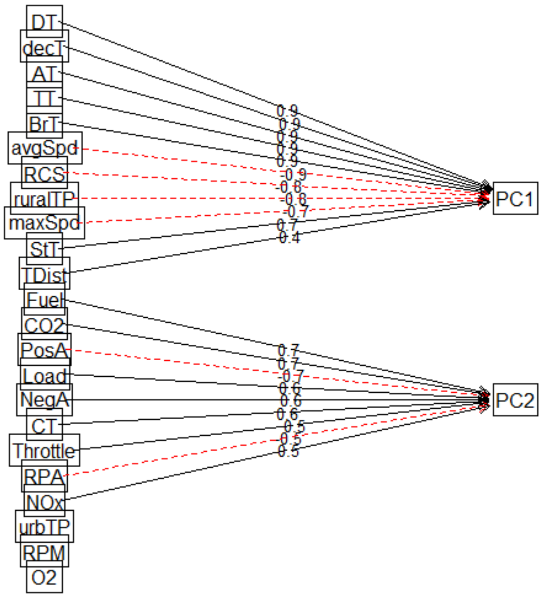

Figure 6. Factor loading diagram for the first two principal components.

The loadings plot in Figure 7 shows the relationship between the dependent variables. Strongly correlated variables lie close to each other (±45°), variables in opposite direction are anti-correlated (135-225°) and variables in orthogonal direction are independent or uncorrelated (45-135°) in the figure. NOx and CO_2 emissions have a strong correlation with engine parameters as expected. In particular, NOx and CO_2 emission have a strong correlation with negative acceleration (NegA) i.e stopping and urban time percentage (urbTP). Therefore, in the city driving the higher number of traffic signals and route features such as a roundabout, speed bumps increase the braking percentage which has a strong influence on emissions. It can also be seen clearly from figure 7 that CO_2 emission has a significant positive correlation with fuel consumption while CO_2 shows strong anti-correlation with O_2, which are in good agreement with previous studies. Time-based variables grouped together have an anticorrelation with speed based parameters. However, both those groups are nearly perpendicular on PC1 with emissions above indicating that has a lack of correlation. Overall the PCA analysis results in three major groups among all the variables. The driving dynamics parameters which have a strong correlation with emission parameters can be used to develop a further model to predict emissions in terms of driving style.

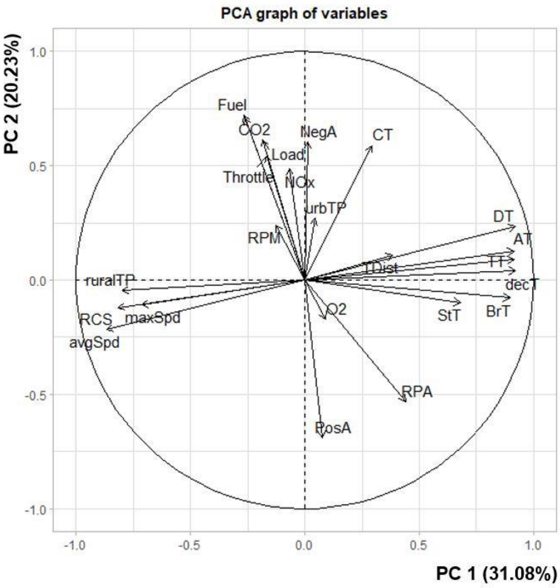

Figure 7. Loadings plot of variables.

Conclusion

The current study presented the real-time measurements of emissions and driving dynamics of a commercial light-duty diesel vehicle in urban traffic. The relationship between the driving dynamics and emissions have been investigated using principal component analysis. Moreover, the impact of different trips, driving periods, and year of experience on driving behaviour and emissions also investigated. The study found that the second trip shows more organised driving than the first trip due to the increase in driving confidence. Busy traffic-driving does not follow a specific pattern and the way of dealing with the busy traffic significantly varies among drivers. Year of experience has a strong influence on driving behaviour. Hence, driver education would have some merit on the reduction of vehicle emissions. Gaseous emissions have a strong positive correlation with negative acceleration and urban time percentage. In the city driving a high volume of transient events (acceleration, decleration, barking) occurs which significantly increases vehicle emissions, which have a negative impact on urban air quality.

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