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Impact of vehicle type, tyre feature and driving behaviour on tyre wear under real-world driving conditions

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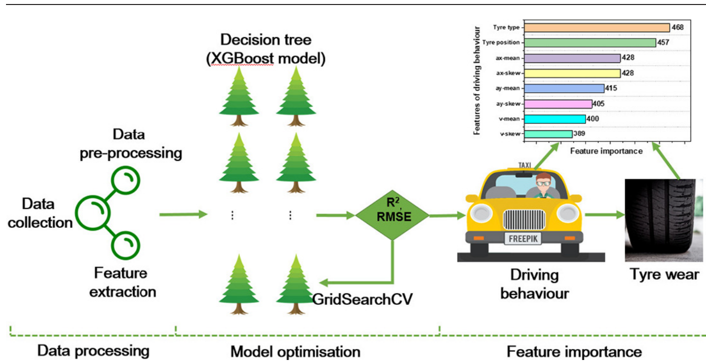
HIGHLIGHTS

- Tyre wear of front-wheel-drive vehicles was measured.
- Tyre wear rate for hybrid vehicles was higher than that for conventional vehicles.
- Tyre wear rate on real roads was highly dependent on tyre type.
- Average wear rate of left-front tyres was 1.8 times that of left-rear tyres.
- Braking and accelerating events presented the most crucial effect on tyre wear rate.

GRAPHICAL ABSTRACT



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ABSTRACT

Tyre wear generates not only large pieces of microplastics but also airborne particle emissions, which have attracted considerable attention due to their adverse impacts on the environment, human health, and the water system. However, the study on tyre wear is scarce in real-world driving conditions. In the present study, the left-front and left-rear tyre wear in terms of volume lost in mm^3 of 76 taxi cars was measured about every three months. This study covered 22 months from September 2019 to June 2021 and included more than 500 measurements in total. Some of the data was used to evaluate the effects of vehicle type and tyre type on tyre wear. In addition, a machine learning method (i.e., Extreme gradient boosting (XGBoost)) was used to probe the effect of driving behaviour on tyre wear by monitoring real-time driving behaviour. The current statistical results showed that, on average, the tyre wear was 72 mg veh^{-1} km^{-1} for a hybrid car and 53 mg veh^{-1} km^{-1} for a conventional internal combustion engine car. The average tyre wear measured for a taxi vehicle configuration featuring winter tyres was 160 mg veh^{-1} km^{-1}, which was 1.4 and 3.0 times as much as those with all-season tyres and summer tyres, respectively. The wear rate of left-front tyres was 1.7 times higher than that of left-rear tyres. The XGBoost results indicated that compared to driving behaviour, tyre type and tyre position had more important effects on tyre wear. Among driving behaviours, braking and accelerating events presented the most considerable impact on tyre wear, followed by cornering manoeuvres and driving speed. Thus, it seems that limiting harsh braking and acceleration has the potential to reduce tyre wear significantly.

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1. Introduction

Tyre wear is unavoidable during usage and is influenced by vehicle type (OECD, 2020; Oroumiyeh and Zhu, 2021), tyre characteristics (Jekel, 2019; Panko et al., 2018), road typology, ambient and driving conditions (Kim and Lee, 2018; Le Maitre et al., 1998; Yan et al., 2021). Some researchers have calculated the tyre wear rate based on the number of passenger cars registered, the total driving distance, and the annual amount of tyre wear. For instance, Lee et al. (2020) reported an average tyre wear rate of 51 mg veh^{-1} km^{-1} for passenger cars in Korea. Lassen et al. (2012) found a tyre wear rate of 132 mg veh^{-1} km^{-1} for passenger cars in Denmark. Hillenbrand et al. (2005) revealed that the tyre wear rate was 90 mg veh^{-1} km^{-1} for passenger cars in Germany. In addition, Luhana et al. (2004) calculated the weight loss of tyres on five-passenger cars during a specified driving distance. The average tyre wear rate for five cars was in the range of 56.4–193.3 mg veh^{-1} km^{-1}.

Tyre wear would generate different sizes of particles, which would damage not only the atmospheric environment and human health but also water systems. On the one hand, the debris with sizes below 5 mm from tyre wear, as the larger categories of microplastics, have a large specific surface area and thus have the capacity to readily adsorb pollutants (Adachi and Tainosho, 2004; Bakir et al., 2014; Gualtieri et al., 2005; Lee et al., 2020). The inflow of tyre wear debris into the water system causes the intake of the debris by aquatic organisms, potentially leading to the bioaccumulation of persistent organic pollutants (Mantecca et al., 2007).

On the other hand, tyre wear is one of important contributors to the non-exhaust airborne particulate matter (PM) from vehicles (Grigoratos and Martini, 2014; Harrison et al., 2012). To meet increasingly strict vehicle exhaust emission regulations, the rapid development of engine combustion control and after-treatment technologies has substantially reduced the amount of exhaust particle emissions (Wang et al., 2016; Woo et al., 2021; Liu et al., 2021, 2022). However, non-exhaust particles, including tyre wear and brake wear, have not been regulated yet. Grigoratos and Martini (2014) revealed that the maximum contribution of tyre wear particles to non-exhaust air particles in traffic by mass was up to 30 %. Harrison et al. (2012) evaluated the tyre wear particle emissions at the sampling site of the Marylebone Road in central London and found that tyre dust accounted for 10.7 % of total PM_{10} mass. Tyre wear particles are predominantly generated through the following two mechanisms: (1) shearing forces between the tyre tread and road surface would primarily produce large and coarse size particles (Kim and Lee, 2018; Kreider et al., 2010); (2) localized high-temperature hot spots on the tyre tread causes the volatilisation and condensation of organic compounds in the tyre tread, emitting fine-sized particles (Kreider et al., 2010; Mathissen et al., 2011; Park et al., 2017; Pohrt, 2019). In the studies by Baensch-Baltruschat et al. (2020) and Oroumiyeh and Zhu (2021), it was found that tyre wear particles accounted for 11 % of the traffic-related particles referring to PM_{10}. Tyre wear particles were mostly reported in the coarse size range of 2.5 to 10 μm (Gustafsson et al., 2008; Thorpe and Harrison, 2008), while ultrafine tyre wear particles were detected in some studies (Kim and Lee, 2018; Kumar et al., 2013; Mathissen et al., 2011).

Several methods have been employed for tyre wear measurement. In addition to the source analysis, the road simulators in the laboratory were used to study tyre wear and tyre wear particles (Gustafsson et al., 2008; Kim and Lee, 2018; Kupiainen et al., 2005; Tonegawa and Sasaki, 2021). Although laboratory measurements can adequately present repeatable results, they are unable to represent real-road driving conditions.

To the best of our knowledge, however, limited information exists concerning the effect of vehicle type, tyre properties, and driving behaviour on tyre wear under real-world driving conditions. The purpose of the current work is to ensure the importance rankings of driving behaviour on tyre wear. The finding regarding the importance rankings of driving behaviour on tyre wear is likely to be beneficial for designing training courses, which improve drivers' knowledge of low tyre wear via the training courses at driving schools and encourage them to adopt more friendly driving behaviours to reduce tyre wear. In addition, this study advances the understanding of the effect of tyre types on tyre wear, which provides preliminary information for users on how to choose low-wear tyres.

2. Methodology

2.1. Data collection and processing

Tyre wear can be evaluated by measuring the loss in tyre weight (Claffey, 1971) or by monitoring tyre-tread depth (Wang and Huang, 2017; Williams and Evans, 1983). In the current work, the tread-depth measurement was obtained using a laser depth gauge (Mitutoyo 571-100-20) with an accuracy of 0.01 mm (see Fig. S1 of the Supplementary data) since this method is easy to operate and can achieve high precision (Wang and Huang, 2017). The tyre wear in terms of volume lost in mm^3 is evaluated by the following equation:

$$V = d_T \cdot w \cdot (r \cdot 25.4 + w \cdot A_r \cdot 3.14) \cdot (1 - V_r) \tag{1}$$

where V is the volume loss of tyre wear (mm^3), d_T is the tyre tread-depth loss (mm), w is the tyre width (mm), r is the rim diameter (inch), A_r is the aspect ratio that refers to the ratio of the height of the sidewall from wheel rim to top of the tread to tyre width, and V_r is the void ratio that is a comparison between the amount of space taken up by gaps and the surface area of the tread face, which is dependent mainly on tyre tread pattern.

In the present study, 76 taxis from the fleets in Rome (Italy) and Athens (Greece) were monitored under actual operating conditions, of which the used vehicle characteristics are summarised in Table S1 of Supplementary data. Three types of tyres from Bridgestone Corporation were used with tyre pressures of about 51 psi, including the summer tyres, winter tyres, and all-season tyres. Summer tyres and all-season tyres were mainly used all year due to the warm climate in Rome and Athens. Few winter tyres were used in winter, which is used to explore the effect of tyre type on tyre wear.

This study covered 22 months from September 2019 to June 2021. The worn state of the vehicle's left front and rear tyres was recorded about every three months, and there were 552 measurements in total. A sub-group of total measurements was used to explore the effect of vehicle type on tyre wear, which was generated from two types of vehicles (Skoda-Octavia and Toyota-Auris), where Skoda-Octavia is a conventional internal combustion engine (ICE) vehicle, while Toyota-Auris is a hybrid vehicle. These two vehicle configurations featuring the same summer tyres of 205/55R16 94V have similar curb weights. A sub-group of total measurements was chosen to explore the effect of tyre type on tyre wear, which was generated from Skoda_octavia and Skoda_superb. In addition, a sub-group of total measurements was chosen as the database to explore the effect of driving behaviour on tyre wear, which was collected from ICE vehicles (Skoda_Octavia, Skoda_Superb and Ford_C-Max). To reduce the experimental error, each variable's missing values and outliers were checked in data preprocessing, and then these data were deleted. The outliers were determined by the following equation (Dekking et al., 2005):

$$Outliers > Q_3 + 1.5 \cdot IQR \text{ or } Outliers < Q_1 - 1.5 \cdot IQR \tag{2}$$

where Q_1 and Q_3 are the first quartile and third quartile, respectively, and IQR is the Interquartile Range.

Between each measurement the tyres have experienced a mix of different weather and road conditions so that it is impossible to isolate these conditions. In this study, it is assumed that in total the different vehicles have been driven in similar average conditions, especially when used in the same area. The left front and left rear tyres of a passenger car are assumed to be worn in the same way as the right front and right rear tyres. Degaffe and Turner (2011) and Klöckner et al. (2019) have reported that the density of tyre tread was approximately 1.2 mg/mm^3. Here, the density of tyre tread was assumed to be 1.2 mg/mm^3, and the tyre wear is proportional to the distance travelled (Owsiak, 1997; Wangs, 2017), so the tyre wear per vehicle per kilometre (i.e. mg veh^{-1} km^{-1}) was calculated based on the following equation:

$$W_T = 2\rho(V_F + V_R)/d \tag{3}$$

where W_T is the tyre wear per vehicle per kilometre, ρ is the density of tyre tread, d is travelled distance, and V_F and V_R are the volume loss of left-front and left-rear tyres, respectively.

2.2. Extreme gradient boosting (XGBoost) decision tree

During each of the measurement periods, the real-time driving behaviour parameters were also recorded through a Xee 4.3 version app installed on mobile. It is noted that vehicle speeds and these longitudinal and lateral accelerations, which are expressed as gravity acceleration g, are not actual values, and instead, they are categorised into bins. In the collected dataset, there are 20 bins between −0.9 g and 1.0 g for longitudinal acceleration (a_x), 20 bins between −1.0 g and 0.9 g for lateral acceleration (a_y), and 15 bins between 0 and 220 km/h for vehicle speed (v), which means there are 20 ∗ 20 ∗ 15 bins reflecting the driving behaviour. Thus, it is very complex to analyse using conventional statistical methods. The XGBoost model can explore this complex issue according to the literature (Ma et al., 2020a, 2020b; Qin et al., 2020). XGBoost is an already well-developed model and was reported in detail by Chen and Guestrin (2016), which has been applied to many engineering fields (Zhou et al., 2021). As a consequence, the Python software was used to implement the XGBoost analysis through the open-source software library to probe the impact of driving behaviour on tyre wear. XGBoost is a supervised machine learning method and stands for eXtreme Gradient Boosting. It is based on the gradient boosting algorithm (Friedman, 2001) and improved the efficacy and computational speed by both algorithm and system enhancements. It is a sequential ensemble learning method and is typically used with decision trees as base learners, whose residuals are minimised by gradient descent algorithms. The general process is that:

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i), f_k \in F$$

where K is the number of decision tree models, f is the functional space of F, and F is the feasible classification and regression trees. Then the objective function is represented as

$$\text{obj}(\theta) = \sum_{\text{i}}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$$

where l is the loss function, and the second term is for regularization. Then by implementing the boosting methodology, the loss will be learned by the additive new tree.

$$\hat{y}_i^{(0)} = 0\hat{y}_i^{(1)} = f_1(x_i) = \hat{y}_i^{(0)} + f_1(x_i)\hat{y}_i^{(2)} = f_1(x_i) + f_2(x_i)$$
$$= \hat{y}_i^{(1)} + f_2(x_i), \ldots \hat{y}_i^{(t)} = \sum_{k=1}^{t} f_k(x_i) = \hat{y}_i^{(t-1)} + f_t(x_i)$$

Specifically, the objective function becomes

$$obj^{(t)} = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^{(t)}\right) + \sum_{i=1}^{t} \Omega(f_i) = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)\right) + \Omega(f_t)$$
$$+\text{constant } obj^{(t)} = \sum_{i=1}^{n} \left(y_i - \left(\hat{y}_i^{(t-1)} + f_t(x_i)\right)\right)^2$$
$$+ \sum_{i=1}^{t} \Omega(f_i) = \sum_{i=1}^{n} \left[2\left(\hat{y}_i^{(t-1)} - y_i\right) f_t(x_i) + f_t(x_i)^2\right] + \Omega(f_t) + \text{constant}$$

$$obj^{(t)} = \sum_{i=1}^{n} \left[l\left(y_i, \hat{y}_i^{(t-1)}\right) + g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i)\right] + \Omega(f_t) + \text{constant}$$

The next step is calculating the gradient and hessian for i:

$$g_i = \partial_{\hat{y}_i^{(t-1)}} l\left(y_i, \hat{y}_i^{(t-1)}\right)$$
$$h_i = \partial^2_{\hat{y}_i^{(t-1)}} l\left(y_i, \hat{y}_i^{(t-1)}\right)$$

The definition of the regularization term is determined by tree models. Normally, it could be represented as

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2$$

where T is the number of tree leaves, and w is the vector of scores on leaves of three. (Note that XGBoost could support other regularization terms too. Here is the description of XGBoost as requirEd.) Finally, the closed-form of the above expression is:

$$obj^{(t)} = \sum_{j=1}^{T} \left[G_j w_j + \frac{1}{2}(H_j + \lambda) w_j^2\right] + \gamma T$$

$$G_j = \sum_{i \in I_j} g_i$$
$$H_j = \sum_{i \in I_j} h_i$$

The advantage of XGBoost is that it improves many techniques in algorithm regularization such as parallelization and cache block, for higher performance in computation. Also, it improves the algorithm for finding the optimal split points by weighting quantile sketches. These advantages make XGBoost perform well in many data science scenarios. In addition, XGBoost could provide the so-called feature importance to help people understand the model. For example, XGBoost provides the value of feature importance, which is an improvement in accuracy brought by a feature to the branches it is on.

In the present study, the XGBoost model mainly consists of three parts, as shown in Fig. 1. The first part includes data collection, data pre-processing, and feature extraction. Data pre-processing has been presented above. The real-time driving parameters, including vehicle speed, and longitudinal and lateral accelerations, were recorded during each of the vehicle tyre measurement periods, while the tyre wear was not a real-time wear amount, but an average value. Thus, the feature extraction based on real-time driving data is required to represent one's driving behaviour during each measurement period. The v_{mean}, $a_{\text{x-mean}}$, and $a_{\text{y-mean}}$ refer to the mean values of vehicle speed and longitudinal and lateral accelerations. The v_{std}, $a_{\text{x-std}}$, and $a_{\text{y-std}}$ are the standard deviations of vehicle speed and longitudinal and lateral accelerations. The v_{skew}, $a_{\text{x-skew}}$, and $a_{\text{y-skew}}$ are the skewness values of vehicle speed and longitudinal and lateral accelerations. The v_{kurt}, $a_{\text{x-kurt}}$, and $a_{\text{y-kurt}}$ refer to the kurtosis values of vehicle speed and longitudinal and lateral accelerations. These parameters were chosen as features to reflect driving behaviour according to the literature (Reddy, 2019; Thørrisen, 2013) since the mean value and standard deviation reflect the average level and variance of the data results, and the skewness and kurtosis reflect the shape of the data distribution. As longitudinal and lateral accelerations can be positive or negative, both of which would increase tyre wear, the absolute values were used. Fig. 2 shows the correlation coefficient of the feature parameters of driving behaviour. It can be observed that the correlation coefficients are all larger than 0.91 between the mean and standard deviation values, as well as between the skewness and kurtosis of collected data, respectively, which means that they show a highly positive correlation, respectively. As a result, the $a_{\text{x-mean}}$, $a_{\text{x-skew}}$, $a_{\text{y-mean}}$, $a_{\text{y-skew}}$, v_{mean} and v_{skew} were chosen as the influential features regarding driving behaviour to explore the impact of the importance rankings of these features on tyre wear.

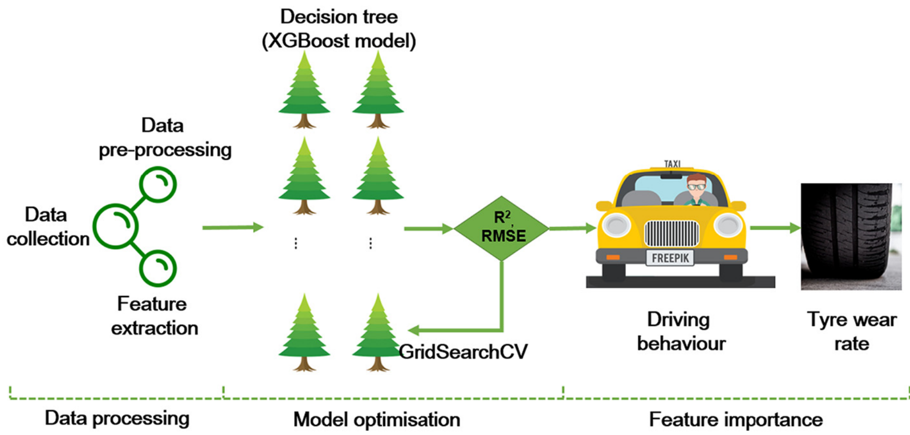

Fig. 1. The framework of the proposed methodology.

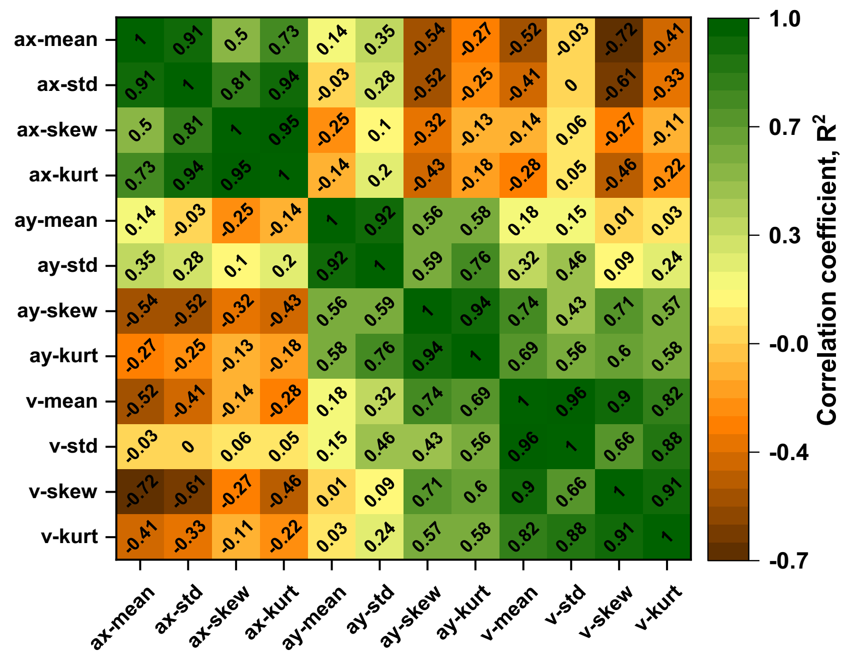

Fig. 2. Relationships among the various features regarding driving behaviour.

After pre-processing and feature extraction of the collected data, the model optimisation was performed. A sub-group from a similar vehicle equipped with various types of tyres and different drivers was used for a machine learning model. Typically, datasets can be divided into 50 % & 50 %, 75 % & 25 % and 80 % & 20 % as training and testing sets for machine learning models. The optimal division of the training and testing sets depends on various factors, such as the choice of model, data size, etc. In our work, 50 % of the data as a training set may not be sufficient to cover the overall trend, while 80 % of the data as a training set may cause overfitting. As a result, a compromise of these two divisions, that is, 75 % of the data, was chosen randomly as a training set in our work. 75 % of the data as a training set was also widely used in the XGBoost model (Chang et al., 2021; Ferreira et al., 2021; Woillard et al., 2021). In the XGBoost, it trained a set of regression trees as base learners in a parallel way and gave the result via summing up the scores of each regression tree. The following parameters are important for affecting the model performance:

- ✓ Learning rate: This parameter is used to adjust the size of the learning step. Too small will result in a local optimal value and slow calculation, while too large may miss the optimum and fail to converge.
- ✓ Min child weight: This parameter determines the minimum sum of instance weight (hessian) needed in a child. The larger min child weight is, the more conservative the model will be. It was used to prevent overfitting.
- ✓ Sample subsampling rate: this represents the fraction of observations to be sampled for each tree. Lower values prevent overfitting but might lead to under-fitting.
- ✓ Maximum tree depth: This refers to the maximum depth of a tree. A larger value may be beneficial to fit the data better.
- ✓ L1 and L2 regular coefficient: An increase in these two parameters will make the model more conservative.

Table 1 lists the final model parameters corresponding to the optimal XGBoost model. Finally, the optimised XGBoost was used to rank the feature importance of driving behaviour via averaging the feature importance in each tree. The feature importance in a single XGBoost tree was

Table 1
The key parameters of the XGBoost model.

Parameter name	Values
Learning rate	0.1
Min child weight	3
Sample subsampling rate	0.5
Maximum tree depth	3
L1 regular coefficient	0.05
L2 regular coefficient	1

determined by the quantity of information obtained after splitting the tree using the feature. More details regarding the calculation process are given in the literature (Ma et al., 2020a, 2020b).

3. Results and discussion

3.1. Effect of vehicle type on tyre wear

A sub-group of total measurements was used to explore the effect of vehicle type on tyre wear, which was generated from two types of vehicles (Skoda-Octavia and Toyota-Auris), as shown in Fig. 3. On average, the tyre wear was 72 mg veh^{-1} km^{-1} for the Toyota-Auris and 53 mg veh^{-1} km^{-1} for the Skoda-Octavia. Compared to the Skoda-Octavia, the tyre wear of Toyota-Auris was worse, with an average increase of 36 %, which is likely closely related to the different powertrain. Compared to a conventional ICE vehicle, a hybrid powertrain vehicle possesses a faster acceleration due to higher instant torque at start-up, which causes more tyre wear. A literature survey was performed by Jekel (2019), who pointed out that electric or hybrid cars would produce more tyre wear due to their high instant torque at start-up. Boretti (2019) reviewed the advantages and disadvantages of conventional vehicles and revealed that as electric vehicles are heavier and have more instant torque than ICE cars, they produce more $PM_{2.5}$ from tyre wear. Timmers and Achten (2016) reviewed the non-exhaust PM_{10} and $PM_{2.5}$ emissions and found that the average PM_{10} and $PM_{2.5}$ values of tyre wear from electric passenger cars in the literature were higher than those from equivalent ICE passenger cars. Beddows and Harrison (2021) determined the vehicle weight dependence of PM_{10} and $PM_{2.5}$ emissions from non-exhaust emissions and revealed more PM_{10} and $PM_{2.5}$ emissions from tyre wear for electric passenger cars than for the corresponding ICE passenger cars.

3.2. Effect of tyre feature on tyre wear

3.2.1. Tyre type

A sub-group of total measurements was chosen to explore the effect of tyre type on tyre wear, which was generated from Skoda_octavia and Skoda_superb with the identical power drive system with summer tyres, winter tyres and all-season tyres (Bridgestone). Fig. 4 presents the descriptive statistic results of the tyre wear. In addition, Table S2 of the Supplementary data list the concrete values of tyre wear. The lowest value was obtained from the summer tyres, while the highest value was detected on the winter tyres. The tyre wear from vehicles configured with all-season tyres varied substantially, ranging from 56 mg veh^{-1} km^{-1} to 175 mg veh^{-1} km^{-1}. The average tyre wear generated from taxi vehicles configured with the winter tyres was 160 mg veh^{-1} km^{-1}, which was 1.4 and 3.0 times more than those configured with all-season tyres and summer tyres, respectively. Such a difference in the tyre wear rate from various types of tyres is likely ascribed to their different rubber compounds and tread patterns. Winter tyres are generally made from a higher natural rubber in their makeup and have a deep tread pattern. The softer they are, the more the tyre can interlock with the road surface, improving grip and handling, which leads to an increase in tyre wear (OECD, 2020; Pokorski et al., 2019). However, summer tyres tend to have less natural rubber content and a simple block-shaped pattern, meaning that summer tyres have a low friction coefficient and thus reduce tyre wear (Pokorski et al., 2019). All-season tyres are composed of an intermediate rubber compound and combine the properties of both summer and winter tyres (Vieira and Sandberg, 2017). Thus, on average, the all-season tyre wear was lower than the winter tyres and higher than summer tyres. Previous studies have shown that tyre wear is strongly dependent on tyre types (Jekel, 2019; van der Gon, 2012; Wagner et al., 2018). Winter tyres have higher natural rubber content and present softer properties, which cause them to wear more quickly at high temperatures (Cheah et al., 2015). It is therefore inferred that the tyre wear rate of winter tyres is likely greater than that of summer and all-season tyres. In addition, it is worth mentioning that the vehicle tyre wear in Northern and Southern Europe would be influenced by the following factors: 1) During the winter season, the mean friction coefficient of the road pavement is lower in Northern Europe than in Southern Europe due to the frequent snowfall and wetter on the road surface after salt application, thus reducing tyre wear (Wallman and Åström, 2001); 2) while the rubber of tyre is generally softer in Southern Europe than in Northern Europe due to higher temperatures, increasing tyre wear.

Table 2 summarises the tyre wear generated from passenger cars in several countries. In the present work, the average tyre wear for summer, all-season, and winter tyres was 53 mg veh^{-1} km^{-1}, 112 mg veh^{-1} km^{-1} and 160 mg veh^{-1} km^{-1}, respectively. Luhana et al. (2004) evaluated tyre wear by monitoring the weight loss of tyres on five-passenger cars over a specific driving distance. In five cars, the maximum and minimum mean tyre wear rates were 56.4 mg veh^{-1} km^{-1} and 193.3 mg veh^{-1} km^{-1}. Moreover, tyre wear rate was found to fluctuate during different specific driving distances, which may be related to the variation in tyre wear resistance with increasing driving distance. In the study by Councell et al. (2004), however, they summarised the tyre wear rate under various driving scenarios from different literature. Most tyre wear rates were reported to be constant without considering the change in tyre wear resistance. Kole et al. (2017) conducted a thorough review of tyre wear in different countries

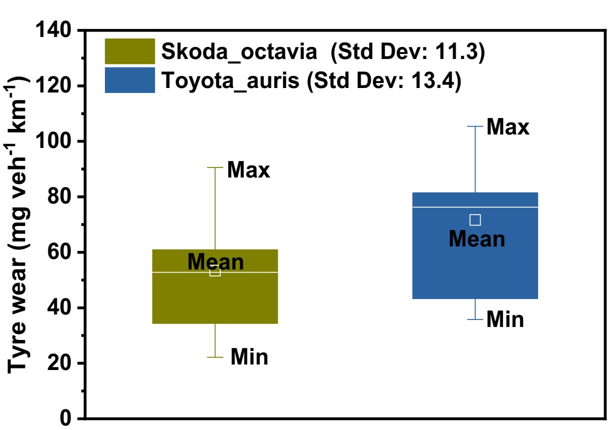

Fig. 3. Tyre wear of summer tyres as functions of vehicle type.

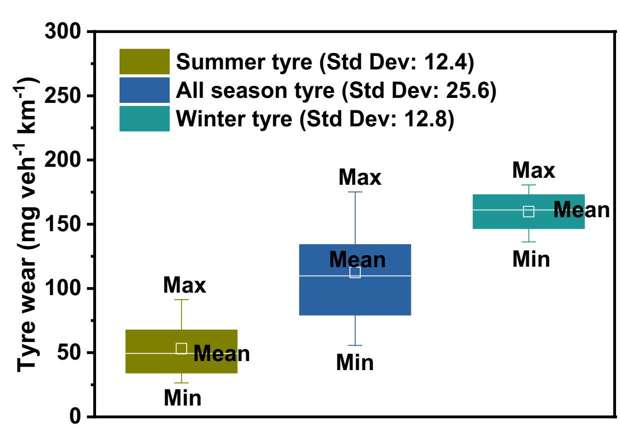

Fig. 4. Tyre wear as functions of tyre type.

Table 2
Summary of the average tyre wear rate from passenger cars.

Tyre wear ($mg\ km^{-1}\ veh^{-1}$)	Country	Reference
53 for summer types 112 for all-season tyres 160 for winter tyres	Italy and Greece	Present work
100	United Kingdom	(Luhana et al., 2004)
50	Sweden	(Gustafsson, 2002)
90	Germany	(Hillenbrand et al., 2005)
80	Germany	(Baumann and Ismeier, 2013)
132	Denmark	(Lassen et al., 2012)
132	Norway	(Sundt et al., 2014)
51	South Korea	(Lee et al., 2020)
132	China	(Kole et al., 2017)
132	USA	(Kole et al., 2017)
132 for urban road 85 for rural road 104 for motorway road	Netherlands	(Verschoor et al., 2016)

from various literature. For instance, Hillenbrand et al. (2005) and Baumann and Ismeier (2013) obtained the tyre wear rates of 90 mg $veh^{-1}\ km^{-1}$ and 80 mg $veh^{-1}\ km^{-1}$, respectively, based on the number of passenger cars registered in Germany, total driving distance and the annual amount of tyre wear. The same method was employed by Lassen et al. (2012), who gained a tyre wear rate of 132 mg $veh^{-1}\ km^{-1}$ in Denmark. Verschoor et al. (2016) calculated tyre wear from passenger cars on urban, rural and motorway roads and found that tyre wear increased in the order of rural, motorway and urban roads. They ascribed this phenomenon to the higher frequency of sudden braking and rapid acceleration of passenger cars in urban areas. Cho et al. (2011) also revealed that the braking and acceleration manoeuvres could generate more tyre wear. Consequently, the higher rates of braking and acceleration on urban roads inevitably increase tyre wear. The tyre wear rates from the studies performed in different countries were in the range of 50–132 mg $veh^{-1}\ km^{-1}$. The substantial difference in tyre wear rate among these countries is probably due to many factors, such as road surface, vehicle characteristics, tyre features, and driving behaviour (Boretti, 2019; Lee et al., 2020).

3.2.2. Tyre position

Tyre wear of left-front and left-rear tyres were evaluated in the present study. The descriptive statistics of left-front and left-rear tyre wear are shown in Fig. 5. On average, the wear rate of left-front tyres was 27 mg km^{-1}, which was 1.7 times as much as the wear rate of left-rear tyres. This is likely ascribed to the following factors: 1) more vehicle weight is applied to the front tyres (Braghin et al., 2006; Perricone et al., 2019); 2) the front wheel for a front-wheel driven vehicle provides acceleration torque (Jekel, 2019); 3) the front wheels are angled slightly inwards to improve handling (Fallah et al., 2009); and 4) the front wheels, as the steering wheel, are more subject to steering movements, which may induce slipping and thus accelerate tyre wear.

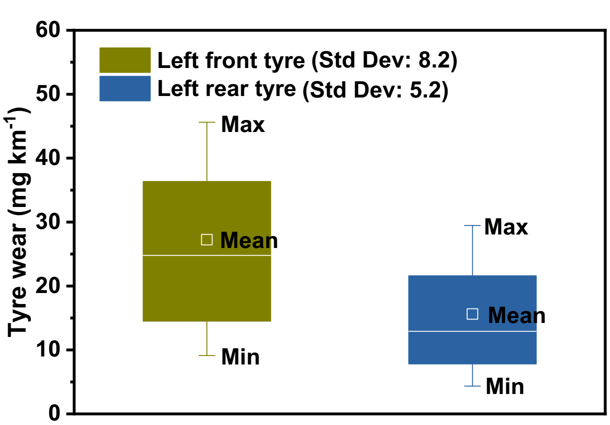

Fig. 5. Tyre wear as functions of tyre position.

3.3. Effect of driving behaviour on tyre wear

A sub-group of total measurements was served as a dataset to probe the effect of driving behaviour on tyre wear. Fig. 6 shows the histogram of all driving behaviour features. It is hard to visualise the joint distribution of all variables. To visualise the effect of driving behaviour on tyre wear, two typical examples were chosen, as shown in Fig. 7. Positive and negative longitudinal accelerations correspond to the vehicle accelerating and braking, and positive and negative lateral accelerations represent cornering right and left, respectively. It can be seen that the average tyre wear rate was distinctly different, which can be interpreted by the differences in the longitudinal and lateral acceleration levels that each driver imposes on the vehicle. From Fig. 7, the driving behaviour of one driver was more radical, with a higher frequency occurring in the larger longitudinal and lateral accelerations, and the longitudinal and lateral accelerations of 0 g only account for 36 %. However, another driver drove the vehicle more moderately, with the longitudinal and lateral acceleration of 0 g accounting for 50 %. The above description is likely to be the main reason for the clear difference in tyre wear. OECD (2020) reported that up to 30 % of tyre wear could be attributed to driving behaviour. Kim and Lee (2018) found that the particles from tyre wear were heavily dependent upon the driving conditions. Le Maitre et al. (1998) reported that there were noticeable differences in the tyre wear between vehicles driven by professional and moderate use drivers. They ascribed this phenomenon to the fact that an experienced driver could drive the vehicle at the speed limit with longitudinal and lateral acceleration levels much higher than moderate use drivers, which caused the difference in tyre wear. To better understand which driving behaviours, including vehicle speed, and longitudinal and lateral accelerations, exert a more significant impact on tyre wear, the XGBoost was used in the present study. More details will be discussed in the following section.

3.3.1. XGBooost model results

Fig. 8 presents the variation curves of the tyre wear rate under various real-world driving behaviours and the predicted value of the XGBoost model. It can be seen that the XGBoost model could successfully predict most peak values of tyre wear under real driving conditions. Compared with the tested values, some of the predicted results obtained from the XGBoost model were large, while others were small. Overall, the XGBoost model presented a good predictive ability for the entire trend, but there was not an accurate prediction of the turning points. A similar study was performed by Ma et al. (2020a,b), who predicted the $PM_{2.5}$ mass concentration using the XGBoost model and found that the turning point of the $PM_{2.5}$ mass concentration could not be forecast accurately. Thus, it may be difficult for the XGBoost model to find perfect regularity in the existing data.

To better understand the prediction accuracy of the model, two extensively used evaluation indexes, including square correlation coefficient (R^2) and root mean square error (RMSE), were introduced. Fig. 9 shows the R^2 and RMSE values between the tested and predicted tyre wear rates from the training and testing databases. The R^2 and RMSE values were 0.86 and 0.106 for the training set and 0.83 and 0.175 for the testing set, respectively. These results indicated that the proposed XGBoost model had a good predictive capability for the tyre wear rate of vehicles driven under real-world driving conditions. In the follow-up work, a deep learning method called "transfer learning" may be developed, which would store the knowledge learned by the previously trained machine learning model as initialisation and hence it could present better performance for new data.

3.3.2. Effect of driving behaviour on tyre wear

Fig. 10 shows the feature importance ranking of driving behaviour based on XGBoost outputs. Compared to driving behaviour, tyre type and tyre position installed on the vehicle were more important factors affecting tyre wear rate. Among driving behaviour, the $a_{x\text{-mean}}$ and $a_{x\text{-skew}}$ presented the most

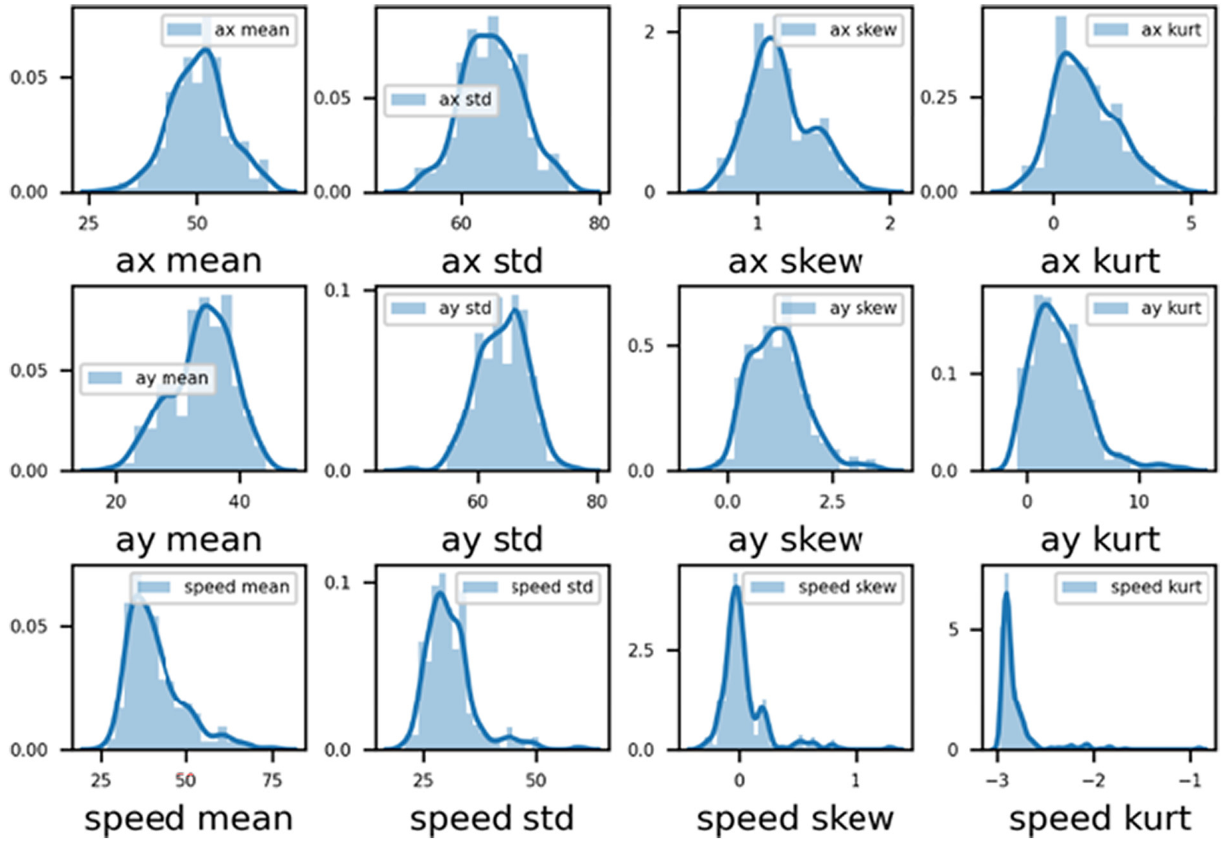

Fig. 6. Histogram of each variable among drivers.

considerable impact on tyre wear rate. It meant that the driver who had a high frequency of harsh braking and accelerating would generate more tyre wear. It has been confirmed that both shearing force and friction heat between the tyre tread and the road pavement would increase tyre wear (Kreider et al., 2010; Mathissen et al., 2011; Piscitello et al., 2021). As a result, the shear force is increased when harsh braking or acceleration occurs, increasing the tyre's mechanical wear and thus generating coarse and even larger particles. In addition, more organic compounds in the tyre tread are volatilized due to the friction heat when harsh braking or acceleration occurs, which may increase the number of ultrafine particles (Mathissen et al., 2011; Zum Hagen et al., 2019). Salminen (2014) created a tyre wear model and found that the tyre wear depended strongly on the longitudinal slip, where the tyre wear varied up to a factor of 2 within a longitudinal slip ranging from −0.3 g to 0.3 g.

Among the driving behaviours, the third and fourth important factors that affect tyre wear rate were the $a_{y\text{-mean}}$ and $a_{y\text{-skew}}$. The current results showed that vehicle cornering events, especially extreme cornering, had a significant impact on tyre wear. Previous studies have proved that the enhanced lateral force would lead to a sharp increase in tyre wear (Pohrt, 2019; Veith, 1992). Thus, the lateral force acting on the tyre surface is increased when the vehicle cornering occurs, which inevitably generates more tyre wear (Pohrt, 2019). In the study by Li et al. (2011), it was found that more tyre wear would be generated during the cornering sections of roads. This conclusion is in agreement with the bench test results performed by Stalnaker et al. (1996), where urban driving with only 5 % of the distance driven accounted for 63 % of tyre wear. The reduction of cornering driving behaviour, especially for high-speed cornering, would

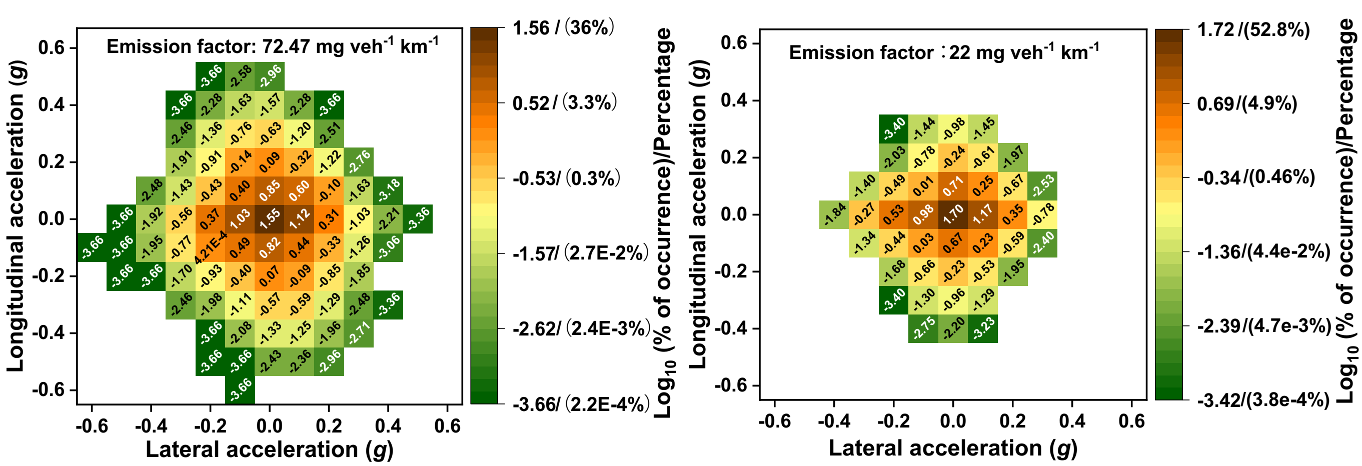

Fig. 7. Tyre wear for the Skoda_octavia configured with summer tyres under typical aggressive (left) and moderate (right) driving behaviours.

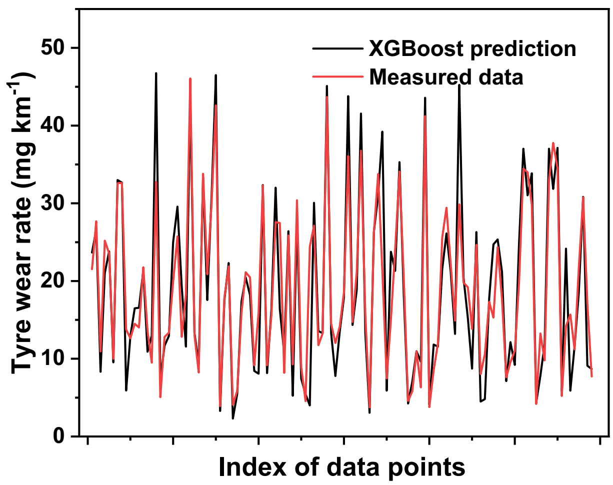

Fig. 8. Predicted and tested tyre wear rate under various driving behaviours.

be one of the most effective strategies to lower tyre wear (AQEG, 2019; Boulter, 2005; Kwak et al., 2013).

The v_{mean} and v_{skew} ranked the fifth and sixth important influential factors for tyre wear rate among driving behaviours, respectively. The results from this work indicated that tyre wear would be more severe when the driver has a high frequency of high speeds. Such a phenomenon is primarily because the adhesion movement becomes more intense with increasing vehicle speed, increasing tyre wear (Gustafsson et al., 2008; Pirjola et al., 2009; Yan et al., 2021). Kim and Lee (2018) reported a rising PM concentration of tyre wear as the driving speed increased. Chen and Prathaban (2013) evaluated the effect of truck speed on tyre wear. It was found that tyre wear showed an exponential increase as the vehicle speed increased. Salminen (2014) also discovered that the tyre wear increased exponentially with the driving speed. However, Li et al. (2011) and Foitzik et al. (2018) found a linear correlation between tyre wear and vehicle speed.

Overall, based on the results from our work, it is recommended that eco-friendly driving behaviour, especially for gently accelerating and braking behaviours, should be incorporated into driver training to have the potential to substantially reduce tyre wear. It is, however, worth mentioning that even though the XGBoost model can evaluate the importance ranking of the effect of driving behaviours on tyre wear, it remains unclear how each variable of driving behaviour quantitatively determines output results. In our follow-up work, it is required to quantitatively identify relationships between driving behaviours and tyre wear.

4. Conclusions

In this study, the tyre wear and driving behaviour of a fleet of taxi cars were measured under real-world driving conditions. Meanwhile, the XGBoost was used to rank the feature importance of driving behaviour in affecting tyre wear. The data from this study indicate, on average, that the tyre wear was 72 mg veh^{-1} km^{-1} from a hybrid car, which was 1.4 times as much as that from an equivalent conventional ICE vehicle, depending on the vehicle type. This phenomenon is likely ascribed to the fact that hybrid vehicles have high instant torque at start-up and thus present faster acceleration, leading to an increase in tyre wear. The mean wear rates for taxis configured with winter tyres, all-season tyres and summer tyres were 160 mg veh^{-1} km^{-1}, 112 mg veh^{-1} km^{-1} and 53 mg veh^{-1} km^{-1}, respectively. The XGBoost results indicated that compared to driving behaviour, tyre type and tyre position presented more important influences on tyre wear. Among driving behaviours, braking and accelerating events had the most considerable impact on tyre wear, followed by cornering events and driving speed. The finding regarding the importance rankings of driving behaviour on tyre wear is likely to be beneficial for designing the training courses, which improve drivers' knowledge of low tyre wear via the training courses at driving schools and encourage them to adopt more friendly driving behaviours to reduce tyre wear. In addition, this study provides the dataset regarding the mass of tyre wear released into the environment and the importance of the different factors affecting tyre wear, which is useful for the development of a methodology to measure the abrasion rate and for the identification of the measures needed to reduce the emissions of microplastics into the environment.

CRediT authorship contribution statement

Ye Liu: Investigation, Methodology, Data visualisation, Writing-original draft. **Haibo Chen**: Conceptualisation, Investigation, Funding acquisition, Project management. **Sijin Wu**: Investigation, Methodology, Software, Formal analysis. **Jianbing Gao**: Methodology, Writing-review & editing. **Ying Li**: Writing-review & editing. **Zihao An**: Investigation, Writing-review & editing. **Baohua Mao**: Writing-review & editing. **Ran Tu**: Writing-review & editing. **Tiezhu Li**: Writing-review & editing.

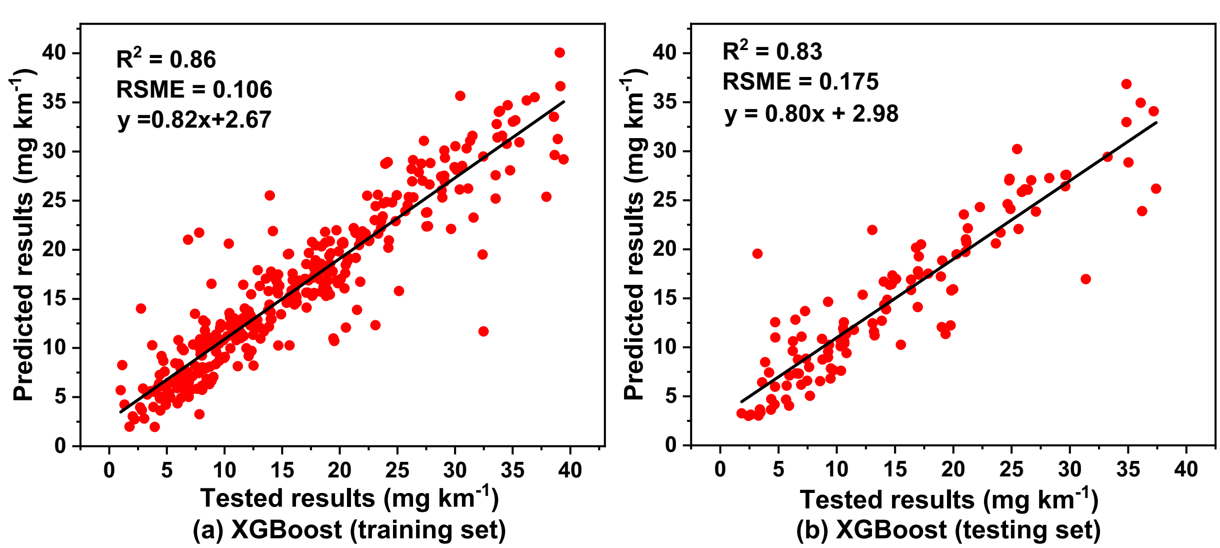

Fig. 9. Relationship between the tested and predicted tyre wear rates for training and testing datasets.

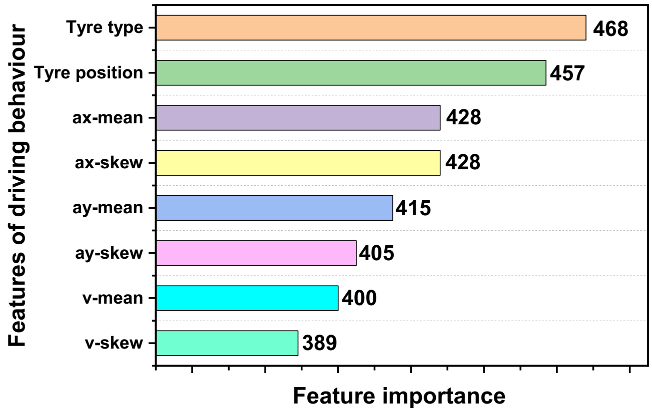

Fig. 10. Feature importance ranking based on the XGBoost outputs.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2022.156950.

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