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Assessing the evolution of railway wheelsets wear using a statistical modelling approach

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Abstract

This paper explores the use of statistical models to assess the evolution of wear trajectories of railway wheelsets. It provides insight into the process of wheelset degradation and their usual maintenance procedures. Using a quantitative basis of data from a fleet of modern electric multiple unit trains from a Portuguese train operating company, different model specifications for the wheelsets' wear evolution are compared using linear mixed models. The wear trajectory is assessed by the evolution of the wheel tread diameter, the flange thickness, the flange height and the flange slope. The variability in the data was associated with several factors, such as the month of measurement, the unit vehicle or the vehicle type, and their influence on the wear trajectories was also analyzed. From the observation of the results obtained, it was possible to conclude that the wheel hardness can have an influence on the wheelset degradation trajectory. Finally, the statistical patterns found seem to be consistent with other train fleets.

Keywords: Wheel Degradation; Wear; Hardness; Linear Mixed Models; Railways

1. Introduction

In a railway system, one of the most important components is the railway wheelset, wherein train operating companies spend a significant part of their maintenance budget. On one hand, its main purpose is to allow the vehicle to curve while assuring the system safety, i.e. preventing derailment. On the other hand, it is responsible for the passenger comfort, avoiding excessive vibrations and undesired noise (Braghin et al. 2006). Therefore, the wheelsets' condition is an important indicator of ride quality and international standards define technical specifications on geometric factors of the wheelsets, load thresholds and frequency weighting characteristics (BS 2012).

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This paper focuses on the wheel condition, particularly on the statistical modelling of the deterioration processes involved in the wheel wear evolution. It provides a quantitative basis, based on a sample collected from a Portuguese train operating company, which may provide a better understanding of the needs in wheelset maintenance processes (renewal, preventive and corrective). It also supports the identification of the main factors that explain the variability in wear predictions. Finally, it also corroborates the theory that the models and variables here adopted can be applied to any fleet of vehicles revealing similar patterns and behaviors (Andrade and Stow 2016).

Statistical approaches to study the wear behavior in the degradation of railway wheelsets are more commonly found in the analysis of physical quantities, such as vertical wheel loads, residual stresses, longitudinal or transverse contact stresses, rather than geometric parameters (Pombo et al. 2011a, Hossein et al. 2015). In fact, most of the studies do not cover the probabilistic issues in their modelling, mainly when irregularities can be considered continuously distributed along the track. In these cases, approaches based on stochastic process theory are more appropriate (Iwnicki 2006). A few studies investigated degradation data from the wheel profile to estimate failure distributions and associated reliability (Freitas et al. 2009, Asplund et al. 2016). Moreover, Lin and Asplund (2014) used Weibull models to estimate lifetime data for a sample of locomotive wheels. Wang et al. (2015) used a data-driven model to optimize the wheel reprofiling strategy, aiming to extend the life cycle of metro wheels. Recently, from the perspective of reducing life cycle cost and managing wheelset maintenance activities, different Markovian approaches were conducted to optimize the reprofiling policy for train wheels, by modelling distinct variables to identify degradation states (Jiang et al. 2017, Braga and Andrade 2018, Mingcheng et al. 2018).

Notwithstanding, none of the above presented statistical studies used linear mixed models (LMMs) or generalized linear mixed models (GLMMs) that are here discussed. The exception was a previous research work of Andrade and Stow (2016), whose analysis was further used as a basis for a new wheelset maintenance strategy, called ‘economic tyre turning’ in Andrade and Stow (2017a). This present paper follows the study and methods used in Andrade and Stow (2016) and tries to give a clear answer to a few main topics left open for further research, as to whether or not the statistical patterns found are consistent in other train fleets. Therefore, it tries to validate the statement that these LMMs can be applied to any fleet of vehicles with consistent results. Secondly, the present research work also introduces a new important variable - the flange slope (qR) - which is in line with what is proposed in Asplund et al. (2016), due to its importance on the control of the degradation and damage of the wheel profile. Finally, this paper also assesses the influence of the wheel hardness in the wheelsets degradation trajectories. The sample analyzed – from a case study on the fleet of a Portuguese train operating company – went through a big renewal program in its train fleet. Every wheelset was renewed by a new one, with wheels with different hardness. Therefore, this paper also makes the distinction between this two operating cycles, considering its influence in the wheelset wear trajectory.

The structure of the present paper is the following: section 1 introduced the need to statistically model the wear and damage trajectories of railway wheelsets and briefly reviewed statistical past researches on this subject. Section 2 provides a general insight into the process of wheelset degradation and their usual maintenance procedures. Section 3 gives a brief overview of the statistical methods used in LMMs. These models are then applied in a case study for wear trajectories in section 4, in which several model specifications are compared and analyzed. Finally, section 5 provides the main conclusions and some guidelines for further research.

2. Comprehensive degradation and maintenance of railway wheelsets

A railway wheelset is a train component that consists of two wheels linked by a rigid axle, allowing the motion to the vehicle when rolling over surfaces (rails), as depicted in Figure 1.

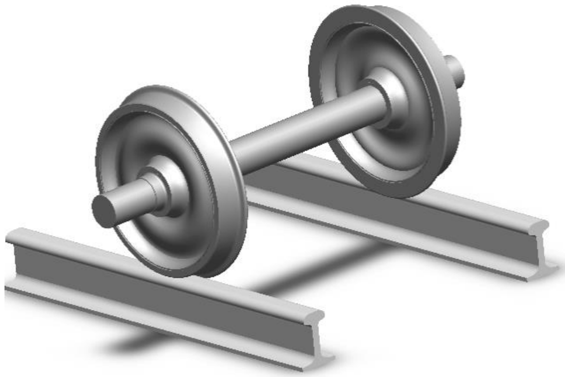

Fig. 1. Railway wheelset and rails.

For a safe use of the wheelsets, it is necessary to guarantee that both the axle and the wheels are not damaged and are within the dimensional safety specifications. Otherwise, both the axle or the wheels have to be reprofiled or replaced by new ones if necessary.

To control the level of degradation of the wheels it is necessary to periodically assess some geometric variables from the wheel tread profile (Figure 2) which are measured relatively to three fixed measurements (a, b, c) and from a tread datum position point (T). If these variables are beyond the safety limits, the wheelset has to be reprofiled or replaced.

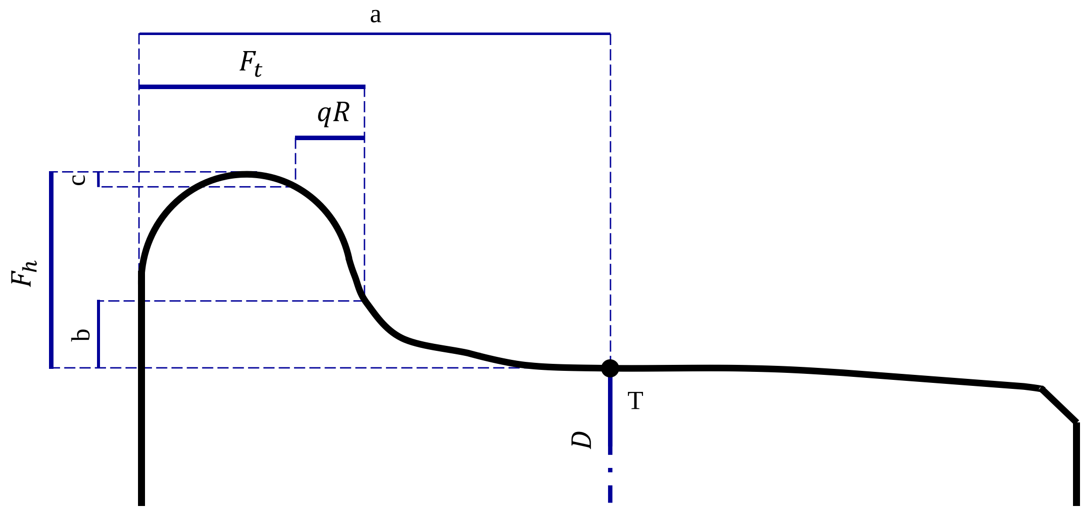

Fig. 2. Wheel diameter (D), flange height (F_h), flange thickness (F_t) and flange slope (qR).

To illustrate schematically typical wear trajectories of railway wheels and their maintenance, Figure 3 is provided, using the wheel diameter (D) as the main indicator. Continuous blue lines represent the actual deterioration process of the wheels on the wear trajectory. Note that, for simpler understanding, it is considered that wheels wear at a constant rate, i.e. the continuous blue lines have the same slope in the graph. The blue dotted lines represent the impact in D due to the maintenance actions performed.

Railway wheels are in service starting from an initial diameter (D_i), when they are new (green squares in Figure 3), until the diameter reaches the scrap diameter (D_s), beyond which it is not safe to continue operating, the vehicle must be removed from service and the wheelset replaced (renewal). Moreover, there are running profile limits for the flange height (F_h^{lim}), flange thickness (F_t^{lim}) and flange slope (qR^{lim}). To avoid the wheelsets reaching these case limits and to prevent them from other non-detected problems, preventive maintenance (turning) is carried out with a certain kilometer interval (or mileage interval).

Typically, train operating companies do this type of maintenance after an established number of unit kilometers, since the last maintenance operation (turning or renewal). This is the reason why, in Figure 3, preceding each preventive maintenance (yellow squares), there is the same wear trajectory, i.e. the same line slope a line with a same length and unit kilometers between maintenance operations. In different circumstances, if the wheels are found beyond the limits before the next preventive maintenance and if the wheels have not reached yet their scrap diameter, the wheels must be reprofiled (turning) to restore the geometric parameters (F_h, F_t, qR) to safer values, this is what is called a corrective maintenance action represented in Figure 3 with the orange square. Moreover, if the wheelset is found at any time with damage, it must also go to the wheel turning lathe for corrective maintenance (red square in Figure 3).

In this paper, each kilometer interval between maintenance operations (turning or renewal) is a variable called kilometers since last turning or renewal operation (K).

Each time a wheel goes to a wheel lathe, it undergoes a diameter loss due to turning (ΔD_T) which can be higher or lower, depending on the maintenance type action being taken and the specific situation (e.g. presence of damage, as wheels flats, cavities or Rolling Contact Fatigue). In a situation of preventive maintenance, it is expected that the wheel goes through the smallest loss of diameter. On the other hand, to correct damaged wheels, it takes a big diameter loss, shortening significantly the wheel life cycle (Pombo et al. 2011b). In fact, this last situation can be seen in Figure 3. It is possible to distinguish two distinct wheel life cycles: the first one that includes K_1, K_2, K_3, K_4 and a second one that includes K_5, K_6, K_7, K_8. The first wheel cycle had an extended life because it went only through regular preventive maintenances. By comparing the cumulative kilometers since turning of the first cycle ($K_1 + K_2 + K_3 + K_4$) with the second one ($K_5 + K_6 + K_7 + K_8$), it is clear that the latter had a much lower span life. This is not only because of the corrective maintenances that this wheel went through, but even more due to the damage correction (red square) that, in Figure 3, occurred at a time of a lower diameter. In fact, Figure 3 goes in line with practical observations reported in the past, in which there is a greater probability of damage occurrence in smaller diameters (Molyneux-Berry and Bevan 2012).

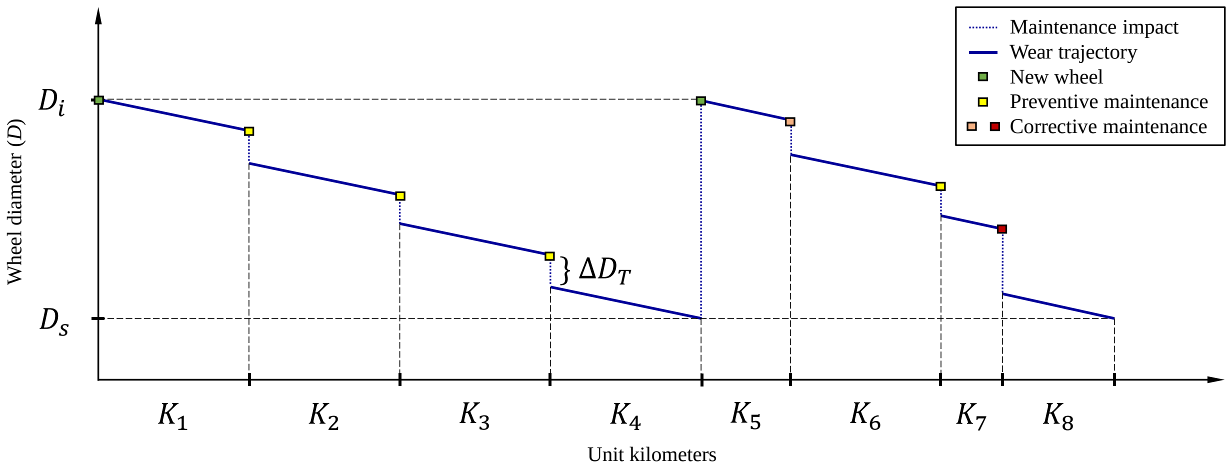

Fig. 3. Schematic wheel maintenance trajectories with wheel diameters and the unit kilometers.

3. Linear mixed models

The use of LMMs in statistical modelling of wheel degradation can be advantageous to infer about the dependence between different explaining variables in the wheel wear evolution, to provide straightforward mechanisms to control for the variability within and between different groups of the wheelset position and technical specifications (Molyneux-Berry and Bevan 2012, Ferreira et al. 2012).

LMMs are linear models that both monitor the fixed effects of different controlling variables ($\boldsymbol{X_i\beta}$) in the expected mean of the dependent variable and the random effects associated with some factor or group ($\boldsymbol{Z_i b_i}$). According to Galecki and Burzykowski (2013), and for a single grouping level, LLMs can be formulated as

$$\boldsymbol{y}_i = \boldsymbol{X}_i \beta + \boldsymbol{Z}_i \boldsymbol{b}_i + \varepsilon_i$$

Where $\boldsymbol{y}_i$ is the dependent variable for the group i, $\boldsymbol{X}_i$ is the designed matrix for that group i, $\boldsymbol{\beta}$ is the slope parameter, $\boldsymbol{\varepsilon}_i$ is the residual error for group i, $\boldsymbol{Z}_i$ is the matrix of covariates for i and $\boldsymbol{b}_i$ its corresponding random effect.

It is assumed that the random effects ($\boldsymbol{b}_i$) and the residual errors ($\boldsymbol{\varepsilon}_i$) follow normal distributions with zero mean and covariance matrices of $\mathcal{D}$ and $\mathcal{R}_i$, with $\boldsymbol{b}_i \perp \boldsymbol{\varepsilon}_i$

$$\boldsymbol{b}_i \sim N(\boldsymbol{0}, \mathcal{D})$$

$$\boldsymbol{\varepsilon}_i \sim N(\boldsymbol{0}, \mathcal{D})$$

Both terms $\boldsymbol{b}_i$ and $\boldsymbol{\varepsilon}_i$ are considered independent for the same group i and between different groups.

The covariance matrices are specified with an unknown scale parameter σ^2 as follows

$$\mathcal{D} = \sigma^2 \boldsymbol{D}$$

$$\mathfrak{R}_i = \sigma^2 \boldsymbol{R}_i$$

Note that there are a few additional constraints that have to be made on the matrices $\boldsymbol{D}$ and $\boldsymbol{R}_i$ - multiples of the identity matrix - to guarantee identifiability to (Galecki and Burzykowski 2013). All the statistical models were estimated using the 'lme4' package for the R software (Bates 2010, 2018).

4. Case study and statistical modelling

This section conducts an exploratory statistical analysis on wear trajectories of different wheelsets from a fleet of modern electric multiple unit trains.

4.1. Case study

Fertagus is a Portuguese train operating company, which is part of Grupo Barraqueiro, and became the first private train operator to guarantee the commercial concession of a railway line in Portugal. This company is responsible for ensuring the suburban passenger transportation between 14 railway stations from Roma-Areeiro (Lisbon) to Setúbal.

The data analyzed comes from wheelset turning maintenance operations, of a fleet of 18 electric multiple unit trains of a single type or class, between October 2000 up to June 2015 (i.e. a 16-year interval). Each unit has four vehicles and each vehicle has eight wheels (i.e. four wheelsets). Figure 4 provides a schematic representation of a four-car unit.

The process of data extraction took several visits to the maintenance yards (situated in Coina) and the access to their maintenance actions archive. The information on the geometric parameters that control the wear evolution of the wheelsets was saved in paper format, since it comes directly printed from the CNC (Computer Numerical Control) machine of the under-flow wheel lathe used each time a reprofiling maintenance action occurs. Because of that, before the data was able to be treated, it was necessary to use Computer Vision procedures, to convert the numerical information in the turning sheets into digital format.

The turning sheets have information of the wheel profile degradation measurements - i.e. wheel diameter (D), flange height (F_h), flange thickness (F_t) and flange slope (qR) - pre and post-turning, in preventive and corrective maintenance actions.

The process of wheelset turning is as follows: the vehicle arrives at the under-flow wheel lathe (which is from the Spanish train manufacturer Talgo) and the technician starts by fixing the wheelset to the turning machine, then, the

CNC machine is calibrated relatively to the wheelset position and, finally, the turning starts. By the time of the turning, the technician has also to guarantee that there is no big difference in diameters between wheels of the same wheelset, wheels of the same bogie and wheels of different bogies. The process of corrective maintenance actions takes more time than preventive maintenance actions, and the influence of the technician experience and sensitivity is more predominant.

Regarding the technician influence in wheel wear maintenance operations, Société Nationale des Chemins de fer Français (SNCF) attempts to combine quantitative data with perceptions and experience of the wheel maintainers (thus, adding a subjective dimension to risk assessment) in order to tackle organizational issues with multiple decision makers and multiple criteria (Tea 2012). Another contribution towards the incorporation of the technician experience focused on the variability between the different wheel lathe operators (Andrade and Stow 2017b).

Regarding other case studies involving Talgo turning lathe machines, Talgo developed a maintenance program called Total Logistic Care that keeps the flange thickness within an ‘optimal’ range of operation, instead of waiting until the wheel is out of the specifications (Pascual and Marcos 2004).

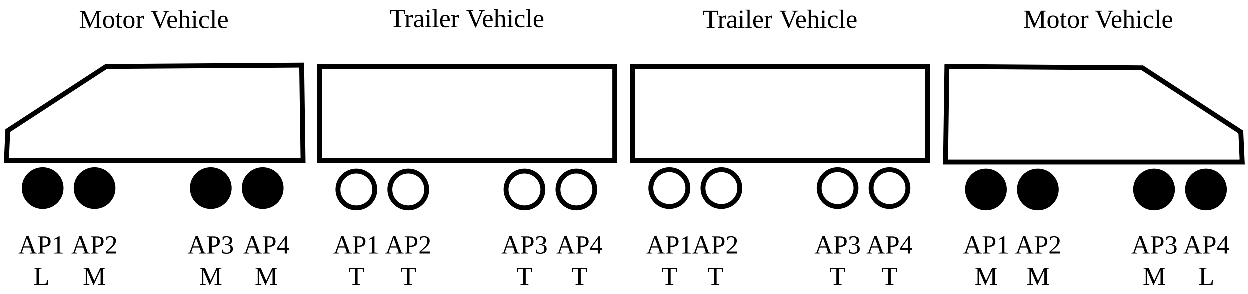

Fig. 4. Schematic representation of a four-car unit with four axle positions (AP1 - AP4).

Fertagus went through a big revision in their train fleet. Every wheelset was renewed by a new one, with wheels made of different materials with different hardness. Each train unit changed every wheel at once at a certain time between 2011 and 2013. Assuming that wheels with different hardness will have different wear trajectories, the following analysis using LMM splits the two operating wheel cycles:

- Cycle 1 (C1): wheels with the material of type 1;
- Cycle 2 (C2): wheels with the material of type 2.

4.2. Statistical modelling

The wheel database used in this paper contained the following information: unit number (18 units), unit running kilometers (cumulative kilometers), vehicle type (motor or trailer), date (cumulative months), wheelset position (16 positions), tread diameter (pre and post-turning), flange height (pre and post-turning), flange thickness (pre and post-turning) and flange slope (pre and post-turning). The CNC machine, from where the measurements of the wheel profiles were withdrawn, has the precision of ±0.05 mm for the wheel diameter and ±0.1 mm for the remaining geometric indicators (the flange height, flange thickness and flange slope). Table 1 provides an overview of the variables used in the analysis, their description, type, some statistics (mean, minimum and maximum), as well as the values precisions.

Table 1. Variables, their description, type, some statistics and precision.

Variables	Description	Type	Mean	Min	Max	Precision
$\|\Delta D\|$	Diameter loss due to wear [mm]	Continuous	5.90	0.05	18.50	±0.05
ΔF_h	Change in the flange height due to wear [mm]	Continuous	2.6	-0.4	8.0	±0.1
ΔFt	The change in the flange thickness due to wear [mm]	Continuous	0.6	-8.2	6.6	±0.1

ΔqR	Change in the flange slope due to wear [mm]	Continuous	0.7	-5.5	4.2	±0.1
K	Kilometers since last turning/renewal [km]	Continuous	161982	5000	343662	±1
D	Tread diameter pre-turning [mm]	Continuous	866.10	797.55	924.70	±0.05
F_h	Flange height pre-turning [mm]	Continuous	30.8	27.8	38.0	±0.1
Ft	Flange thickness pre-turning [mm]	Continuous	31.6	16.1	36.4	±0.1
qR	Flange slope pre-turning [mm]	Continuous	11.2	4.6	15.7	±0.1
W	Wheelset type (3 types: motor, trailer, motor leader)	Nominal	–	–	–	–
H	Hardness (2 types: C1, C2)	Nominal	–	–	–	–
U	Unit number (18 units)	Nominal	–	–	–	–
V	Vehicle type (2 types: motor vehicle, trailer vehicle)	Nominal	–	–	–	–
M	Month of measurement (cumulative)	Nominal	–	–	–	–

On the wear trajectory, it is necessary to study the variables that assess the evolution of the geometrical measures of the wheel profile, which are the change in the tread diameter due to wear (ΔD), the change in the flange height due to wear (ΔF_h), the change in the flange thickness due to wear (ΔF_t) and the change in the flange slope due to wear (ΔqR). Going back to Figure 3, to the case of the wheel tread diameter (D), the change in diameter due to wear (ΔD) is the difference between the final and the initial wheel diameter for each graph segment in continuous blue lines (i.e. each wear period). Similarly, it is possible to extend this difference to the remaining wheel profile measurements and define the quantities ΔF_h, ΔF_t and ΔqR. Note that, in this paper, the change in the tread diameter due to wear (ΔD) is represented in its absolute value, in a variable called diameter loss due to wear ($|\Delta D|$).

If plotted several observations of the diameter loss due to turning ($|\Delta D|$), the change in the flange height due to wear (ΔF_h), the change in the flange thickness due to wear (ΔF_t) and the change in the flange slope due to wear (ΔqR), respectively Figures 5 – 8 , associated with the kilometers since last turning/renewal (K), it is possible to see a lot of unexplained variability (Table 2), i.e. variability that is not explained by the variation in the kilometers since last turning/renewal.

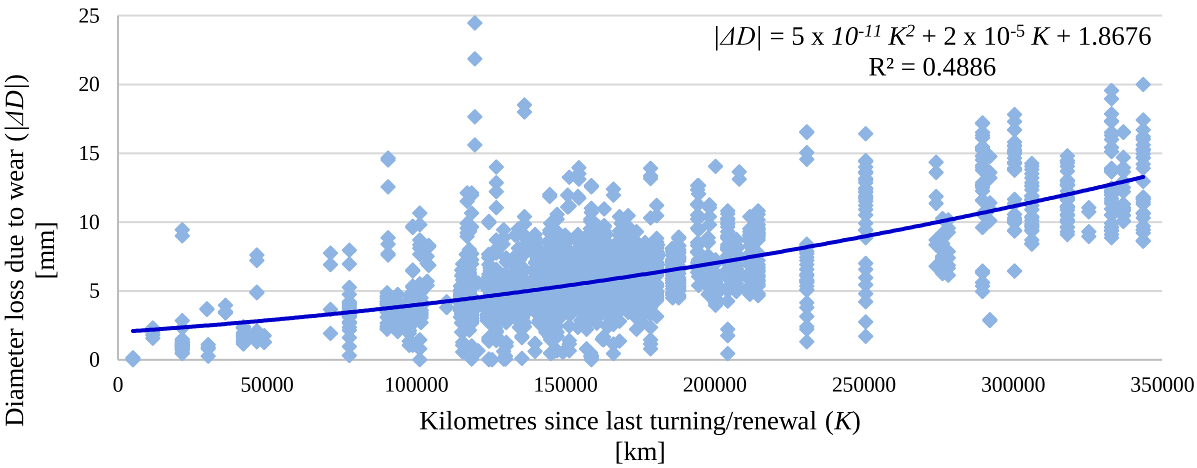

Fig. 5. Diameter loss due to wear with the kilometers since turning/renewal.

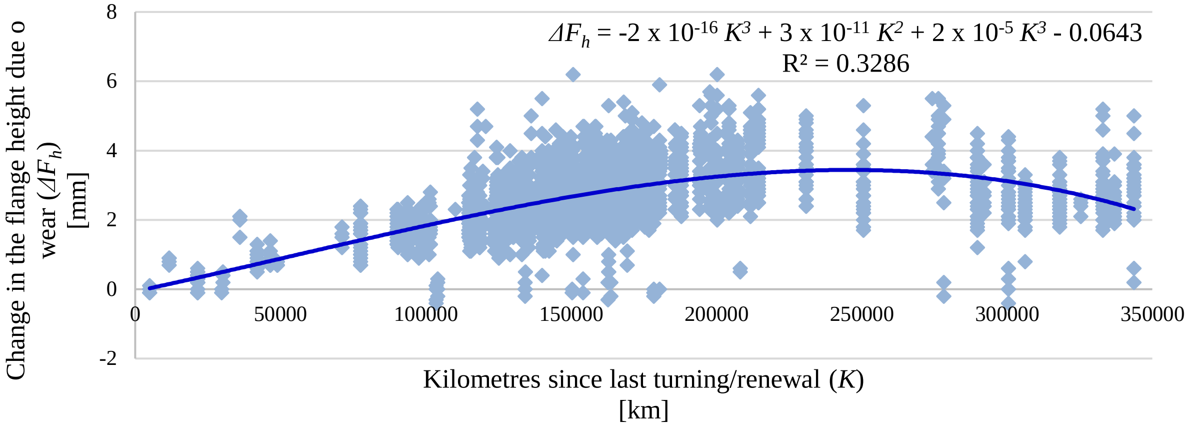

Fig. 6. Change in the flange height due to wear with the kilometers since turning/renewal.

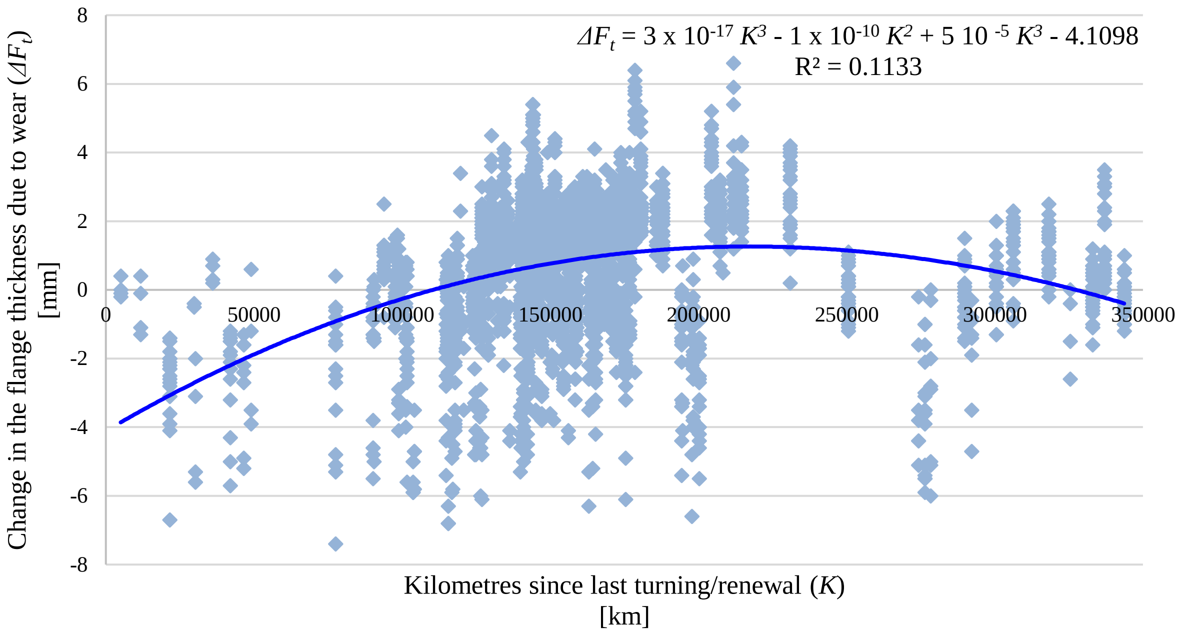

Fig. 7. Change in the flange thickness due to wear with the kilometers since turning/renewal.

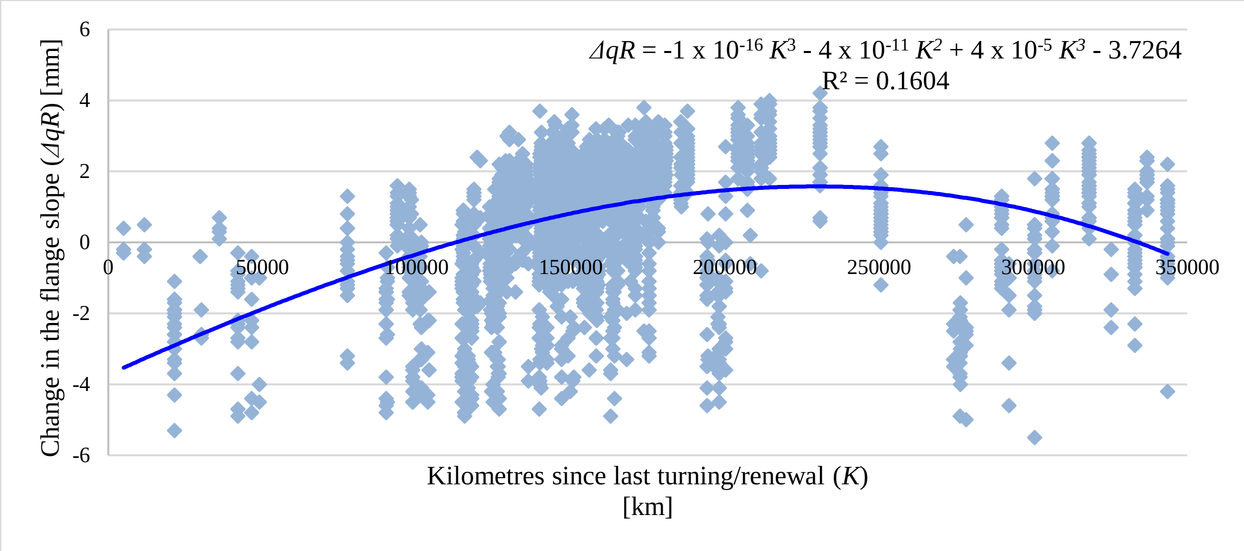

Fig. 8. Change in the flange slope due to wear with the kilometers since turning/renewal.

Table 2. Variability (R^2) in the wheel profile measurements.

	R^2
ΔD	0.4886
ΔF_h	0.3286
ΔF_t	0.1133
ΔqR	0.1604

All this unexplained variability may be explained by several factors, such as the unit number, the vehicle type and the month of measurement from Table 1. In fact, an LMM concept can handle these factors treating them as random effects in its modelling. There are two ways of modelling random effects with multiple groups: considering them as crossed random effects or nested random effects. For example, modelling the wheelset degradation from a wheelset in a given vehicle, it is possible to consider random effects in wheelset position ‘nested’ within each vehicle type, or not consider the random effect of wheelset position within each vehicle type and instead model these random effects in a crossed manner. In line with Andrade and Stow (2016), only crossed random effects were used because no statistically significant increase in information is found when nested random effects are considered.

From 6556 wheel profiles measured, different LMMs were specified for the dependent variables that assess the wheelset’s degradation trajectory:

i. The diameter loss due to wear – $|\Delta D|$;
ii. The change in the flange height due to wear – ΔF_h;
iii. The change in the flange thickness due to wear – ΔF_t;
iv. The change in the flange slope due to wear – ΔqR.

Table 3 compiles and identifies all the fixed effects, random effects and variance structure for each dependent variable in the models here specified (M0 – M4b). The models are associated with the fixed effects of the kilometers since turning/renewal (K), the wheelset type (*W*) and the wheel hardness (*H*) - parameters that are known to be strongly related with the wheel degradation trajectory and that are ‘fixed’ factors inherent to a wheelset, at any time. Then, random effects are added: the month of measurement (*M*), the unit number (*U*) and then vehicle type (*V*).

Models M0 are the simplest ones only with an intercept and a slope parameter, considering only the kilometers since last turning/renewal (*K*) as the explaining fixed effect variable, since it is the most important fixed effect here analyzed. Models M1 are the reference models which consider all the fixed effects here analyzed for the dependent variables, but do not take into account random effects.

Note that, some of the models explored were specified in the same way as in Andrade and Stow (2016), i.e. using kilometers since turning/renewal (*K*) as an explaining variable with two terms: a linear and a quadratic term (M1a – M4a), and others with three terms: a linear, a quadratic and a cubic term (M1b – M4b).

For the models with random effects (M2 – M4), the number of random factors increase, i.e. to the month of measurement (*M*) in the M2, the unit number (*U*) was added in the M3, followed by the addition of the vehicle type (*V*) in M4. This specific adding order was followed by Andrade and Stow (2016), since in their case study this would better identify which random factors added more variability around the expected mean (i.e. controlling for different values for the fixed effects).

In terms of variance structure, the variances for the different groups within each different random effect factor are all considered the same – VC.

Table 3. Linear Mixed Models explored for each dependent variable with fixed effects, random effects and variance structure.

Dependent variable	Models	Fixed effects	Random effects	Variance structure
$\|\Delta D\|$	M0	1, K	–	–
	M1a	1, K, K^2, W, H	–	–
	M2a	1, K, K^2, W, H	M	VC
	M3a	1, K, K^2, W, H	M, U	VC, VC
	M4a	1, K, K^2, W, H	M, U, V	VC, VC, VC
ΔF_h	M0	1, K	–	–
	M1b	1, K, K^2, K^3, W, H	–	–
	M2b	1, K, K^2, K^3, W, H	M	VC
	M3b	1, K, K^2, K^3, W, H	M, U	VC, VC
	M4b	1, K, K^2, K^3, W, H	M, U, V	VC, VC, VC
ΔF_t	M0	1, K	–	–
	M1b	1, K, K^2, K^3, W, H	–	–
	M2b	1, K, K^2, K^3, W, H	M	VC
	M3b	1, K, K^2, K^3, W, H	M, U	VC, VC
	M4b	1, K, K^2, K^3, W, H	M, U, V	VC, VC, VC
ΔqR	M0	1, K	–	–
	M1b	1, K, K^2, K^3, W, H	–	–
	M2b	1, K, K^2, K^3, W, H	M	VC
	M3b	1, K, K^2, K^3, W, H	M, U	VC, VC
	M4b	1, K, K^2, K^3, W, H	M, U, V	VC, VC, VC

For instance, a specific second degree polynomial, that could model any dependent variable as $|\Delta D|$, ΔF_h, ΔF_t or ΔqR, would result in the following expression

$$\boldsymbol{y}_{mui} = \boldsymbol{\beta_0} + \boldsymbol{\beta_K} \boldsymbol{K}_{mui} + \boldsymbol{\beta_{K^2}} \boldsymbol{K}^2_{mui} + \boldsymbol{\beta_W} \boldsymbol{W} + \boldsymbol{\beta_H} \boldsymbol{H} + \boldsymbol{b}_{0m} + \boldsymbol{b}_{0u} + \boldsymbol{\varepsilon}_{mui}$$

Considered for the fixed effects on the kilometers since turning/renewal (***K***), the wheelset type (***W***) and the wheelset hardness (***H***), where *m* indexes the month of measurement, *u* indexes the train unit, *i* indexes the individual measurement of the wheel, $\boldsymbol{b}_{0m}$ and $\boldsymbol{b}_{0u}$ are crossed random effects and $\boldsymbol{\varepsilon}_{mui}$ is the traditional normally distributed random error.

In the analysis followed hereinafter, the Akaike information criterion (AIC) is used solely to compare models with different fixed effects and without random effects. On the other hand, the restricted maximum likelihood (REML) criterion, namely a 'goodness of feet' measure: the −2 restricted log likelihood, is used to compare models with the same fixed effects but different random effects. The reason why the model comparison is conducted using the restricted maximum likelihood (REML) criterion is due to the 'lme4' package fits the model using that same criterion (Bates et al. 2014). For a deeper discussion on the use of different criteria in model comparison in LMM, see Müller et al. (2013), namely on the lack of consensus on how to approach model selection in LMM.

i. The diameter loss due to wear – $|\Delta D|$

The first dependent variable that needs to be modelled is the diameter loss due to wear ($|\Delta D|$). As explained before in Figure 5, there is a lot of unexplained variability around the second-order polynomial describing the evolution of the diameter loss due to wear with the kilometers since last turning/renewal. This variability is then explored again through LLMs, comparing the different specifications in Table 3 for the models M0–M4a. Table 4 provides the REML estimates for the parameters of the models explored. Note that, all the coefficients are statistically significant at the 5% significance level for all fixed effects. Comparing the variances with the total variance ($\sigma^2 + d_M + d_U + d_V = 3.804$), it is possible to find out that the measurement noise still captures 85.4%, the factor month of measurement (M) captures 12.3%, the factor unit (U) captures 2.2% and finally the factor vehicle (V) captures 0.1% of the total variance.

Table 4. Restricted maximum likelihood estimates for the parameters of models M0 – M4a for the dependent variable change in the tread diameter (ΔD).

		ΔD				
Param.		M0	M1a	M2a	M3a	M4a
		Fixed effects				
1	β_0	0.1714	2.795	1.667	1.509	1.509
	(a)	(0.1130)	(0.2454)	(0.2935)	(0.3165)	(0.3191)
K	β_K	3.541 x 10^{-5}	1.562 x 10^{-5}	2.572 x 10^{-5}	2.796 x 10^{-5}	2.796 x 10^{-5}
	(a)	(6.605 x 10^{-7})	(2.435 x 10^{-6})	(2.785 x 10^{-6})	(3.010 $^{-6}$)	(3.010 x 10^{-6})
	β_{K^2}	–	5.151 x 10^{-11}	2.906 x 10^{-11}	2.242 x 10^{-11}	2.242 x 10^{-11}
	(a)		(5.997 x 10^{-12})	(6.941 x 10^{-12})	(7.629 x 10^{-12})	(7.629 x 10^{-12})
W	β_{motor}	–	-0.1214	-0.1219	-0.1264	-0.1264
	(a)		(0.1076)	(0.1031)	(0.1025)	(0.1025)
	$\beta_{trailer}$	–	-1.710	-1.692	-0.1697	-0.1697
	(a)		(0.1046)	(0.1005)	(0.09997)	(0.1152)
	β_{leader}	–	0 (b)	0 (b)	0 (b)	0 (b)
H	β_{C2}	–	-0.6792	-0.2443	-0.4862	-0.4862
	(a)		(0.1473)	(0.3251)	(0.3288)	(0.3288)
	β_{C1}	–	0 (b)	0 (b)	0 (b)	0 (b)
		Random effects				
M	$\sqrt{d_M}$	–	–	0.6859	0.6838	0.6838
U	$\sqrt{d_U}$	–	–	–	0.2903	0.2903
V	$\sqrt{d_V}$	–	–	–	–	0.04042
		Scale				
	σ	2.086	1.896	1.815	1.803	1.803
		−2 restricted log likelihood				
		–	–	13414.6	13394.3	13394.3

Akaike information criterium						
		14126.9	13503.6	–	–	–
Number of parameters						
		3	7	8	9	10

(a) Approximate standard errors for fixed effects.

(b) This parameter is redundant.

ii. The change in the flange height – ΔF_h

The second dependent variable being modelled is the change in the flange height due to wear (ΔF_h). As explained before in Figure 6, there is a lot of unexplained variability around the third-order polynomial describing the evolution of the flange height due to wear with the kilometers since last turning/renewal. This variability is then explored again through LLMs, comparing the different specifications in Table 3 for the models M0–M4b. Table 5 provides the REML estimates for the parameters of the models explored. Note that, all the coefficients are statistically significant at the 5% significance level for all fixed effects. Comparing the variances with the total variance ($\sigma^2 + d_M + d_U + d_V = 0.8054$), it is possible to find out that the measurement noise still captures 52.4%, the factor month of measurement (*M*) captures 17.9%, the factor unit (*U*) captures 1.3% and finally the factor vehicle (*V*) captures 28.4% of the total variance.

Table 5. Restricted maximum likelihood estimates for the parameters of models M0 – M4b for the dependent variable change in the flange height (ΔF_h).

				ΔF_h		
Param.		M0	M1b	M2b	M3b	M4b
Fixed effects						
1	β_0	1.597	0.2386	0.004362	-0.01876	-0.01876
	(a)	(0.04645)	(0.1278)	(0.1436)	(0.1617)	(0.5048)
K	β_K	6.342×10^{-6}	1.881×10^{-5}	2.534×10^{-5}	2.608×10^{-5}	2.608×10^{-5}
	(a)	(2.715×10^{-7})	(2.348×10^{-6})	(2.666×10^{-6})	(3.122×10^{-6})	(3.122×10^{-6})
	β_{K^2}	–	2.680×10^{-11}	-2.250×10^{-11}	-2.664×10^{-11}	-2.664×10^{-11}
	(a)		(1.440×10^{-11})	(1.731×10^{-11})	(2.043×10^{-11})	(2.043×10^{-11})
	β_{K^3}	–	-1.748×10^{-16}	-7.748 x 10-^{17}	-7.269×10^{-17}	-7.269×10^{-17}
	(a)		(2.628×10^{-17})	(3.234×10^{-17})	(3.813×10^{-17})	(3.813×10^{-17})
W	β_{motor}	–	-0.09266	-0.09339	-0.09374	-0.09374
	(a)		(0.03929)	(0.03713)	(0.03692)	(0.03692)
	$\beta_{trailer}$	–	-0.7379	-0.7545	-0.7521	-0.7521
	(a)		(0.03818)	(0.03621)	(0.03604)	(0.6772)
	β_{leader}	–	0 (b)	0 (b)	0 (b)	0 (b)
H	β_{C2}	–	-0.1409	-0.3868	-0.3764	-0.3764
	(a)		0.05379	0.1615	0.1675	0.1675
	β_{C1}	–	0 (b)	0 (b)	0 (b)	0 (b)
Random effects						
M	$\sqrt{d_M}$	–	–	0.3681	0.3804	0.3804
U	$\sqrt{d_U}$	–	–	–	0.1008	0.1008
V	$\sqrt{d_V}$	–	–	–	–	0.4782
Scale						
	σ	0.8573	0.6920	0.6532	0.6495	0.6495

			−2 restricted log likelihood			
		–	–	6844.14	6830.07	6830.07
			Akaike information criterium			
		8297.42	6897.38	–	–	–
			Number of parameters			
		3	8	9	10	11

(a) Approximate standard errors for fixed effects.

(b) This parameter is redundant.

iii. The change in the flange thickness – ΔF_t

The third dependent variable being modelled is the change in the flange thickness m due to wear (ΔF_t). As explained before in Figure 7, there is a lot of unexplained variability around the third-order polynomial describing the evolution of the diameter thickness due to wear with the kilometers since last turning/renewal. This variability is then explored again through LLMs, comparing the different specifications in Table 3 for the models M0–M4b. Table 6 provides the REML estimates for the parameters of the models explored. Note that, all the coefficients are statistically significant at the 5% significance level for all fixed effects. Comparing the variances with the total variance ($\sigma^2 + d_M + d_U + d_V = 3.493$), it is possible to find out that the measurement noise still captures 39.0%, the factor month of measurement (*M*) captures 55.4%, the factor unit (*U*) captures 1.4% and finally the factor vehicle (*V*) captures 4.2% of the total variance.

Table 6. Restricted maximum likelihood estimates for the parameters of models M0 – M4b for the dependent variable change in the flange thickness (ΔF_t).

			ΔF_t			
Param.		M0	M1b	M2b	M3b	M4b
			Fixed effects			
1	β_0	-0.08539	-3.805	-1.269	-1.670	-1.670
	(a)	(0.1049)	(0.3208)	(0.3071)	(0.3461)	(0.5168)
K	β_K	4.182×10^{-6}	4.803×10^{-5}	2.441×10^{-5}	3.096×10^{-5}	3.096×10^{-5}
	(a)	(6.131×10^{-7})	(5.894×10^{-6})	(4.955×10^{-6})	(6.114×10^{-6})	(6.114×10^{-6})
	β_{K^2}	–	-1.233×10^{-10}	-8.984×10^{-11}	-1.232×10^{-10}	-1.232×10^{-10}
	(a)		(3.614×10^{-11})	(3.226×10^{-11})	(4.016×10^{-11})	(4.016×10^{-11})
	β_{K^3}	–	2.889×10^{-17}	9.630×10^{-17}	1.506×10^{-16}	1.506×10^{-16}
	(a)		(6.596×10^{-17})	(6.023×10^{-17})	(7.482×10^{-17})	(7.482×10^{-17})
W	β_{motor}	–	0.1658	0.2093	0.2045	0.2045
	(a)		(0.09863)	(0.06685)	(0.06642)	(0.06642)
	$\beta_{trailer}$	–	0.2797	0.3028	0.2894	0.2894
	(a)		(0.09586)	(0.06521)	(0.06487)	(0.5465)
	β_{leader}	–	0 (b)	0 (b)	0 (b)	0 (b)
H	β_{C2}	–	-2.685	-3.342	-3.441	-3.441
	(a)		0.1350	0.5675	0.5722	0.5722
	β_{C1}	–	0 (b)	0 (b)	0 (b)	0 (b)
			Random effects			
M	$\sqrt{d_M}$	–	–	1.383	1.391	1.391
U	$\sqrt{d_U}$	–	–	–	0.218	0.218
V	$\sqrt{d_V}$	–	–	–	–	0.383

Scale					
σ	1.936	1.737	1.176	1.168	1.168
–2 restricted log likelihood					
	–	–	10775.9	10776.4	10756.4
Akaike information criterium					
	13638.6	12931.7	–	–	–
Number of parameters					
	3	8	9	10	11

(a) Approximate standard errors for fixed effects.

(b) This parameter is redundant.

iv. The change in the flange slope – *ΔqR*

Finally, the fourth dependent variable being modelled is the change in the flange slope due to wear (*ΔqR*). As explained before in Figure 8, there is a lot of unexplained variability around the third-order polynomial describing the evolution of the diameter thickness due to wear with the kilometers since last turning/renewal. This variability is then explored again through LLMs, comparing the different specifications in Table 3 for the models M0–M4b. Table 7 provides the REML estimates for the parameters of the models explored. Note that, all the coefficients are statistically significant at the 5% significance level for all fixed effects. Comparing the variances with the total variance ($\sigma^2 + d_M + d_U + d_V = 3.278$), it is possible to find out that the measurement noise still captures 28.4%, the factor month of measurement (*M*) captures 50.0%, the factor unit (*U*) captures 0.1% and finally the factor vehicle (*V*) captures 21.5% of the total variance.

Table 7. Restricted maximum likelihood estimates for the parameters of models M0 – M4b for the dependent variable change in the flange slope (*ΔqR*).

			ΔqR			
Param.		M0	M1b	M2b	M3b	M4b
Fixed effects						
1	β_0	-0.2254	-3.583	-0.5998	-0.6364	-0.6364
	(a)	(0.09199)	(0.2893)	(0.2647)	(0.2707)	(0.8819)
K	β_K	5.627 x 10^{-6}	3.729 x 10^{-5}	5.419 x 10^{-6}	5.836 x 10^{-6}	5.836 x 10^{-6}
	(a)	(5.376e x 10^{-7})	(5.315 x 10^{-6})	(4.085 x 10^{-6})	(4.286 x 10^{-6})	(4.286 x 10^{-6})
	β_{K^2}	–	-3.994 x 10^{-11}	4.218 x 10^{-11}	4.084 x 10^{-11}	4.084 x 10^{-11}
	(a)		(3.259 x 10^{-11})	(2.659 x 10^{-11})	(2.800 x 10^{-11})	(2.800 x 10^{-11})
	β_{K^3}	–	-1.257 x 10^{-16}	-1.503 x 10^{-16}	-1.490 x 10^{-16}	-1.490 x 10^{-16}
	(a)		(5.949 x 10^{-17})	(4.964 x 10^{-17})	(5.227 x 10^{-17})	(5.227 x 10^{-17})
W	β_{motor}	–	0.08834	0.1316	0.1312	0.1312
	(a)		(0.08894)	(0.05494)	(0.05490)	(0.05490)
	$\beta_{trailer}$	–	0.3335	0.3558	0.3544	0.3544
	(a)		(0.08645)	(0.05360)	(0.05358)	(0.05358)
	β_{leader}	–	0 (b)	0 (b)	0 (b)	0 (b)
H	β_{C2}	–	-0.09933	-1.632	-1.634	-1.634
	(a)		(0.1218)	(0.5253)	(0.5265)	(0.5265)
	β_{C1}	–	0 (b)	0 (b)	0 (b)	0 (b)
Random effects						

M	$\sqrt{d_M}$	–	–	1.288	1.280	1.280
U	$\sqrt{d_U}$	–	–	–	0.05599	0.05599
V	$\sqrt{d_V}$	–	–	–	–	0.8393
				Scale		
	σ	1.698	1.567	0.9661	0.9654	0.9654
				−2 restricted log likelihood		
		–	–	9508.04	9507.55	9507.55
				Akaike information criterium		
		12776.9	12254.3	–	–	–
				Number of parameters		
		3	8	9	10	11

(a) Approximate standard errors for fixed effects.

(b) This parameter is redundant.

5. Conclusions and further research

This paper provided a more comprehensive understanding on the topic of exploring wear trajectories of railway wheelsets. It introduced a new important variable - the flange slope (*qR*) - on the analysis of the wheelset degradation process. It also introduced the wheel hardness (*H*) as an explaining variable for the wheelset wear trajectories.

From the data analysis, the statistical patterns found were consistent with other train fleets and, therefore, it validated the statement that these "models can be applied to any fleet of vehicles".

The kilometers since last turning/renewal (*K*) is the variable with more influence in the wheelset wear trajectories among the variables analyzed, but also the variable wheelset type (*W*) and wheelset hardness (*H*) are statistically significant.

The factor month of measurement (*M*) exhibit a high variance in every model, which is likely to be due to adhesion variations (i.e. lower in Autumn), and it is something that goes in line with a previous study of Andrade and Stow (2016). Comparing to this previous research study for a different train fleet - where random effects associated with the factor month of measurement (*M*) exhibit a higher variance, followed by the factors unit (*U*) and vehicle (*V*) – the influence order of these same random effects was not the same in this case study, existing some variations in this order for each dependent variable here analyzed. This could say that the factors that exhibit more variance to the wheelsets degradation trajectories depend on the fleets analyzed, their technical specifications, as well as the climate conditions of each country.

As further steps for this specific case study analysis, two additional factors of the technician's influence and the wheelset damaged trajectories could be included. The assessment of data on the wear and damage trajectories can also be monitored by more sophisticated methods, such as doing some survival analysis for the data analyzed. Moreover, the assessment of the wheel deterioration trajectories should consider the influence of the rail contact points and its deterioration processes as well (Lewis and Olofsson 2004). The inclusion in the models of the rail line data where this railway company operates would definitively improve this research study.

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