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Modelling Tyre-Road Noise with Data Mining Techniques

Elisabete FREITAS[(1)], Joaquim TINOCO[(1)], Francisco SOARES[(1)],
Jocilene COSTA[(1)], Paulo CORTEZ[(2)], Paulo PEREIRA[(1)]

[(1)] *CTAC, Department of Civil Engineering, University of Minho*
Campus de Azurém, 4800-058 Guimarães, Portugal;
e-mail: {efreitas, jabtinoco, ppereira}@civil.uminho.pt, a61864@alunos.uminho.pt, jocilene.mt@gmail.com

[(2)] *ALGORITMI Centre, Department of Information Systems, University of Minho*
Campus de Azurém, 4800-058 Guimarães, Portugal; e-mail: pcortez@dsi.uminho.pt

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The research aimed to establish tyre-road noise models by using a Data Mining approach that allowed to build a predictive model and assess the importance of the tested input variables. The data modelling took into account three learning algorithms and three metrics to define the best predictive model. The variables tested included basic properties of pavement surfaces, macrotexture, megatexture, and unevenness and, for the first time, damping. Also, the importance of those variables was measured by using a sensitivity analysis procedure. Two types of models were set: one with basic variables and another with complex variables, such as megatexture and damping, all as a function of vehicles speed. More detailed models were additionally set by the speed level. As a result, several models with very good tyre-road noise predictive capacity were achieved. The most relevant variables were Speed, Temperature, Aggregate size, Mean Profile Depth, and Damping, which had the highest importance, even though influenced by speed. Megatexture and IRI had the lowest importance. The applicability of the models developed in this work is relevant for trucks tyre-noise prediction, represented by the AVON V4 test tyre, at the early stage of road pavements use. Therefore, the obtained models are highly useful for the design of pavements and for noise prediction by road authorities and contractors.

Keywords: tyre-road noise, data mining, model, texture, damping, surface characteristics.

1. Introduction

The noise control policies implemented from the 1980s forced road administrations and builders to implement noise mitigation measures. However, only recently these policies focus on reducing noise at the source, drawing research attention to low noise surfaces. The advantages of this measure are the relative low cost and capacity to reduce annoyance directly (Freitas *et al.*, 2012), which is not the case of traffic related measures (Kaczmarek, Preis, 2010). The disadvantages are the lower mechanical durability and lower detectability of vehicles by pedestrians (Mendonça *et al.*, 2013), as well as low acoustic durability when they have high voids contents (Gołębiewski, 2008). Even though, at the present, it is much preferred noise mitigation measure. In the process of developing a low noise surface a number of factors should be considered such as aggregate size, porosity, and texture, which somehow guarantee that the final product will have a certain acoustic performance.

Tyre-road noise prediction models are a tool that can be applied during the design and formulation of road pavement surface in order to indicate the performance of that surface according to its characteristics and in some cases depending on the characteristics of the tyres. Such models are, therefore, very useful. However, some prediction models are extremely complex and others have a limited reliability, due to modelling simplifications.

Data mining (DM) techniques allow for an automatic creation of data-driven models from raw data, and can be used in vast databases or with complex relationships (Domingos, 2012). These techniques were used for the first time in this study for modelling the tyre-road noise obtained by the CPX method as a function of testing speeds, air temperature, pavement sur-

face characteristics such as texture spectrum and evenness, and noise related characteristics such as sound absorption and damping.

In this work, three different DM learning algorithms were applied to model tyre/road noise. Also, three metrics were used to select the best predictive model. Moreover, based on a detailed sensitivity analysis, the relative importance of each variable integrated in the models was determined.

This paper is organized as follows. Section 2 briefly discusses the methods of assessment of noise and tyre-road prediction models. Next, in Sec. 3 the data modelling methodology is presented. Then, Sec. 4 describes materials and methods. Next, Sec. 5 details the adopted dataset. Then, the experiments conducted are presented and analysed in Sec. 6. Finally, the main conclusions are drawn in Sec. 7.

2. Tyre-road noise modelling overview

A model to predict the tyre-road contact noise should integrate parameters describing the road pavement surface and the tyre. The interaction mechanisms between pavement surface and tyre are complex, which makes the use of extremely complicated mathematical expressions to model them difficult. So there are models able to predict noise simulating only some of its mechanisms and others to simulate all mechanisms. These models can be classified into simple empirical models, semi-empirical and theoretical models, and complete models (Sandberg, Ejsmont, 2002).

The simple empirical models simulate the impact of tread blocks on the road surface or simulate the noise due to pavement characteristics, or both, which is the case of the model developed by Mak and Hung (2014). The semi-empirical and theoretical models can predict noise considering air pumping and vibration of the tyre carcass. One example of such models is that improved by Larsson (2002). Another reference model is the TINO model because it considers realistic vehicle operating conditions (Sandberg, Ejsmont, 2002). The complete models, such as TRIAS, are based on tyre characteristics such as size, material, and thread pattern, and on pavement surface characteristics such as aggregate size, the bitumen percentage, layer density, and type. This information is used in sub-models to simulate the pavement surface and all the mechanisms of generation and propagation of noise. Another example of complete models is the Deufrako model, developed jointly by France and Germany, which was based on Speron (Statistical Physical Explanation of Rolling Noise). This model considers tyre visco-elastic characteristics and a noise propagation prediction module close to buildings facades. It was adapted to be used as a design tool (Deufrako, 2009).

3. Data mining definition and application to road transportation/highway engineering

The capability to automatically learn from data is a very attractive approach to extract useful knowledge. Therefore, in the last decades the use of data mining (DM) has spread rapidly throughout computer science and beyond. In effect, DM techniques have been applied successfully in different knowledge domains, e.g., web search, spam filters, recommender systems, and fraud detection (Domingos, 2012). Taking advantage of its strong flexibility to deal with high dimensionality problems, DM techniques were applied to solve complex problems in the civil engineering field as well (Tinoco *et al.*, 2014; Gomes Correia *et al.*, 2013; Miranda *et al.*, 2011; Chou *et al.*, 2011).

Also known as Knowledge Discovery in Databases (KDD), Analytics and more recently Data Science, DM can be defined as a nontrivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data (Fayyad *et al.,* 1996b). The term "nontrivial" means that some search or inference is involved. This means that DM is not a straightforward computation of predefined quantities, such as computing the average value of a set of numbers. DM is interactive and iterative, involving numerous steps with many decisions made by the user (Fayyad *et al.*, 1996a). The full DM process can be resumed in five main steps: data selection, pre-processing, transformation, modelling, and interpretation.

Thus, DM is an area of computer science that lies at the intersection of statistics, machine learning, data management and databases, pattern recognition, artificial intelligence, and other areas. DM allows finding trends and relationships between variables with the objective of predicting their future state.

Despite their potential, DM techniques are not yet widely used in transportation. There are a few examples of application of DM techniques such as Pavement Management Decision Making (Zhou *et al.*, 2010), pavement classification (Taylor *et al.*, 2012), and predicting road traffic noise, as discussed in Kumar *et al.* (2012), which lead to a probable successful application of DM to tyre-road noise modelling.

4. Materials and methods

4.1. Selection of testing sites

This study considered nine 200 m long straight road sections, located in national roads, covering a wide set of pavement surfaces used in Portugal, whose superficial layers are described as follows:

- Open texture asphalt, OTA, (1 section);
- Gap graded asphalt rubber – medium rubber percentage, GGARm, (1 section);
- Gap graded asphalt rubber, GGAR, (2 sections);

- Dense asphalt, DA, (2 sections);
- Slurry seal, SS, (2 sections);
- Open graded asphalt, OGA, (1 section).

4.2. Selection of model variables

The target dependent variable is the noise level. The independent variables of the model are related to vehicle's travel characteristics (speed – V), climatic conditions (air temperature – *Temp*), test tyre and surface characteristics (unevenness, texture, absorption, damping). These data were obtained by the following tests:

- Tyre-road noise, measured by the close proximity method (CPX) in sections of 10 m;
- Unevenness obtained through a high-speed profilometer every 10 m;
- Surface texture obtained through a high-speed profilometer every 10 m;
- Sound absorption measured through an impedance tube, constructed for measurements on road pavements (Freitas *et al.*, 2010), every 10 m;
- Damping, measured every 10 m.

Following, the selected variables are described after a brief presentation of the test methods.

4.2.1. Tyre-road noise

Currently there is a set of methods for assessing tyre-road noise (e.g. ISO 11819-1, 1997 and ISO CD 11819-2, 2000). From the point of view of the road network management, the most interesting method is the CPX one, because it is carried out at traffic speeds and enables the measurement of an equivalent noise level on a spatial rather than temporal basis, as it is a common practice for the evaluation of the functional quality of pavements at a network level. Therefore, this method was adopted in the study. Supported by two microphones' assemblage installed on a wheel, as shown in Fig. 1a, the equivalent noise level (L) was recorded for a base length of 10 m at speeds between 30 km/h and 90 km/h.

AVON V4 was used as the test tyre, being representative of truck tyres as recommended in (Morgan *et al.*, 2009). The air and the surface temperatures were recorded due to their influence on tyre-road noise (Bueno *et al.,* 2011), but they were not used for correction of noise levels. Instead, the air temperature was considered a model variable.

4.2.2. Surface texture

Surface texture ranges that influence tyre-road noise are within the macrotexture and megatextura ranges (Sandberg, Ejsmont, 2002). Macrotexture is defined by the deviation of a pavement surface from a true planar surface with the characteristic dimensions along the surface of 0.5 mm to 50 mm, corresponding to texture wavelengths with one-third-octave bands including the range from 0.63 mm to 50 mm of centre wavelengths. Similarly, megatexture corresponds to dimensions along the surface of 50 mm to 500 mm, including one-third-octave from 63 mm to 500 mm. These parameters were calculated by a routine devel-

a)
b)
c)
d)

Fig. 1. Details of performance of the assessment tests: a) configuration of microphones coupled to tyre; b) CPB test method; c) field sound absorption test; d) mechanical impedance test.

oped in MATLAB®, which returns the texture level spectrum as a function of spatial frequency, every 10 m. In each section, the input data was the surface profile acquired by a high speed profilometer (Fig. 1b).

The variables extracted were the ones recommended in the standard ISO 13473-5 (2009) to characterize megatexture, as described below:

- *Ltx63* is the texture profile level in the octave band with a 63 mm centre wavelength;
- *Ltx500* is the texture profile level in the octave band with a 500 mm centre wavelength;
- *Lme* is the texture profile level in the full range of megatexture (between 63 mm and 500 mm).

The variables chosen to characterize macrotexture were the mean profile depth (*MPD*), obtained according to EN ISO 13473-1 (2004), and Route Mean Square (*RMS*), as these texture parameters are acquired frequently. The maximum aggregate size (*Dmax*) was also considered.

4.2.3. Unevenness

Unevenness or Roughness is defined as the deviation of a surface from the true planar surface with characteristic dimensions that affect vehicle dynamics and ride quality, as it is expressed through the parameter International Roughness Index (*IRI*). *IRI* is calculated from a measured longitudinal road profile by accumulating the output from a quarter-car model and dividing by the profile length to yield an overall roughness index with units of a slope (Sayers, 1995). It is defined as a characteristic of the longitudinal profile of a travelled wheel track and summarizes the roughness qualities impacting on vehicle response. For this work the base length adopted to calculate *IRI* was 10 m, to be consistent with other characteristics.

4.2.4. Sound absorption

The sound absorption was measured with a self-made impedance tube where two microphones were coupled as described in (Freitas *et al.*, 2010). This tube has an open end which is placed on the road surface as shown in Fig. 1c. The absorption coefficient was calculated from the acoustic impedance for the frequency range from 250 Hz to 2.5 kHz (1/3 octave band).

The maximum absorption frequency peak depends on thickness and porosity of each pavement surface material. In surfaces with reduced porosity (voids content nearby 5% of the total volume) this peak occurs at frequencies above 2000 Hz (Raimundo *et al.*, 2010), which interferes little with human hearing. As the location of absorption peak is highly variable and may occur out of the test limits, the parameter selected to characterize absorption was the arithmetic average of the absorption coefficient (*Absm*) from 250 Hz to 2.5 kHz (1/3 octave band).

4.2.5. Damping

Damping is a measure of energy dissipation within a structure. It can be obtained from the frequency response function (FRF), which is the ratio of a specific response (output) measured at a point i and excitation (input) caused at point j of the structure, both measured simultaneously. To obtain the FRF an instrumented hammer and accelerometer were utilized (Fig. 1d). The impact point was set as close as possible from the accelerometer.

The bandwidth method can be used to estimate the relative modal damping in a system with multiple degrees of freedom and spaced resonant frequencies, assuming that in each band of the resonance, response is dominated by the respective mode and the contribution of the other modes is irrelevant (Ewins, 2000), which is the case for road materials. To determine the damping ratio ξ of frequencies ωA and ωB which define the bandwidth $\Delta\omega = \omega_A - \omega_B$, an approximate expedited solution was used assuming that $\xi \ll 1$ (Eq. (1)).

$$\xi_i = \frac{\omega_{B_i} - \omega_{A_i}}{\omega_{B_i} + \omega_{A_i}}, \tag{1}$$

A and B are located at frequencies where the magnitude is $1/\sqrt{2}$ the value of the maximum magnitude of the resonance frequency (Chopra, 1995).

The values of resonance frequencies and damping were obtained, every 10 m, from the average of three frequency response functions (FRF) (three successive impacts), with a coherence above 95%.

For each test surface the average values of damping in each 1/3 octave band were determined. From these values, regression curves were set to estimate the damping between 500 Hz and 3500 Hz. Based on the analysis of these curves, the frequencies of 800 Hz and 2000 Hz and the corresponding damping ratio were selected for the modelling.

4.3. Modelling, evaluation, and prediction

To model tyre-road noise, three different DM regression algorithms were applied, namely: Multiple regression (MR), Artificial Neural Network (ANN), and Support Vector Machine (SVM).

The MR model was used in this work essentially as a baseline comparison. It is a simple statistical technique that allows predicting the dependent variable based on a linear combination of one or more independent variables. Due to its additive nature, this model is very easy to interpret and it is widely used in regression tasks.

ANNs is a computational technique inspired by the nervous system structure of the human brain (Kenig *et al.*, 2011). This technique has shown a high performance in modelling complex nonlinear mappings and is robust in exploration of scatter data. It is particularly useful for problems that do not have an an-

alytical formulation or where explicit and accessible knowledge does not exist. In the present work, the ANN consists in a fully connected multilayer perceptron (Ertel, 2009), with one hidden layer with H processing units, bias connections, and logistic activation functions $1/(1+e^{(-x)})$. To find the best value for H, a grid search within the range $\{2,\ 4,\ \ldots,\ 10\}$ under an internal (i.e., applied over training data) 10-fold cross validation was used (Hastie *et al.*, 2009). During this grid search, the H value that produces the lowest mean absolute error is selected and then the selected ANN is retrained with all training data.

SVM (Steinwart, Christmann, 2008) was initially proposed for classification tasks (i.e., to model a discrete labelled output) by Vladimir Vapnik and his co-workers (Cortes, Vapnik, 1995). Later, after the introduction of an alternative loss function, called ε-insensitive loss function, it was possible to apply SVM to regression problems (Smola, Schölkopf, 2004). When compared with other types of base learners, SVM represents a significant enhancement in functionality. The supremacy of SVM lies in their absence of local minima in the learning phase as well as in their use of non-linear kernel functions (Schölkopf, Smola, 2002) that implicitly map inputs into high dimensional feature spaces (Hamel, 2009). These attractive features and promising empirical performance are responsible for its gain of popularity. In the present work the popular Gaussian kernel was adopted. To reduce the search space, we adopted the heuristics proposed in Cherkassky and Ma (2004) to set the complexity penalty parameter, C=3, and the size of the insensitive tube, $\varepsilon = \widehat{\sigma}/\sqrt{N}$, where $\widehat{\sigma} = 1.5/N \cdot \sum_{i=1}^{N} (y_i - \widehat{y}_i)^2$, y_i is the measured value, $\widehat{y}_i$ is the value predicted by a 3-nearest neighbor algorithm, and N is the number of examples. The most important SVM parameter, the kernel parameter γ, was set using a grid search within $\{2^{-15},\ 2^{-13},\ \ldots,\ 2^{3}\}$, under the same 10-fold internal cross validation scheme.

Before fitting the ANN and SVM models, the data attributes were standardized to a zero mean and one standard deviation. Then, before analysing the predictions, the outputs were post-processed with the inverse transformation (Hastie *et al.*, 2009).

In a regression task, the main goal is to induce a model that minimizes the error measurement between observed and predicted values considering N examples. For this purpose three common metrics were calculated (Tinoco *et al.*, 2011): mean absolute deviation (MAD), root mean squared error (RMSE), and coefficient of correlation (R^2). The first two metrics should present low values and R^2 should be close to the unit value.

The model generalization performance was accessed by 5 runs under a cross-validation (*k-fold* = 100) approach (Hastie *et al.*, 2009), where the data (P) are randomly sampled into k mutually exclusive subsets ($P_1,\ P_2,\ \ldots,\ P_k$), with the same length. Training and testing is performed k times and the overall error of the model is taken as the average of the errors obtained in each iteration. Under this scheme, all of the data are used for training and testing. Yet, this method requires approximately k (the number of subsets) times more computation, because k models must be fitted.

Additionally to the model performance, it is also important to extract human understandable knowledge from the data-driven model. Since several of the tested DM models are complex (e.g. ANN and SVM), in this work we use a novel visualization approach based on a sensitivity analysis (SA) procedure (Cortez, Embrechts, 2013). SA is a simple method that is applied after the training phase and it measures the model responses when a given input is changed, allowing to quantify the relative importance of each attribute, as well as its average effect on the target variable. In particular, we applied the global sensitivity analysis (GSA) method (Cortez, Embrechts, 2011) which is able to detect interactions among input attributes. This is achieved by performing a simultaneous variation of F inputs (that can range from 1, one dimensional SA, denoted as 1-D, to I, I-D SA). Each input is varied through its range with Z levels and the remaining inputs are kept fixed to a b baseline value. In this work, we set $Z = 12$, which allows an interesting detail level under a reasonable amount of computational effort, and b as the average input variable value. First, the DM model is fit to the whole dataset. Then, the GSA algorithm is applied to the DM model, being the respective sensitivity responses stored. Next, using these responses, two important visualization techniques can be computed. The input importance bar plot shows the relative influence of each input in the model (from 0% to 100%). The rational of SA is that the higher the changes produced in the output, the more important the input is. To measure this effect, following the suggestion of Cortez and Embrechts (2011), we adopted the gradient metric:

$$g_a = \sum_{j=2}^{Z} |\widehat{y}_{a,j} - \widehat{y}_{a,j-1}| \,/\, (Z-1)\,, \tag{2}$$

where a denotes the input variable under analysis, $\widehat{y}_{a,j}$ is the sensitivity response for $x_{a,j}$. After computing the gradient for all inputs the relative importance (R_a) is calculated using:

$$R_a = g_a \Big/ \sum_{i=1}^{I} g_i \cdot 100(\%). \tag{3}$$

To analyse the average impact of a given input x_a in the fit model, the variable effect characteristic (VEC) curve can be used, which plots the attribute Z level values (x-axis) *versus* the SA responses (y-axis). Be-

tween two consecutive $x_{a,j}$ values, the VEC plot performs a linear interpolation. To enhance the visualization analysis, several VEC curves can be plotted in the same graph. In such case, the x-axis is scaled (e.g., within [0,1]) for all x_a values. Similarly, when a pair of inputs (x_{a1}, x_{a2}) is simultaneously varied ($F > 2$), the VEC surface can be plotted, showing the average responses to changes in the pair.

All experiments were implemented in R tool (R, 2009), using the rminer package (Cortez, 2010), which is particularly suitable for SVM training through the use of advanced functions (particularly mining and fit). The R environment is a multiple platform (e.g., Windows, Mac OS) and free open-source tool that is based on a high-level matrix programming language, broadly used for statistical and data analysis, and has gained attention of the DM community in the past few years. Since R was not specifically developed for conducting DM projects, we take advantage of the rminer library capabilities that is an integrated framework that uses a console based approach and facilitates the use of DM algorithms in classification and regression tasks (Cortez, 2010). Moreover, rminer is particularly suited for ANN and SVM (two of the main DM algorithms used in the present work), making use of a short and coherent set of functions (e.g., fit and mining).

The procedure followed to define the variables to be included in the models considered in the first place those that are well known (*V*, *T*, *Dmax*, and *P*), then those that are commonly monitored in the scope of quality control plans (*MPD*, *SMTD*, *IRI*), and finally variables requiring improved testing methods as well as traffic disruption such as (*Absm*, *Amort800*, *Amort2000*, *Ltx63*, *Ltx500*, *Lme*). Further, among the models defined one was chosen to better understand the importance of each variable per speed level due to the high impact of speed on tyre-road noise.

5. Data characterization

In the present study, a database with 1148 records was used. Table 1 presents some descriptive statistics

Table 1. Descriptive statistics of quantitative variables.

Surface	Statistic	Temp [°C]	Lme [dB]	Ltx63 [dB]	Ltx500 [dB]	IRI [m/km]	RMS [μm]	MPD [mm]	Dmax [mm]	Absm	Amort800 [%]	Amort2000 [%]	L [dB]
OTA	Av.	30.36	47.12	44.01	43.01	1.56	554	0.90	7.00	0.05	16.41	6.81	91.80
	Max.	31.20	53.00	50.00	47.80	2.62	621	1.01	7.00	0.07	16.41	6.81	105.80
	Min.	29.50	44.50	41.50	37.90	0.72	494	0.82	7.00	0.03	16.41	6.81	77.10
GGARm	Av.	30.29	48.02	45.41	41.86	1.44	600	0.78	10.00	0.29	17.30	8.80	89.08
	Max.	31.20	63.40	53.30	61.10	2.92	689	0.90	10.00	0.31	17.30	8.80	102.60
	Min.	27.80	45.30	43.30	35.20	0.79	531	0.70	10.00	0.25	17.30	8.80	73.80
GGAR (1)	Av.	30.56	47.20	44.86	42.73	2.37	422	0.69	12.00	0.06	12.39	2.07	91.27
	Max.	31.40	52.70	48.90	48.90	3.56	547	0.87	12.00	0.08	12.39	2.07	104.80
	Min.	29.20	43.10	41.50	37.00	1.54	360	0.62	12.00	0.04	12.39	2.07	78.20
GGAR (2)	Av.	27.02	51.02	48.66	44.00	2.77	274	0.54	10.00	0.08	17.50	4.80	93.06
	Max.	28.60	57.50	51.50	53.70	4.53	305	0.61	10.00	0.09	17.50	4.80	106.90
	Min.	24.00	48.00	45.80	35.50	1.39	250	0.46	10.00	0.07	17.50	4.80	77.90
DA (1)	Av.	31.38	46.53	42.86	44.55	1.49	420	0.73	16.00	0.04	16.11	6.27	92.91
	Max.	32.90	50.20	47.10	50.50	2.47	520	0.92	16.00	0.06	16.11	6.27	106.30
	Min.	29.80	44.10	39.80	38.50	0.70	325	0.54	16.00	0.02	16.11	6.27	77.50
DA (2)	Av.	30.58	48.60	45.16	44.46	2.37	422	0.69	16.00	0.04	14.69	7.48	89.28
	Max.	33.80	52.00	48.30	48.90	3.56	547	0.87	16.00	0.06	14.69	7.49	101.00
	Min.	26.30	46.20	41.00	40.50	1.54	360	0.62	16.00	0.03	14.69	7.49	75.80
SS (1)	Av.	33.16	50.52	40.80	49.32	2.77	274	0.54	8.00	0.04	19.30	5.77	88.61
	Max.	35.40	55.50	52.60	54.50	4.53	305	0.61	8.00	0.05	19.30	5.77	99.60
	Min.	31.60	46.10	37.00	44.90	1.39	250	0.46	8.00	0.02	19.30	5.77	77.10
OGA	Av.	29.15	53.80	51.08	46.78	1.53	714	1.07	12.00	0.05	18.22	4.31	92.02
	Max.	32.60	58.80	55.00	52.10	2.66	895	1.31	12.00	0.07	18.23	4.31	104.00
	Min.	26.10	48.50	46.30	40.10	0.90	590	0.93	12.00	0.03	18.23	4.31	77.60
SS (2)	Av.	21.71	51.25	45.27	49.44	2.22	323	0.64	8.00	0.04	17.41	8.05	90.83
	Max.	27.30	55.10	48.70	53.30	4.05	406	0.82	8.00	0.07	17.41	8.05	103.80
	Min.	17.40	48.60	36.70	45.50	0.88	278	0.54	8.00	0.03	17.41	8.05	78.40

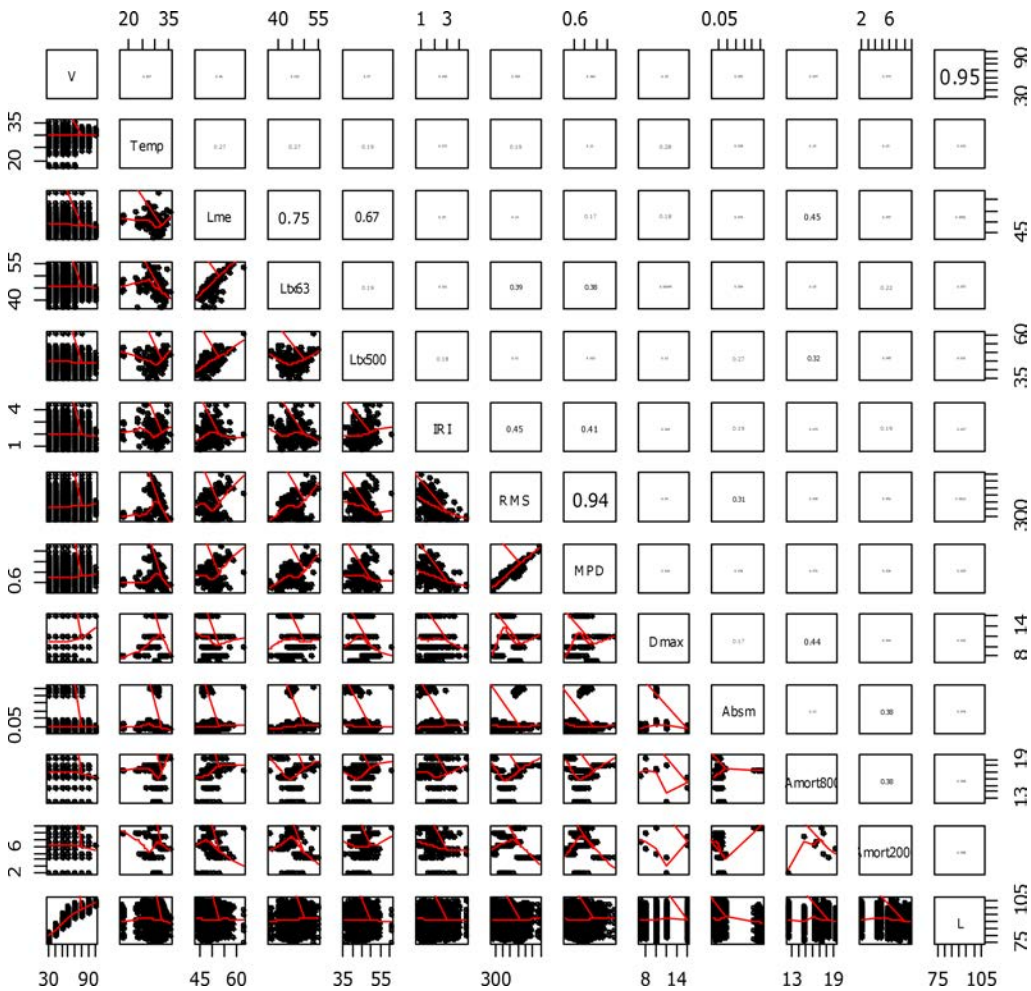

Fig. 2. Correlation matrix between all variables considered in this study.

(average, maximum, and minimum) of the variables analysed. Figure 2 summarizes the correlation matrix between all variables considered in this study. While on the right side of the figure the correlation coefficients are indicated, on the left side the corresponding graphs are plotted. From their analysis it is possible to observe a strong correlation between L and V and also between *MPD* and *SMTD*, as expected. Variables describing the megatexture have correlations among them lower than 0.76 and therefore may be used together. The remaining variables have weak correlations. For these reasons all variables were used in the models presented in the following sections.

6. Results and analysis

To better understand the importance of each variable on tyre-road noise prevision, two approaches of the problem were considered. Initially, basic variables which are currently and easily measured, whose effects on tyre-road noise are recognized, were introduced in the models. Those variables were *V*, *Temp*, and *Dmax*. To this basic set of variables other variables related to surface irregularity such as *MPD*, *RMS*, and *IRI* were added. In order to verify whether the identification of the type of surface (P) affected models' quality, this variable was also considered.

In the second stage, variables which are not frequently measured and characterise sound absorption and damping were added to the basic set (*Absm*, *Amort800*, *Amort2000*). Afterwards all variables characterizing pavement irregularities, including megatexture, were added to the model (*MPD*, *RMS*, *IRI*, *Ltx63*, *LTx500*, and *Lme*), because these variables were expected to have a significant importance in the models.

Finally, from the 13 models tested, one was chosen to model tyre-road noise by speed level. Therefore, four additional models were set and analysed.

6.1. Results considering basic and irregularity variables

Table 2 presents the global metrics of the 5 models first set. The metric R^2 does not seem to be adequate to analyse models performance due to its lack of sensitivity to variable changing, which is not the case of the

Table 2. Global metrics of the models considering basic and irregularity variables (**bold** denotes best predictive metric values.

Variables		Model				
		M1	M2	M3	M4	M5
P				✓	✓	✓
V		✓	✓	✓	✓	✓
Temp		✓	✓	✓	✓	✓
Dmax		✓	✓	✓	✓	✓
MPD		✓		✓		✓
RMS			✓		✓	
IRI						✓
R^2	MR	0.93	0.93	0.93	0.93	0.93
	NN	**0.96**	**0.96**	**0.96**	**0.96**	**0.96**
	SVM	**0.96**	**0.96**	**0.96**	**0.96**	**0.96**
RMSE	MR	2.07	2.05	2.03	2.05	2.05
	NN	1.57	1.57	**1.47**	1.49	1.48
	SVM	1.59	1.60	1.49	1.51	1.53
MAD	MR	1.60	1.59	1.56	1.58	1.58
	NN	1.25	1.24	**1.15**	1.16	1.16
	SVM	1.26	1.25	**1.15**	1.16	1.19

other metrics. Nevertheless, it should be highlighted that high quality R^2 values (i.e., > 0.9) were achieved for all 5 models.

With respect to the performance of the modelling algorithm, the ANN provided the lowest RMSE and MAD values and it is less sensitive than the SVM model to variable changes.

The effect of each variable added to the base set of variables was analysed by comparing the models' metrics (RMSE and MAD). By comparing model M1 to M2, it can be concluded that *RMS* and *MPD* have similar results. Moreover, introducing the variable that identifies the type of surface (P) improves significantly the results. The best model was achieved in this way (M3). Hence, adding IRI reduced the performance of the model (M5).

Because the number of surfaces of each type is relatively small and their designation/classification might be different in several countries, it was decided to not include this variable in the next modelling phases.

As a result of these findings, Fig. 3 compares the relative importance of each variable according to M1, M2, M3, and M4 models (algorithm ANN). From its analysis, it is clearly observed that V has the highest impact in L prediction, presenting a relative importance higher than 60%. This was already expected due to the strong correlation between V and L, as shown in Fig. 2. Among the remaining variables, *Dmax* seems to be the second variable more preponderant in L prediction. Comparing *RMS* and *MPD* variables in M1 and M3 models as well as in M2 and M4, we can conclude that both variables have a similar impact on L prediction and so it is equivalent to use one or another, which validates previous conclusions about these variables. Because *MPD* is used to characterize road pavement materials more often than *RMS* and is adopted by many road administrations, preference will be given to *MPD* in modelling.

The importance of *Temp* is similar among all models and close to the importance of *MPD*.

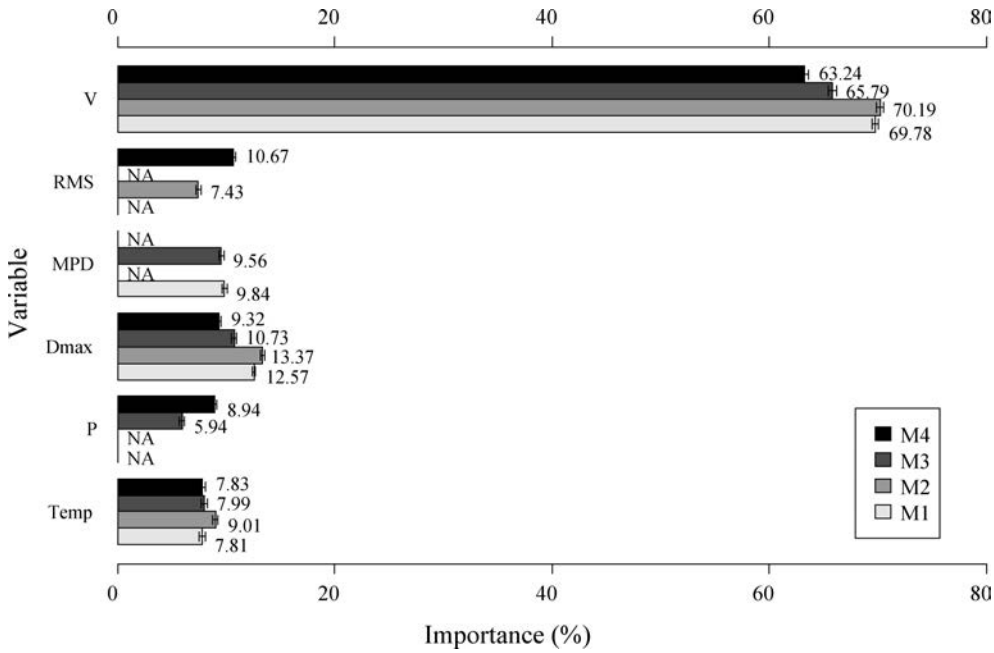

Fig. 3. Relative importance of each variable according to models M1, M2, M3, and M4.

6.2. Results considering basic and enhanced variables

Table 3 presents the metrics of the models considering basic variables, absorption, damping, macro and megatexture, and unevenness.

Table 3. Global metrics of the models considering basic and enhanced variables (**bold** denotes best predictive metric values).

Variables		Model							
		M6	M7	M8	M9	M10	M11	M12	M13
V		✓	✓	✓	✓	✓	✓	✓	✓
Temp		✓	✓	✓	✓	✓	✓	✓	✓
Dmax		✓	✓	✓	✓	✓	✓	✓	✓
Abs		✓							
Amort800			✓	✓	✓	✓	✓	✓	✓
Amort2000			✓	✓	✓	✓	✓	✓	✓
MPD				✓	✓	✓	✓	✓	✓
RMS					✓	✓			✓
IRI						✓	✓	✓	✓
Ltx63								✓	✓
Ltx500								✓	✓
Lme								✓	✓
R^2	MR	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93
	ANN	**0.96**	**0.96**	**0.96**	**0.96**	**0.96**	**0.96**	**0.96**	**0.96**
	SVM	**0.96**	**0.96**	**0.96**	**0.96**	**0.96**	**0.96**	**0.96**	**0.96**
RMSE	MR	2.05	2.01	2.00	1.99	1.98	2.00	2.00	1.99
	ANN	1.59	1.48	1.48	**1.47**	1.48	1.48	1.52	1.50
	SVM	1.57	1.48	1.54	1.53	1.52	1.53	1.56	1.56
MAD	MR	1.59	1.54	1.53	1.53	1.53	1.53	1.52	1.53
	ANN	1.26	1.15	1.15	**1.14**	1.15	1.15	1.19	1.17
	SVM	1.23	1.15	1.19	1.17	1.17	1.18	1.20	1.20

As far as model metrics and techniques are concerned, some of the previous results were confirmed. Thus, although excellent R^2 values were achieved, this metric is not adequate to analyse models' performance due to its lack of sensitivity to changes in the variables adopted. The ANN model delivered the best performance and it is again less sensitive than SVM to changes in the variables used.

The effect of each variable added to the base set of variables on models performance was analysed once more by comparing models metrics (RMS and MAD).

With model M6, it was intended to analyse the effect of sound absorption on the results. When compared to the effect of *MPD* (M1) the effect of absorption (M6) was small, probably due to the fact that most of the surfaces are reflective, and therefore absorption variability is low. For these reasons this variable was excluded from further analysis. Nevertheless, future research should include more open graded and porous surface layers because absorption might be important at near field measurements.

After introducing the damping variables (M7), MAD improved by about 10% regarding M6.

Moreover, adding *MPD* to the base set and damping variables did not affect the results (M8). It should be noted that a slight improvement was achieved when using *MPD* and RMS together (M9). This performance was not expected because these variables are highly correlated as shown in Fig. 2. The introduction of *IRI* (M10 and M11) and then megatexture (M12 and M13) variables did not improve models' performance; in fact it decreased their performance.

Given the fact that in terms of engineering *MPD* and *RMS* are not used together, the best results were achieved with model M7 which included the basic set of variables (*V*, *Temp*, *Dmax*) and damping variables (*Amort800* and *Amort2000*). Interestingly, M7 and M3 performances are similar and considerably better, by about 10% for MAD, than M1 and M2 performances (see Table 2). This means that damping variables have an effect on model results equivalent to the type of surface.

An interesting feature of DM models is the possibility to compare the importance of each variable integrated in the model. Considering the reasons presented before, within this group of eight models, four were chosen for a more detailed study: M7, M8, M11, and M12. From the analysis of Fig. 4 that compares the relative importance of each input variable in L prediction according to those models (ANN algorithm), once again the high importance of V in L prediction can be observed. Figure 4 also shows that *Amort2000* and *Amort800* are also important in L prediction and depend on the importance of the remaining variables, which is not the case of *Dmax*. On the other hand, *Ltx63*, *Ltx500*, and *IRI* present the lowest influence in L prediction. In its turn, *Lme* had a similar importance to *Temp* and *MPD* (about 6%).

The low influence of the megatexture on noise is probably due to the fact that the pavements tested had no visible degradations. Megatexture might be important to predict tyre-road noise in old pavements, such as other parameters like cracking. *IRI* is related to pavement long wave deviations and therefore the expected impact of this variable was low. Similar to the megatexture, this pavement condition parameter might have a higher contribution in an advanced stage of pavements lifespan. These parameters reflect construction quality defects which evolve with time due to vehicles' loading and degradations development. Furthermore, the effect of degradations on tyre-road noise was not sufficiently studied to be incorporated in noise modelling. Therefore *IRI* and megatexture seem to be good parameters to predict tyre-noise of old pavements.

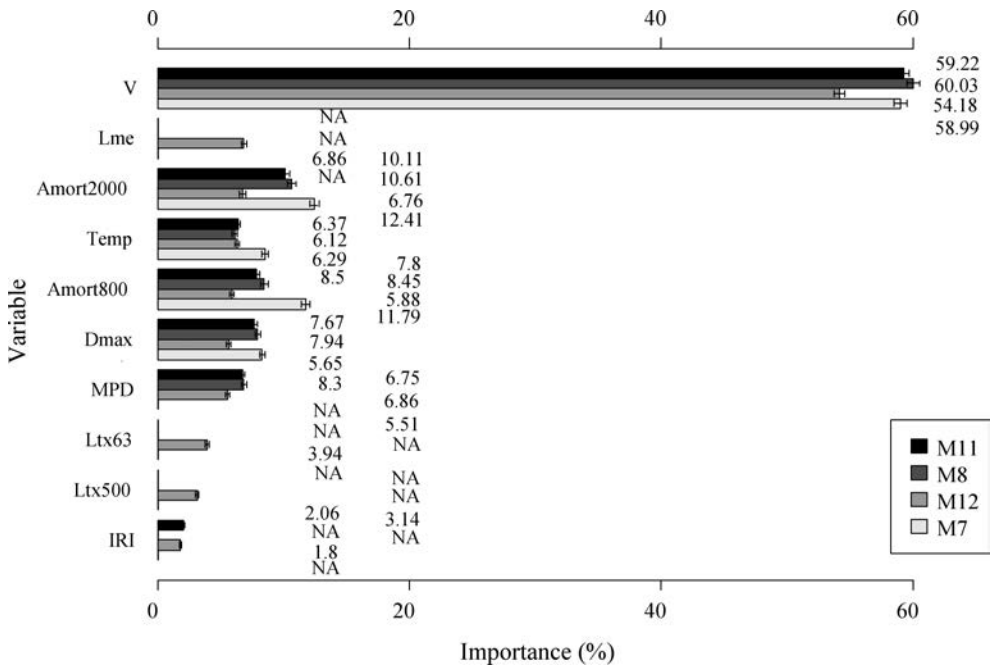

Fig. 4. Relative importance of each variable according to models M7, M8, M11, and M12.

In this context, the models developed in this work are capable of predicting tyre-road noise when surfaces are still new or in an early stage of their lives and therefore they can be used for design.

Among the set of the four models previously analysed, M8 was chosen to study the average impact of the input variables in the fit model for the ANN algorithm through the VEC curves as is displayed in Fig. 5. These variables were: *Temp*, *MPD*, *Dmax*, *Amort800*, and *Amort2000*.

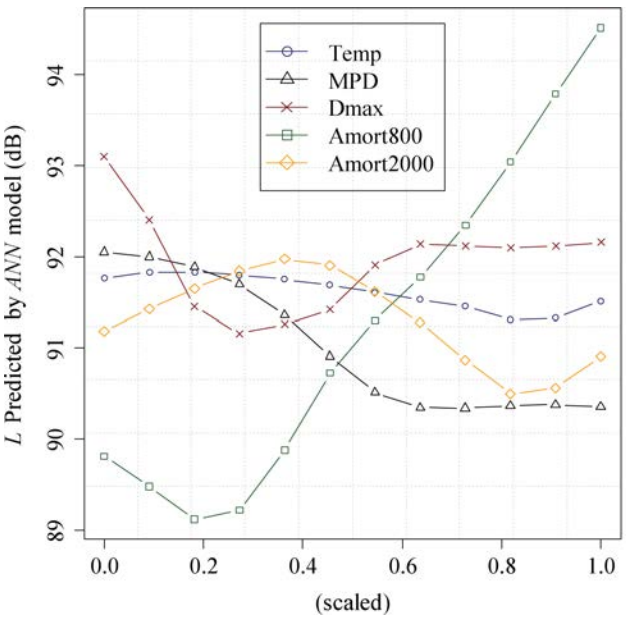

Fig. 5. VEC curves showing the average effect of *TEMP*, *MPD*, *Dmax*, *Amort800*, and *Amort2000* in the predicted output, according to model M8 (ANN algorithm).

In general terms, model variables do not have a linear trend with the predicted noise. Bearing in mind that noise was measured with truck reference tyres, in terms of engineering the VEC curves show quite well the input variables sensitivity.

6.3. Models' results per speed level

Based on the previous results, variables *Temp*, *MPD*, *Dmax*, *Amort800*, and *Amort2000* were chosen to model tyre-road noise by speed level. Table 4 shows the global metrics for speeds from 30 km/h to 90 km/h.

Table 4. Global metrics of the models for speed level (**bold** denotes best values).

Speed (km/h)		30	50	70	90
R^2	MR	0.33	0.30	0.40	**0.35**
	ANN	0.38	0.41	0.44	0.32
	SVM	**0.39**	**0.42**	**0.50**	0.34
RMSE	MR	1.32	1.53	1.82	**1.73**
	ANN	1.29	**1.41**	1.80	1.78
	SVM	**1.26**	**1.41**	**1.68**	1.76
MAD	MR	0.99	1.20	1.43	**1.41**
	ANN	1.00	**1.11**	1.40	1.44
	SVM	**0.97**	**1.11**	**1.33**	1.44

In general all metrics are sensitive to speed changes. The metric R^2 decreased significantly, while RMSE and MAD had similar results, when compared to the models presented in Tables 2 and 3. Additionally, the algorithm SVM delivered the best performance which

depends on speed. From Fig. 6 and Table 4 it can be seen that with the increase of the speed of the tyre-road in noise tests the models' performance decreases. The highest decrease is observed between 50 km/h and 70 km/h. This can be the result of a higher variability of noise level at the speed of 70 km/h, as it can been seen in Fig. 7.

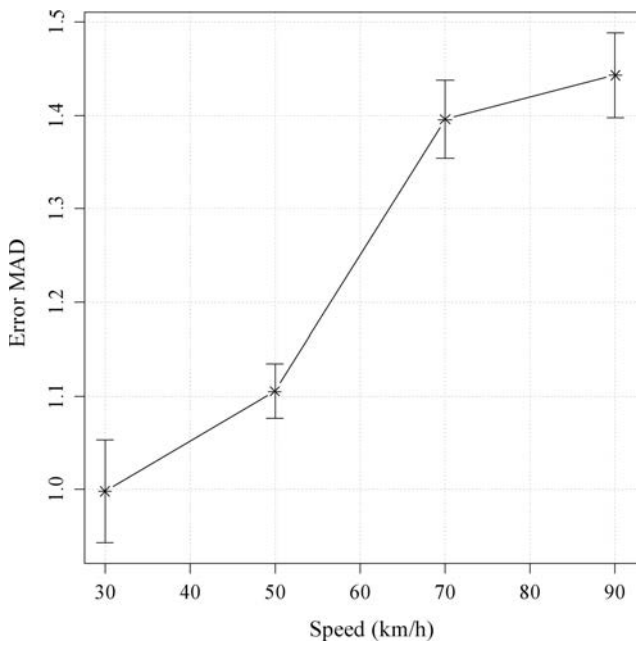

Fig. 6. Models performance (based on MAD error) as a function of traffic speed (mean and standard deviation).

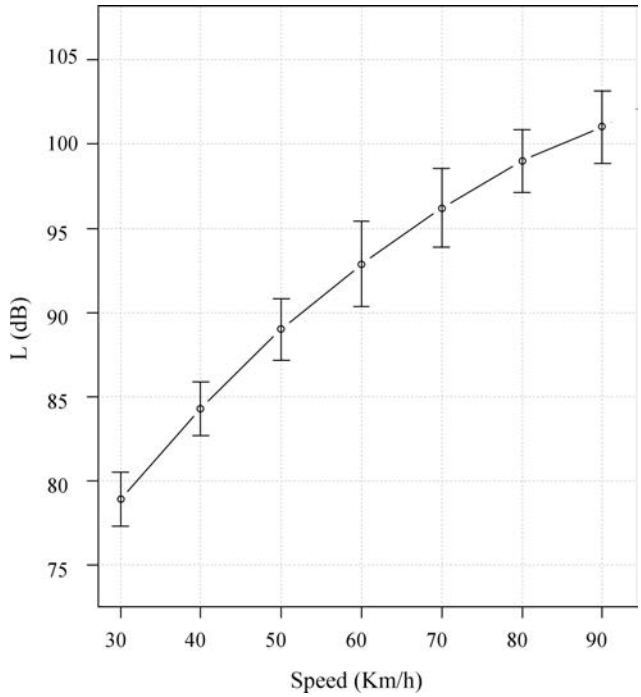

Fig. 7. Relationship between tyre-road noise and traffic speed (mean and standard deviation).

This suggests that an optimal testing speed may exist for tyre-road noise modelling at low speed levels and high speed levels.

From the comparison of the relative importance of each variable presented in Fig. 8, it can be observed that for tyre-road noise tests carried at 30 km/h,

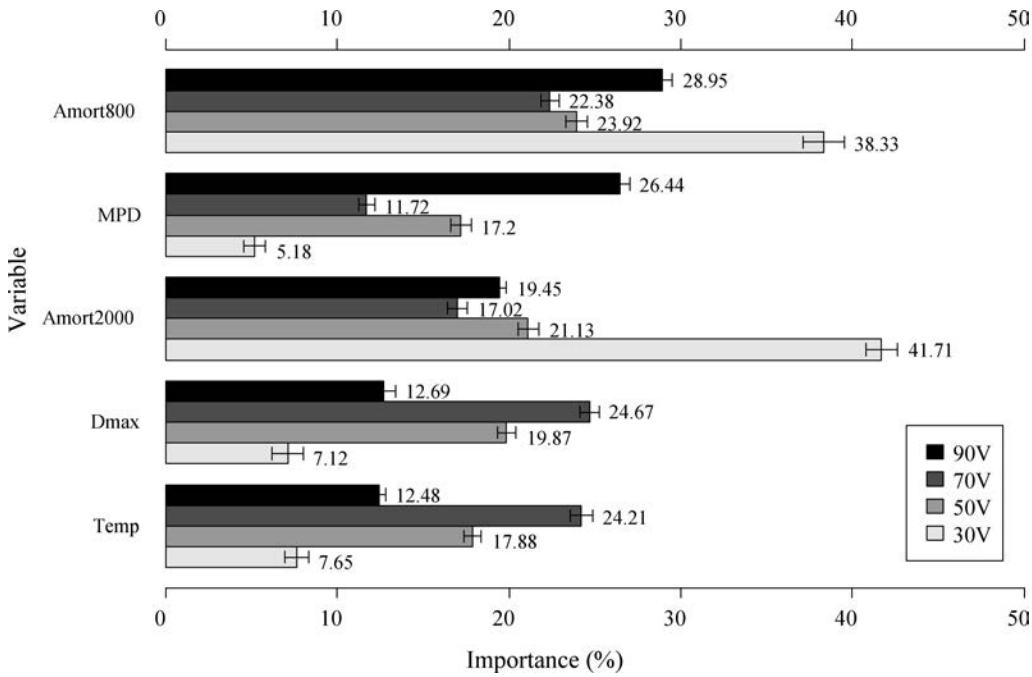

Fig. 8. Comparison of the relative importance of each variable per speed level.

Amort800 and *Amort2000* have a total relative importance higher than 75%, whereas at 50 km/h, *Dmax* and *Temp* have the highest relative importance, totalling around 50%.

The importance of the damping variables seems to reduce with increasing speed, while *MPD*, *Dmax*, and *Temp* seem to raise their importance with increasing speed. This may be a result of the lower contact time between the tyre and the road, and consequently of the effect of each noise generation mechanism.

The sensitivity of modelling variables is displayed in Figs. 9 and 10 which show the VEC curves of *TEMP*, *MPD*, *Dmax*, *Amort800*, and *Amort2000*, according to the SVM model, for 30 km/h and 70 km/h respectively.

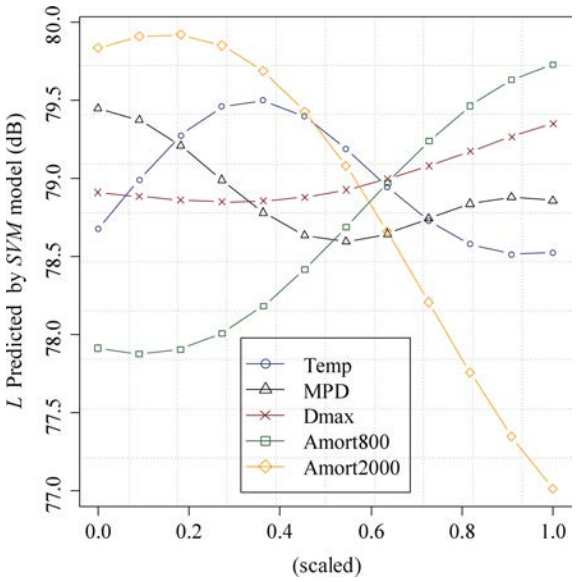

Fig. 9. VEC curves showing the average influence of *Temp*, *MPD*, *Dmax*, *Amort800*, and *Amort2000* in the predictive output, according to the SVM model for 30 km/h.

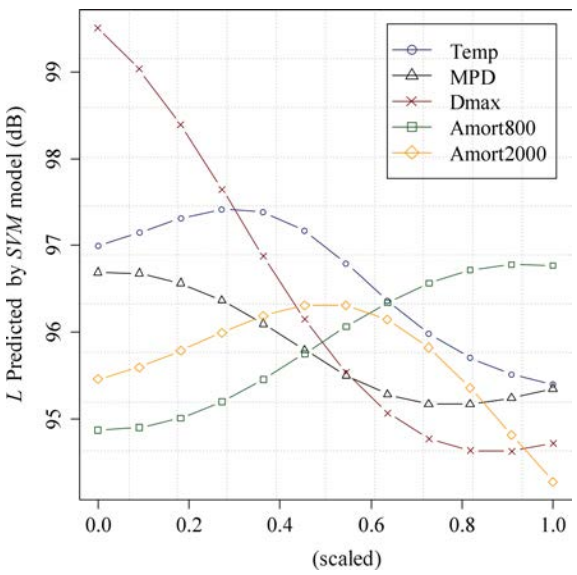

Fig. 10. VEC curves showing the average influence of *Temp*, *MPD*, *Dmax*, *Amort800*, and *Amort2000* in the predicted output, according to the SVM model for 70 km/h.

In general terms, model variables do not have a linear trend with the predicted noise. Bearing in mind that noise was measured with truck reference tyres, in terms of engineering, the VEC curves are suitable.

By comparing Figs. 9 and 10 it is clearly seen that *Amort800* and *Amort2000* have more impact at low speeds. The slope of the curve is clearly higher at 30 km/h than at 70 km/h, while for *Dmax* the opposite is true.

7. Conclusions and future work

In this paper it was demonstrated that Data Mining (DM) can be used successfully in tyre-road noise prevision. DM algorithms were applied for the first time in this work to model trucks tyre-road noise and to assess the importance of each variable integrated in the model. Furthermore, it allowed for carrying out a sensitivity analysis useful for verifying the appropriateness of the model in terms of engineering meaning.

By applying DM techniques, several models with very good tyre-road noise predictive capacity, as a function of speed and by speed level were achieved. From the thirteen variables tested, the combination of five of them has shown to be the most appropriate to predict noise: Speed, Temperature, Aggregate size, Mean Profile Depth, and predominantly damping at 800 Hz and 2000 Hz. The performance of the models with more than those five variables decreased; showing that the selection of appropriate variables is more important than the amount of variables included in the model. Also, they might be more important in late stages of pavements life because they evolve with time which is the case of *IRI* and megatexture. This issue should be object of further research.

Other significant results were also found:

- The metric R^2 is not appropriated to analyse models' performance due to its lack of sensitivity to changes in the variables used;
- While the SVN and ANN algorithms have high quality predictive performances, the MR is not recommended, as it consistently produced the worst results;
- The separate performance of the macrotexture indicators *RMS* and *MPD* is similar, however, being highly correlated, these variables improved models' performance in combination;
- Damping variables had the highest importance in the models after speed, followed by *Dmax*, *MPD*, and *Temp* which had the approximately the same importance;
- *Ltx63*, *Ltx500*, and *IRI* present the lowest influence in L prediction;

- There was a clear decrease of model performance with speed. This may indicate that an optimal speed exists for tyre-road noise modelling;
- Importance of variables depends on the speed level. There is a clear trend for damping;
- VEC curves show a nonlinear trend of most variables with noise as expected.

The applicability of the models developed in this work is relevant for tyre-noise prediction in an early stage of road pavements surfaces' lives and therefore they can be used for design, however, it is limited to low voids surfaces and to measurements with the AVON V4 tyre which is expected to represent trucks tyre-noise. These limitations may be easily overcome in the future by repeating the experiment with other type of tyres, representative of light vehicles, including porous surfaces, and consequently absorption and other parameters such as surface cracking and other relevant pavement surface degradations.

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References

1. Bueno M., Luong J., Viñuela U., Terán F., Paje S.E. (2011), *Pavement temperature influence on close proximity tire/road noise*, Applied Acoustics, 72, 11, 829–835.
2. Cherkassky V., Ma Y. (2004), *Practical Selection of SVM Parameters and Noise Estimation for SVM Regression*, Neural Networks, **17**, 1, 113–126.
3. Chopra A.K. (1995), *Dynamics of structures*, Prentice Hall Inc.
4. Chou J., Chiu C., Farfoura M., Al-Taharwa I. (2011), *Optimizing the prediction accuracy of concrete compressive strength based on a comparison of data-mining techniques*, Journal of Computing in Civil Engineering, **25**, 3, 242–253.
5. Cortes C., Vapnik V. (1995), *Support-vector networks*, Machine learning, **20**, 3, 273–297.
6. Cortez P., Embrechts M. (2011), *Opening black box data mining models using sensitivity analysis*, IEEE Symposium on Computational Intelligence and Data Mining, CIDM 2011, IEEE, Paris, France, 341–348.
7. Cortez P., Embrechts M. (2013), *Using sensitivity analysis and visualization techniques to open black box data mining models*, Information Sciences, **225**, 1–17.
8. Cortez P. (2010), *Data mining with neural networks and support vector machines using the R/rminer tool*, Perner P. 10th Industrial conference on data mining, advances in data mining: applications and theoretical aspects, Berlin, Germany: LNAI 617: Springer, 572–583.
9. DEUFRAKO (2009), *Prediction and Propagation of Rolling Noise*, Final Report.
10. Domingos P. (2012), *A few useful things to know about machine learning*, Communications of the ACM, **55**, 10, 78–87.
11. EN ISO 13473-1 (2004), *Characterization of pavement texture by use of surface profiles – Part 1: Determination of Mean Profile Depth.*
12. Ertel W. (2009), *Introduction to Artificial Intelligence*, Springer.
13. EWINS (2000), *Modal Testing: Theory, Practice and Application*, Research Studies Press Ltd., UK.
14. Fayyad U., Piatetsky-Shapiro G., Smyth P. (1996a), *From data mining to knowledge discovery in databases*, AI magazine, **17**, 3, 37–54.
15. Fayyad U., Piatetsky-Shapiro G., Smyth P. (1996b), *The KDD process for extracting useful knowledge from volumes of data*, Communications of the ACM, **39**, 11, 27–34.
16. Freitas E., Raimundo I., Inácio O., Pereira P. (2010), *In situ assessment of the normal incidence sound absorption coefficient of asphalt mixtures with a new impedance tube*, 39th International Congress and Exposition on Noise Control Engineering – INTER-NOISE 2010, Lisbon.
17. Freitas E., Mendonça C., Santos J.A., Murteira C., Ferreira J.P. (2012), *Traffic noise abatement: How different pavements, vehicle speeds and traffic densities affect annoyance levels*, Transportation Research Part D: Transport and Environment, **17**, 4, 321–326.
18. Gołębiewski R. (2008), *Changes in the acoustic properties of road porous surface with time*, Archives of Acoustics, **33**, 2, 151–164.
19. Gomes Correia A., Cortez P., Tinoco J., Marques R. (2013), *Artificial Intelligence Applications in Transportation Geotechnics*, Geotechnical and Geological Engineering, **31**, 3, 861–879.
20. Hamel L. (2009), *Knowledge Discovery with Support Sector Machines*, Wiley-Interscience.
21. Hastie T., Tibshirani R., Friedman J. (2009), *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*, 2nd Edition, Springer-Verlag.
22. ISO 11819-1 (1997), *Acoustics – Method for measuring the influence of road surfaces on traffic noise – Part 1: statistical pass-by method.*
23. ISO CD 11819-2 (2000), *Acoustics – Method for Measuring the Influence of Road Surfaces on Traffic Noise – Part 1: The Close Proximity Method.*
24. ISO 13473-5 (2009), *Characterization of pavement texture by use of surface profiles – Part 5: Determination of megatexture.*
25. Kaczmarek T., Preis A. (2010), *Annoyance of time-varying road-traffic noise*, Archives of Acoustics, **35**, 3, 383–393.

26. Kenig S., Ben-David A., Orner M., Sadeh A. (2001), *Control of properties in injection molding by neural networks*, Engineering Applications of Artificial Intelligence, **14**, 819–823.

27. Kumar K., Parida M., Katiyar V. (2011), *Road Traffic Noise Prediction with Neural Networks – A Review*, An International Journal Of Optimization And Control: Theories & Applications (IJOCTA), **2**, 1, 29–37.

28. Larsson K. (2002), *Modelling of dynamic contact – exemplified on the tyre-road interaction*, PhD Thesis, Department of Applied Acoustics, Calmers University of Technology, Gothenburg, Sweden.

29. Mak K.-L., Hung W.-T. (2014), *Statistical tyre/road noise modeling in Hong Kong on friction course*, Applied Acoustics, **76**, 0, 24–27.

30. Mendonça C., Freitas E., Ferreira J.P., Raimundo I., Santos J.A. (2013), *Noise abatement and traffic safety: The trade-off of quieter engines and pavements on vehicle detection*, Accident Analysis & Prevention, **51**, 0, 11–17.

31. Miranda T., Comes Correia A., Santos M., Sousa L., Cortez P. (2011), *New Models for Strength and Deformability Parameter Calculation in Rock Masses Using Data-Mining Techniques*, International Journal of Geomechanics, **11**, 44–58.

32. Morgan P., Sandberg U., Blokland G. (2009), *The selection of new reference test tyres for use with the CPX method, to be specified in ISO/TS 11819-3*, 38th International Congress and Exposition on Noise Control Engineering – INTER-NOISE, Ottawa.

33. R DEVELOPMENT CORE TEAM (2009), *R: A language and environment for statistical computing*, R Foundation for Statistical Computing, Vienna, Austria, Web site: http://www.r-project.org/.

34. Raimundo I., Freitas E., Inácio O., Pereira P. (2010), *Sound absorption coefficient of wet gap graded asphalt mixtures*, 39th International Congress and Exposition on Noise Control Engineering – INTER-NOISE 2010, Lisbon.

35. Sandberg U., Ejsmont J. (2002), *Tyre/Road Noise Reference Book*, Informex SE – 59040, Kisa, Sweden.

36. Sayers M.W. (1995), *On the calculation of International Roughness Index from Longitudinal Road Profile*, Transportation Research Record 1501, Transportation Research Board, Washington D.C., 1–12.

37. Schölkopf B., Smola A.J. (2002), *Learning with Kernels: Support Vector Machines, Regularization, Optimization, and Beyond*, The MIT Press.

38. Smola A.J., Schölkopf B. (2004), *A tutorial on support vector regression*, Statistics and Computing, **14**, 3, 199–222.

39. Steinwart I., Christmann A. (2008), *Support Vector Machines*, Springer.

40. Taylor P., Anand S., Griffiths N., Adamu-Fika F., Dunoyer A., Popham T. (2012), *AutomotiveUI '12*, Proceedings of the 4th International Conference on Automotive User Interfaces and Interactive Vehicular Applications, 233–240.

41. Tinoco J., Gomes Correia A., Cortez P. (2011), *Application of data mining techniques in the estimation of the uniaxial compressive strength of jet grouting columns over time*, Construction and Building Materials, **25**, 1257–1262.

42. Tinoco J., Gomes Correia A., Cortez P. (2014), *A novel approach to predicting young's modulus of jet grouting laboratory formulations over time using data mining techniques*, Engineering Geology, **169**, 50–60.

43. Zhou G., Wang L., Wang D., Reichle S. (2010), *Integration of GIS and Data Mining Technology to Enhance the Pavement Management Decision Making*, Journal of Transportation Engineering, **136**, 4, 332–341.