Estimation of energy consumption on the tire-pavement interaction for asphalt mixtures with different surface properties using data mining techniques

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Abstract

The energy or fuel consumption of the millions of vehicles that daily operate in road pavements has a significant economic and environmental impact on the use phase of road infrastructures regarding their life cycle analysis. Therefore, new solutions should be studied to reduce the vehicles energy consumption, namely due to the tire-pavement interaction, and contribute towards the sustainable development. This study aims at estimating the energy consumption due to the rolling resistance of tires moving over pavements with distinct surface characteristics. Thus, different types of asphalt mixtures were used in the surface course to determine the main parameters influencing the energy consumption. A laboratory scale prototype was developed explicitly for this evaluation. Data mining techniques were used to analyze the experimental results due to the complex correlation between the data collected during the tests, providing meaningful results. In particular, the artificial neural network allowed to obtain models with excellent capacity to estimate energy consumption. A sensitive analysis was carried out with a five input parameter model, which showed that the main parameters controlling the energy consumption are the vehicle speed and the mean texture depth.

Keywords: road pavements; surface characteristics; energy consumption; rolling resistance; tire-pavement interaction; data mining techniques

1. Introduction

This work presents a new approach to evaluate energy consumption in the tire-pavement interaction and applies data mining techniques in an unexplored research area to study solutions for sustainable roads. No other work has been identified in the literature for evaluation of energy consumption in the tire-pavement interaction based on a purpose-built laboratory prototype. In the future, this approach will allow the study of the energy consumption of different surface materials in their design phase, with clear advantages for developing sustainable solutions for road paving surface layers.

The environmental consequences resulting from road pavement construction and maintenance during its life cycle are not yet fully known, although some authors (Ozer et al., 2017) have tried to quantify sustainable strategies for these activities. Santero et al. (2011) analyzed several Life Cycle Assessment (LCA) methodologies for road pavements, concluding that among five life cycle phases (raw materials and production, construction, use, maintenance, and end of life) only a few include the use phase in the analysis, and in a noticeably incomplete way. Those studies mainly focused on the extraction, production, transportation, and application of materials. However, depending on the traffic volume during the lifetime of a road, its energy consumption can be around 95% to 98% of the total energy consumption, while the energy used for production, construction, and maintenance of the road represents less than 2% to 5% (EAPA/Eurobitume, 2004). Therefore, the use phase is predominant regarding the energy (fuel) consumption and resulting greenhouse gas emissions of the road (Huang et al., 2009; Mohd Hasan and You, 2015; Pérez-Martínez and Miranda, 2014).

Moreover, according to Pérez-Martínez (2012), road transport is one of the highest sources of emissions among the different economic sectors, accounting for up to 30% of the total energy consumption and CO_2 emissions. Taking this into account, the importance of investigating energy consumption estimation during the road pavement use phase becomes evident.

Currently, some factors are still not taken into account when assessing energy consumption on roads, namely the quality of road pavement surfaces. That property is mainly associated with safety and comfort of road users, but also closely related to the rolling resistance (Mclean and Foley, 1998; Schmidt and Ullidtz, 2010; Willis et al., 2014) and therefore with the environment and sustainability. In fact, some pavement structures or layers, namely the surface course can have a significant influence on the rolling resistance or energy consumption. Some studies indicate that stiffer (Taylor and Patten, 2006; Wathne, 2010) and smoother (Bryce et al., 2014) pavements require a lower fuel consumption.

Some variables, such as pavement texture and skid resistance, influence the rolling resistance (Rajaei et al., 2016) and, consequently, the energy consumption (Wang et al., 2012; Zaabar and Chatti, 2010). Thus, the present work aims at evaluating the influence of different pavement surface courses on the energy consumption required for a tire to continuously travel over them, based on laboratory tests. Those tests were conducted under controlled conditions (e.g., speed and load) using a purpose-built laboratory scale prototype, to select surfaces originating lower energy consumption for similar test circumstances which may indicate a similar trend for real pavement and traffic conditions.

Several works have been carried out in the last few years to assess the energy/fuel consumption of vehicles or the rolling resistance of tires, which demonstrates the importance of this topic on the research activity carried out nowadays. Accordingly, MIRIAM (Bergiers et al., 2011) and ROSANNE (Anfosso-Ledee et al., 2016; Zöller and

Haider, 2014) can be highlighted as two of the leading research projects recently concluded in Europe related to this subject, although other researchers in Northern Europe have also been dedicated to that (Andersen, 2015; Karlsson et al., 2011). In the United States, the University of California and Caltrans (Wang et al., 2012), the Michigan State University and the Transportation Research Board (Chatti and Zaabar, 2012; Rajaei et al., 2016), and the Minnesota State University and the Minnesota DoT (Ejsmont et al., 2012; Ejsmont et al., 2014) have also carried out important research in this topic.

The main types of tests used to evaluate the road surface influence on rolling resistance, as stated in the previously mentioned works, were: a) measurements on drums in laboratories; b) specially equipped trailers for measurements on roads; c) coast down measurements on roads. Among these, the last two types of tests cannot be carried out in laboratories, while the first is more suitable for comparing the performance of different tires instead of assessing the influence of road surface characteristics on rolling resistance (Karlsson et al., 2011). The purpose-built laboratory prototype developed in this work presents a new approach to evaluate the energy consumption of a rolling tire on different pavement surfaces. This method can be used to study innovative materials for road surface layers in their design phase, with clear advantages for developing sustainable solutions for road paving.

The results of the test developed in this work may be used together with existing models to predict vehicles consumption. Among those, the models established under the MIRIAM project, as described in Hammarström et al. (2012), or in the NCHRP report 720 (Chatti and Zaabar, 2012), which is based on the HDM-4 model, may be highlighted. Ultimately, these may be used in the scope of Life Cycle Analysis (LCA) methods that incorporate the road pavement use phase, like those developed by Araújo et al. (2014) and Bryce et al. (2014).

Taking the accumulated effect of millions of vehicles passing over the pavement surface during its life cycle into consideration, a small reduction in each vehicle energy consumption on the tire-pavement interaction, as a result of improving the pavement characteristics, could have a significant effect on the sustainability of the paving solution. Thus a considerable reduction in the fossil fuels consumption and on the respective user costs, and consequently on the amount of exhaust emissions may be obtained.

The development of a rational and reliable method to accurately estimate the energy consumption on the tire-pavement interaction becomes relevant, due to its influence on the transportation system sustainability. That method should be able to deal with a significant amount of data collected during the experimental tests using the purpose-built laboratory scale prototype and the tests carried out to characterize the studied surface materials. Therefore, knowledge discovery techniques in databases, using a modeling process known as data mining (DM), were applied in this study to predict the energy consumption due to the rolling resistance that takes place on the tire-pavement interaction.

Data mining is generally used to obtain patterns or models from databases applying specific algorithms to retrieve useful knowledge from data, in this case, collected during the tests with the prototype. There are many regression methods that can be employed in data mining, among which artificial neural networks (ANN) (Androjić and Dolaček-Alduk, 2018; Basheer and Hajmeer, 2000), support vector machines (SVM) (Burges, 1998; Naseri et al., 2017), k-nearest neighbors (Aksoy et al., 2012; Seidl and Kriegel, 1998) and regression trees (Chou et al., 2014; Loh, 2011) can be mentioned.

The use of data mining techniques in the field of road pavements is not original, but it has not yet been applied to predict the energy consumption of motor vehicles due to the road-pavement interaction. Nevertheless, data mining was already used to predict the rolling resistance of an agricultural tractor tire moving over a clay loam soil (Taghavifar et al., 2013), and to forecast energy consumption in asphalt plants during hot mix asphalt production (Androjić and Dolaček-Alduk, 2018). Furthermore, this work has also based its development on examples of other data mining applications in road pavements, such as those presented in the following paragraphs.

Asadi et al. (2014) used data mining techniques, namely artificial neural networks and neuro-fuzzy models, to predict NO_x concentration in the air as a function of traffic volumes (T_r) and weather conditions including humidity, temperature, solar radiation, and wind speed before and after the application of TiO_2 on the pavement surface. Artificial neural networks and genetic algorithms have also been used to define a procedure to make use of the available economic resources in the best way possible for flexible pavement maintenance operations (Bosurgi and Trifirò, 2005).

Ceylan et al. (2008) developed an approach based on artificial neural networks for non-destructive estimation of rigid airfield pavement stiffness properties, subjected to full-scale dynamic traffic testing, namely by using simulated new generation aircraft gears. Examples of artificial neural networks use in road infrastructures can also be found in other works. Commuri et al. (2011) used ANN to design an intelligent asphalt compaction analyzer. Fakhri and Ghanizadeh (2014) modeled the 3D response pulse at the bottom of an asphalt layer with ANN. Gajewski and Sadowski (2014) carried out a sensitivity analysis to crack propagation of an asphalt pavement layered structure using ANN and the finite element method. Hamad et al. (2017) modeled traffic noise in a hot climate using ANN. Zhang et al. (2015) compared in situ and lab simulated asphalt aging with ANN.

Gopalakrishnan et al. (2013) used data mining tools to predict the non-linear layer moduli of asphalt road pavement structures based on the deflection profiles obtained from non-destructive deflection testing, while Saltan et al. (2011) have used data mining techniques for back-calculating pavement layer moduli and Poisson's ratio based on the results of similar tests.

Soltani et al. (2015) estimated the stiffness of polyethylene terephthalate (PET) modified asphalt mixtures using support vector machine-firefly algorithm (SVM-FFA), genetic programming, artificial neural network and support vector machine. The last method (SVM) was also used for modelling the mechanical behavior of hot-mix asphalt (Gopalakrishnan and Kim, 2011), predicting the performance of stabilized aggregate bases subjected to wet-dry cycles (Maalouf et al., 2012), classifying vehicles into five types using embedded strain gauge sensors (Zhang et al., 2008), and for developing an aggregated CO_2 emission model for light-duty cars (Zeng et al., 2017).

The techniques used in this work were the ANN (a simplified model of the biological structure of the human brain) and the SVM (used as an alternative method). In fact, these two methods were those most commonly used in the previous examples of data mining application to road pavement engineering studies. They are both highly nonlinear and do not need prior knowledge about the nature of relationships among the data (Stulp and Sigaud, 2015), thus being suitable to define new models for data measured with the new prototype used in the experimental phase of this work. In fact, they can capture complex interactions among a significant amount of data (Nguyen, 2018) that are difficult to model with the traditional statistical methods.

2. Materials and methods

2.1. Materials

During this work, four pavement surfaces were tested to evaluate their influence on the energy consumption on the tire-pavement interaction. Thus, paving materials with significantly different surface characteristics were selected to represent a wide range of road pavements.

One of the selected materials was a conventional asphalt concrete mixture (AC 14), the most common surface course used in Portuguese roads. The second surface was a slurry seal bituminous material with a 4 mm maximum aggregate size. This surface was selected as a solution generally used for pavement maintenance operations. A porous asphalt (PA 12.5) was tested as the third surface material, representing a mixture with a rougher surface texture used in highways located in warm and rainy areas. Finally, a grouted macadam was used to test a stiffer and smoother material for pavement surface courses.

All these surfaces were characterized, according to several methods presented in Section 2.3, and their energy consumption evaluated in a purpose-built prototype described in the following section.

2.2. Purpose-built prototype

The laboratory prototype (Fig. 1) specially developed for the present work is a piece of equipment comprising a central element (shaft), which holds the prototype to the floor and assures the necessary stability of the system, and two symmetrical arms provided with wheels at the outer ends. One of the wheels (driving wheel) is engaged to an electric motor, which controls the movement of the prototype around the central element. The choice of electric power was imposed by the use of the motor in closed spaces (laboratory) but also resulted from the better control in energy consumption data acquisition with this system (which is essential to evaluate how it is influenced by surface characteristics). The motor is a fundamental component and was equipped with a reduction gearbox and a variable frequency controller to allow slow starting movements and avoid sudden stops. A third arm, perpendicular to the other two, is also coupled to the central shaft and is provided with a laser to evaluate the pavement surface profile. A specific software program was created using LabVIEW to control the electric motor (e.g., the speed) and to collect data from the prototype, with special consideration to the motor energy consumption and laser readings.

Fig. 1. Prototype developed for energy consumption evaluation.

The arms have a length of 1.25 meters between the rotation shaft and the center of the wheels. Spherical plain bearings connect the arms to the central part to ensure permanent contact between the tires and the pavement, and to minimize undesirable effects of pavement unevenness. The prototype speed may vary between 0 and 20 km/h.

In a base scenario, each wheel represents a 700 N force. However, additional weights can be added to each arm to simulate different wheel loads, up to a maximum value of 1000 N. Even though the prototype has some limitations regarding the maximum speed and load (mainly due to safety reasons and space availability), the study of the energy consumption in different surfaces (which is the primary goal of this work) is still possible.

The tires chosen for the prototype (195/50 R15 82V) are commonly available on the market and used in several car models with 15-inch wheel rims. The temperature of any tire generally increases after starting its movement, stabilizing after a certain period. As the tire temperature increases, the rolling resistance (and consequent energy consumption) decreases. According to the ISO 18164 standard, a period of 30 minutes should be enough to stabilize tire temperature for passenger cars.

The testing speed of the rolling wheels and the corresponding energy consumption, measured through a multimeter installed in the electrical cable, were acquired with the abovementioned software.

2.3. Methods

2.3.1. Energy consumption measurement on the tire-pavement interaction

The experiments carried out to measure the energy consumption consist in rolling the wheels of the prototype over selected pavement surfaces during some time, at a preset constant speed, while measuring the electric energy consumption of the motor with the multimeter. Some of the conditions used in the tests that were carried out with the prototype are different from those specified in ISO 18164 standard for determining the rolling resistance of passenger car tires. Thus, some preliminary tests were carried out to assess the time required to stabilize the energy consumption measured in the prototype (corresponding to the rolling resistance stabilization). From these preliminary tests, it was possible to conclude that a 60-minute warming-up period was necessary for the first testing speed before collecting the energy consumption data. For the other testing speeds (increased at 5 km/h intervals), a 20-minute warming-up period was enough for stabilizing the energy consumption.

The differences in the energy consumption measurements obtained in this work can be related to the tire-pavement interactions because all testing conditions were the same for the different pavement surface materials. Furthermore, as the test speed is limited to 20 km/h, the influence of variables such as the air resistance is considerably reduced.

The influence of pavement surface characteristics on the prototype energy consumption was modeled using data mining techniques. However, to obtain the necessary data, several tests were carried out to evaluate the pavement skid resistance, texture, and the surface profile. Skid resistance and pavement texture were estimated using the Pendulum Test Value (PTV) and the sand patch test (Mean Texture Depth or MTD). The surface profile was measured using the prototype's laser device (to obtain the Mean Profile Depth or MPD). The Estimated Texture Depth (ETD) was also calculated using the MPD values.

2.3.2. Evaluation of pavement skid resistance properties

The PTV value was obtained using the pendulum test according to the EN 13036-4 standard. This method used to determine the slip/skid resistance of a surface comprises a device which remains stationary at the test location and a pendulum arm including a standard rubber coated slider assembly. The PTV corresponds to the loss of energy of the rubber assembly sliding across the test surface and provides a standardized value of slip/skid resistance.

2.3.3. Evaluation of pavement surface texture

EN 13036-1 standard specifies a method for determining the average depth of pavement surface macrotexture (mean texture depth, MTD). This test (known as the “volumetric patch method”), uses a predetermined volume of calibrated glass spheres dropped on the pavement surface, and calculates the resulting area.

This method was designed to provide an average depth value of the pavement macrotexture. The mean texture depth (MTD, in millimeters) is calculated using the Eq. (1), where, V is the sample volume, expressed in cubic millimeters (mm3), and D is the average diameter of the area covered by the material, expressed in millimeters (mm).

$$\boldsymbol{MTD} = \frac{\boldsymbol{4 \times V}}{\boldsymbol{\pi \times D^2}} \tag{1}$$

2.3.4. Evaluation of pavement surface profile

ISO 13473-1 sets the procedure to determine the mean profile depth (MPD). This test method calculates the average surface macrotexture depth, by measuring its profile and converting it to texture depth. The technique is considered insensitive to pavement microtexture and unevenness. The MPD values are calculated using Eq. (2), based on the concepts presented in Fig. 2.

$$\boldsymbol{MPD} = \frac{\boldsymbol{Peak\ level\ (1^{st}) + Peak\ level\ (2^{nd})}}{\boldsymbol{2}} - \boldsymbol{Average\ level} \tag{2}$$

This method also allows estimating the surface texture depth (ETD) from MPD values using Eq. (3), specified in ISO 13473-1, where ETD and MPD are in millimeters (mm).

$$ETD\,(mm) = 0.2 + 0.8 \times MPD \tag{3}$$

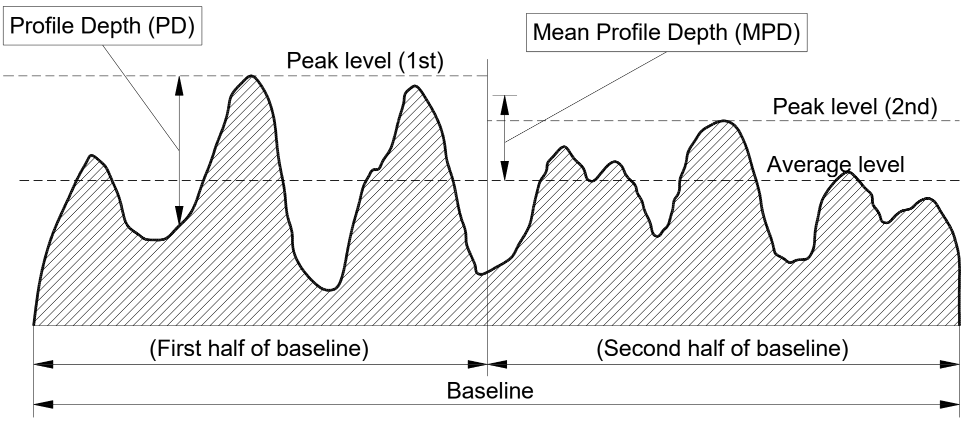


Fig. 2. Illustration of concepts used in the MPD calculation (ISO 13473-1).

2.3.5. Data mining methods

The data mining process was used in this study to model the energy consumption. The R environment and a previously developed RMiner library were the tools used for the necessary computations using (Cortez, 2010).

A brief explanation of ANN and SVM tools used in this work is given in the next paragraphs. However, further details can be found in previous works related to ANN (Aleksander and Morton, 1990; Ilonen et al., 2003) or to SVM (Cristianini and Shawe-Taylor, 2000; Dibike et al., 2001; Vapnik, 1998). Simpler methods for data analysis, like multiple regressions (MR), can be used in data mining (Awang et al., 2012). However, they were not included in this study since they showed a poor performance in comparison with ANN and SVM (i.e., MR models presented higher errors than ANN and SVM, which may indicate that they are unable to capture the nonlinear relationships between the variables used in this work).

Eq. (4) shows the general model used in the artificial neural network (ANN) process (Hastie et al., 2001), where x_i are the input parameters or nodes, I is the number of input parameters, and o is the output parameter.

$$\hat{y} = w_{o,0} + \sum_{j=I+1}^{o-1} f\left(\sum_{i=1}^{I} x_i \times w_{j,i} + w_{j,0}\right) \times w_{o,i} \tag{4}$$

The multilayer perceptron architecture (Haykin, 1998) used in this work (Fig. 3) is composed by three layers with HN nodes in the hidden layer and adopted the logistic activation function $1/(1+e^{-x})$. The number of hidden nodes was optimized through a grid search HN $\in \{0, 2, 4, 6, 8, 10, 12, 14, 16, 18, 20\}$.

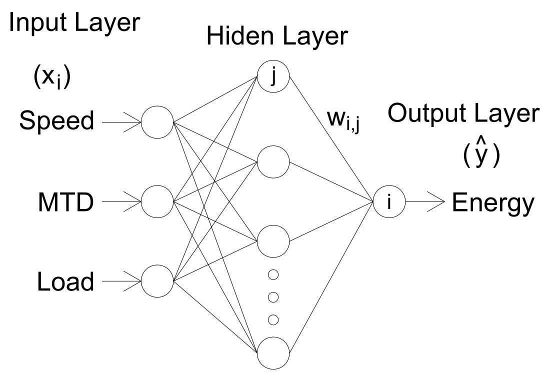


Fig. 3. Scheme of the multilayer perceptron used in this work.

The application of SVM techniques (Cortes and Vapnik, 1995) to regression tasks only became possible with the introduction of the ε-insensitive loss function (Smola and Schölkopf, 2004), based on a nonlinear mapping transformation of the input data into a multidimensional feature space.

After this transformation, the SVM finds the best hyperplane inside the feature space. The nonlinear mapping depends on a kernel function *k(x,x')*, where *γ* is the kernel parameter.

In this work, the Gaussian kernel function presented in Eq. (5) was adopted, because it presents fewer hyperparameters and numerical difficulties then those of other kernels (e.g., polynomial) (Cortez, 2010).

$$\boldsymbol{k}(\boldsymbol{x},\boldsymbol{x}') = \boldsymbol{e}^{(-\boldsymbol{\gamma}\cdot\|x-x\prime\|^2)}, \qquad \boldsymbol{\gamma} > \boldsymbol{0} \tag{5}$$

The performance of the regression is affected not only by the kernel parameter, γ, but also by a penalty parameter, C, and the width of the ε-insensitive zone. Taking the large size of the search space of these parameters into account, the search performed in this work was limited to the γ parameter. Thus, a value of C = 3 and the heuristic model $\varepsilon = \hat{\sigma}/\sqrt{N}$ (Cherkassky and Ma, 2004) were considered in this study, where $\hat{\sigma} = 1.5 \times \sum_{i=1}^{N}(y_i - \hat{y}_i)$, $\hat{y}_i$ is the value predicted by a 3-nearest neighbor algorithm and N the number of examples. Then, the grid used for γ search was $\{2^{-15}, 2^{-13}, 2^{-11}, 2^{-9}, 2^{-7}, 2^{-6}, 2^{-5}, 2^{-4}, 2^{-3}, 2^{-2}, 2^{-1}, 2^{0}, 2^{1}, 2^{2}, 2^{3}\}$.

The dataset was divided randomly into two subsets, the training and the testing sets (respectively, 144 and 72 records), to assess the predictive capacity of the DM techniques. The model was trained using a cross-validation procedure, fitting it with data from nine subsets and testing it with the remaining subset, repeating the process for all subsets.

The model with the best performance in the training process (loaded with the 144 records) was tested later with the 72 testing records not used in the training process.

The coefficient of determination (R^2), the root mean square error (*RMSE*), and the mean absolute deviation (*MAD*) results were used to assess the models' performance. The higher the R^2, the better the performance of the model is. The lower the values of *RMSE* and *MAD*, the better the predictive capacity of the model is.

Finally, a sensitivity analysis method was used to measure the importance of each parameter (Kewley et al., 2000). This analysis is designed to evaluate the model's response to the change of each of the input parameters. The importance of a given input parameter may be assessed by changing its value from a minimum to a maximum, maintaining the average values of the remaining input parameters. Thus, the consequent variance induced in the model output represents the importance of the input parameter.

2.3.6. Research outline

In order to summarize the relationship between the data processing and analysis methods involved in this paper, the research outline followed in this work is schematically represented in Fig. 4.

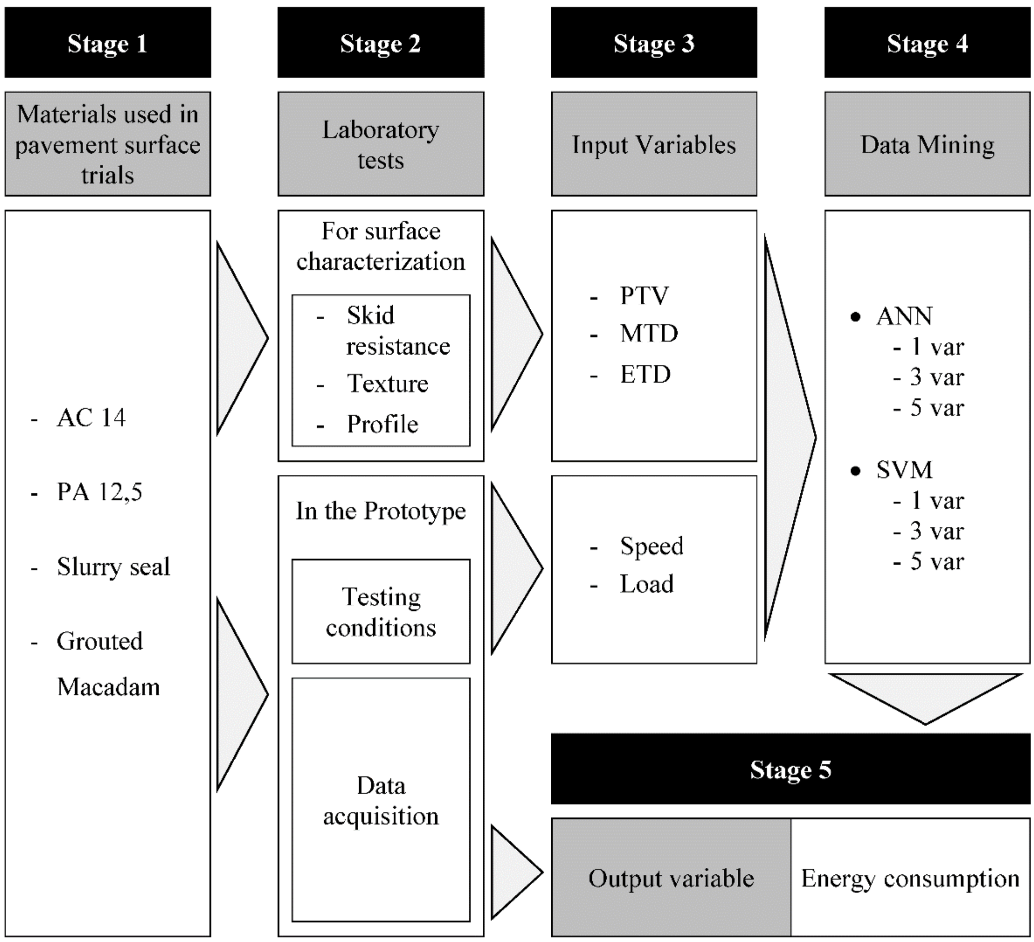


Fig. 4. Schematic representation of research outline used in this work.

3. Results and discussion

In this work, the energy consumption on the tire-pavement interaction was measured using a laboratory scale prototype, by adopting different testing conditions (wheel load and speed) and surface pavement characteristics (PTV, ETD, and MTD). The results obtained were analyzed using data mining techniques to evaluate the possibility of estimating the energy consumption from the previously mentioned testing conditions (input variables).

Table 1 shows the statistical assessments of the parameters measured during the laboratory tests carried out with the prototype, for different pavement surfaces, as described in Section 2. The database obtained with these results was then evaluated using data mining techniques.

Table 1. Statistic assessment of the used parameters.

Parameter	Minimum	Mean	Maximum	Standard deviation	Coefficient of variation
PTV	23	45.94	68	15.99	34.81
ETD	0.505	0.854	2.441	0.536	62.75
MTD	0	0.615	2.529	0.778	126.56
Speed (m/s)	5	11.67	20	5.28	45.28
Load (kN)	0.7	0.85	1	0.103	12.08
Energy (J/s)	3.11	7.42	19.64	3.61	48.61

Since the objective of this work is to analyze the influence of different parameters on the measured energy consumption, the range of those parameter values should be as extensive as possible to represent a higher number of scenarios. The variation of some parameter values fulfills that objective (Table 1), while others present a smaller difference (e.g., load), as a consequence of laboratory testing limitations.

Two data mining techniques (ANN and SVM) were tested using up to five input variables (PTV, ETD, MTD, speed, and load) to predict the energy consumption. The models obtained with both techniques were labeled M#, where # represents the number of input parameters used in the model (5, 3 and 1). Some metrics (MAD, RMSE and R^2) were used to evaluate the quality or performance of the different models obtained with ANN and SVM techniques, as presented in Table 2.

Both data mining techniques have presented predictive models with a good performance, despite the complex and previously unknown relationships between the variables. In fact, these results were only possible because both methods are highly nonlinear and do not need prior knowledge about the nature of relationships among the data. However, and regardless of the number of input variables used, the ANN technique showed lower values of MAD and RMSE and higher values of R^2, in comparison with the SVM models. Thus, further analysis of data mining results will only be carried out for ANN models. There is an explicit dependence of DM model performance on the number of input variables. The higher the number of input variables, the higher the quality of the DM model, but its complexity also increases. Thus, the minimum number of input variables needed to assure adequate performance of the DM model must be determined, as subsequently discussed. This problem may be particularly relevant when input data requires complex and time-consuming tests that stakeholders may not have conditions to carry out.

Table 2. Cross-validation scheme results obtained in the training process.

Metric	M5		M3		M1	
	ANN	SVM	ANN	SVM	ANN	SVM
MAD	0.112	0.180	0.217	0.240	0.992	1.001
RMSE	0.162	0.303	0.337	0.410	1.341	1.389
R^2	0.998	0.996	0.990	0.986	0.836	0.832

Note: MAD – Mean Absolute Deviation; RMSE – Root Mean Square Error; R^2 – Coefficient of determination

Initially, the whole training set was used to fit the ANN model with five input variables (M5), as presented in Fig. 5. Fig. 6 shows the values obtained in similar conditions but with the testing set. Both results confirm the high predictive capacity of the ANN model, even though the testing set is unknown for the DM models.

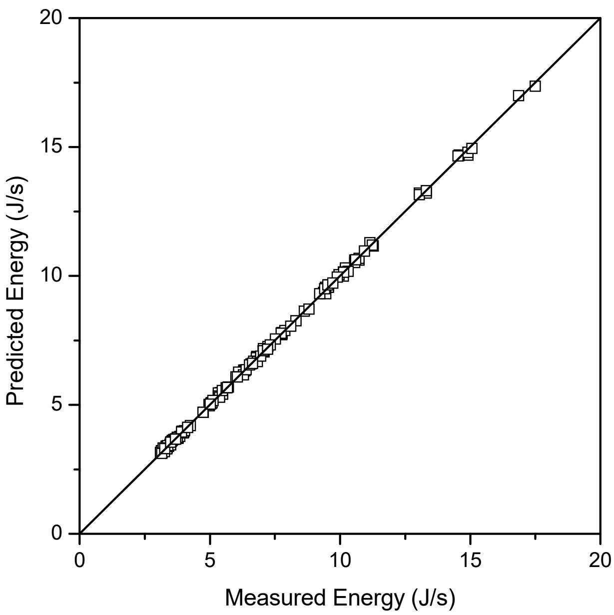


Fig. 5. Performance of five input variable ANN model (M5) using the training dataset.

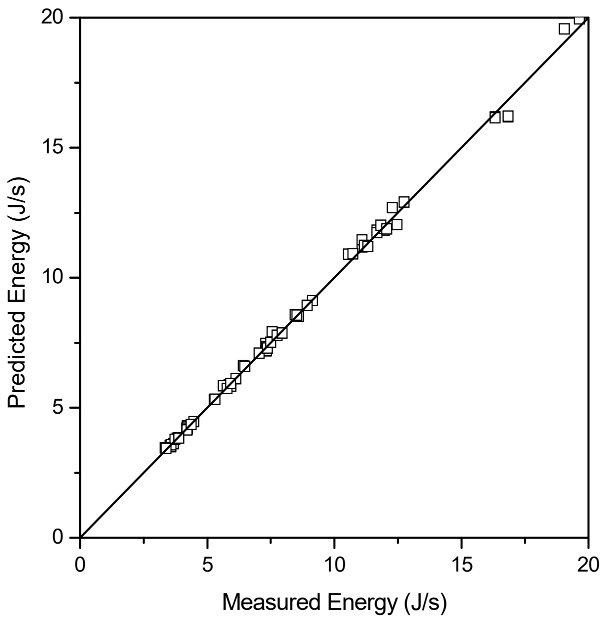


Fig. 6. Performance of five input variable ANN model (M5) using the testing dataset.

A sensitivity analysis was performed to obtain the relative importance given by the ANN technique to each one of the five input parameters used in the model, as shown in Fig. 7.

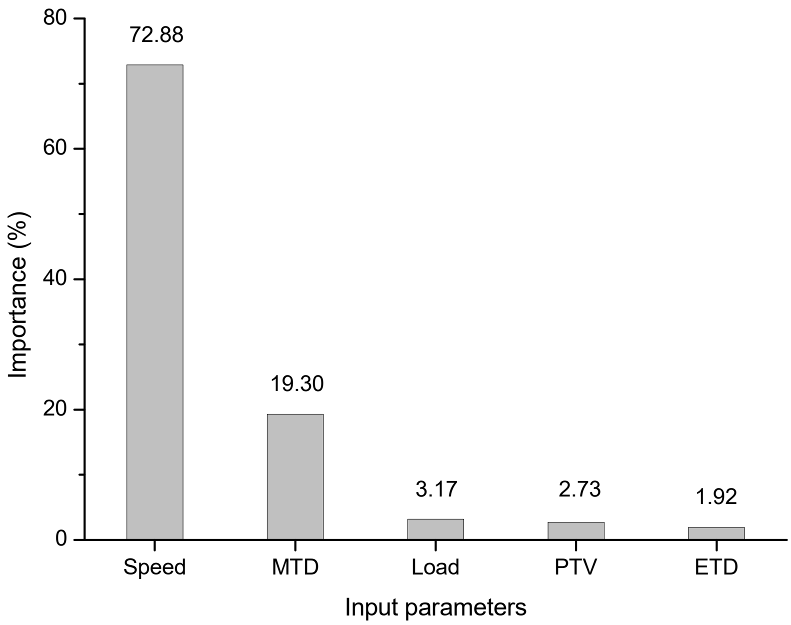


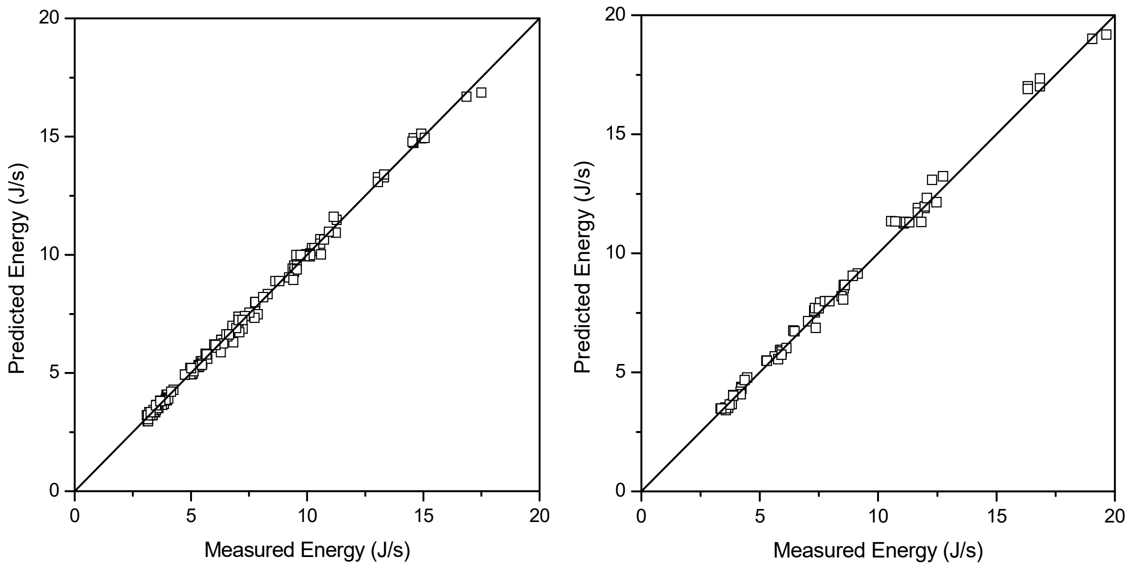
Fig. 7. Importance of each parameter in the ANN model with five input variables (M5).

The strong influence of the wheel speed in the predicted energy consumption during the laboratory test is evident. However, the MTD value (surface texture) has also a significant influence on the energy consumption. The other input variables have a negligible impact on the ANN model.

The high influence of speed on the energy consumption corroborates the practical knowledge (Freitas Salgueiredo et al., 2017; Suyabodha, 2017), as well as the observations carried out during the laboratory tests. However, a higher influence of the load in the energy consumption was expected (Hernandez et al., 2017), but not observed due to the limited variation of this parameter during the tests (as previously mentioned). ANN model selected mean texture depth as the second most influencing parameter in the energy consumption. In fact, it is recognized that the rolling resistance is influenced by pavement macrotexture (Ejsmont et al., 2017), with higher energy consumption in smooth than in rough surfaces. Both MTD and ETD values are related to texture, thus justifying the strong correlation observed between these parameters (R^2=0.981). This fact may also explain the low importance given by the ANN model to ETD variable, since texture influence may be already considered in the model by MTD parameter. Although MTD and ETD are well correlated, the first is used to measure the pavement surface texture properties based on an area, while the latter infers the texture characteristics of the corresponding area based on a single profile of the surface (which may be less accurate). It is also clear that fuel consumption is not significantly affected by skid resistance (PTV value).

The accumulated importance of speed, MTD, and load in the ANN model with five input variables, used for energy consumption prediction, is greater than 95 percent. Therefore, a second data mining analysis was carried out with only three input parameters (M3). Table 2 already presented the metrics obtained in the cross-validation scheme of this simplified model M3. The analysis of those metrics pointed out increased errors in the M3 model in comparison with the DM analysis with five input parameters. However, the results predicted with M3 model remain good, and the best results were obtained using the ANN technique.

The ANN models with three input variables (M3) were fitted with the training set (Fig. 8a) and with the testing set (Fig. 8b). Both results confirm the high predictive capacity of the ANN model M3 to predict the energy consumption. Although there is a negligible decrease in the accuracy of this model in comparison with the ANN model with five input variables, the simplified ANN model with three variables (M3) maintains an excellent performance.



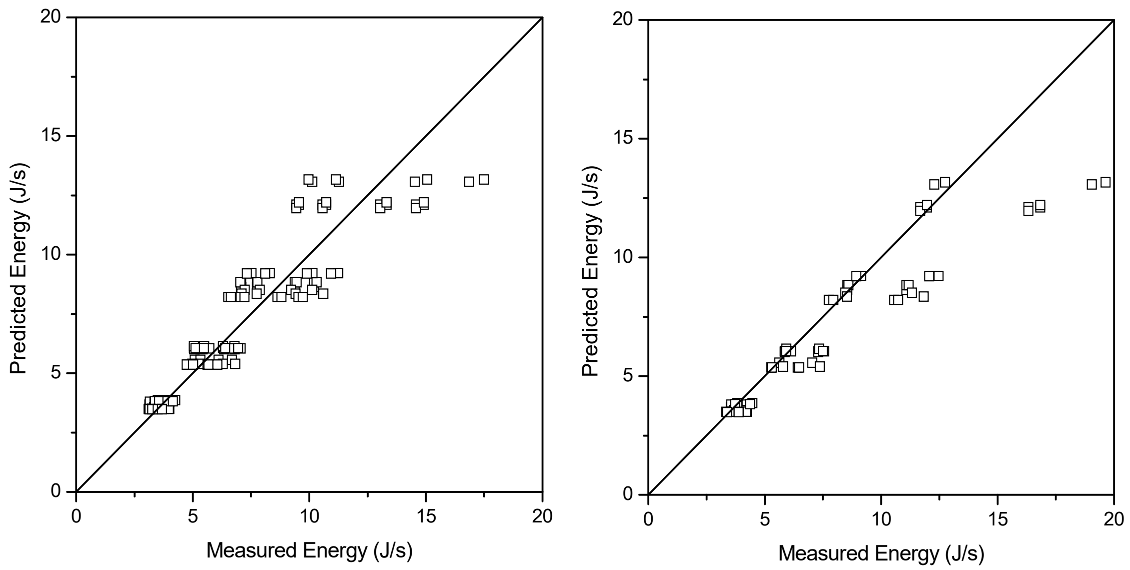
(a) (b)

Fig. 8. Performance of the ANN model with three input variables (M3) using (a) the training dataset or (b) the testing dataset.

Finally, and taking into account the high influence of speed variable on the predicted energy consumption, a data mining analysis using speed as the single input parameter

(M1) was also performed. The metrics obtained during the validation of this single variable model M1 were presented previously in Table 2. Those metrics showed unacceptable errors for this M1 model, significantly higher than those observed in the DM analyses with five or three input parameters. Thus, the prediction performance of M1 models obtained with both DM techniques (ANN or SVM) cannot be considered satisfactory.

Nevertheless, Figs. 9a and 9b present the ANN models fitted with a single input variable (M1), respectively for the training set and the testing set.



(a) (b)

Fig. 9. Performance of ANN model with a single input variable (M1) using (a) the training dataset or (b) the testing dataset.

The results obtained confirm the low predictive capacity of the ANN model with a single input variable (M1), especially when using testing data unknown by the model. Thus, although the DM models used for this specific work can be simplified using a lower number of input variables, the accuracy of the models reduces and becomes unacceptable for models with less than three input variables.

4. Conclusions

The results obtained in this work highlight the importance of the pavement characteristics for the energy consumption estimation. In fact, the tire-pavement interaction influences the vehicle energy consumption and should be considered to assess the sustainability of pavement construction/maintenance techniques. The purpose-built laboratory prototype and the use of data mining techniques were essential to understanding the relationships between the measured variables and their relative importance for the energy consumption estimation. The main conclusions to be drawn from this work are:

- A new laboratory test is proposed in this work to assess energy consumption on the tire-pavement interaction, with the possibility of controlling the load and speed conditions while measuring the surface characteristics (e.g., surface profile/texture) and the energy consumed for operating the prototype.
- Two DM techniques were successfully used, namely ANN and SVM, and have provided predictive models with meaningful results, while multiple regression models were unable to capture the nonlinear relationships between variables.
- ANN proved to be the technique with the best performance for energy consumption estimation.
- Data from a group of variables were collected during the experimental tests to feed the database, and their variation proved to influence the results obtained for energy consumption prediction with the developed data mining models.

- Models developed with five (PTV, ETD, MTD, speed, and load), three (MTD, speed, and load) and a single input parameter (speed) were tested, to evaluate the variables relative importance. The prediction performance decreased with a reduction in the number of variables, although models with at least three input parameters maintain the prediction quality.
- For the model with five input parameters, a sensitivity analysis was carried out, showing that the main parameters controlling the energy consumption are speed and surface texture (MTD).
- The purpose-built laboratory prototype presented in this paper is a new approach that can prospectively contribute to study innovative materials for road surface layers in their design phase, with clear advantages for developing sustainable solutions for road paving.

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