Use of Data Mining Techniques to Explain the Primary Factors Influencing Water Sensitivity of Asphalt Mixtures

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ABSTRACT

The water sensitivity of asphalt mixtures affects the durability of the pavements, and it depends on several parameters related to its composition (aggregates and binder) and the production and application processes. One of the main parameters used in the European Standards to measure the water sensitivity of asphalt mixtures is the indirect tensile strength ratio (ITSR). Therefore, this work aims to obtain a predictive model of ITSR of asphalt mixtures using several parameters that affect water sensitivity and assess their relative importance. The database used to develop the model comprises thirteen parameters collected from one hundred sixty different asphalt mixtures. Data Mining techniques were applied to process the data using Multiple Regression, Artificial Neural Networks, and Support Vector Machines (SVM). The different metrics analysed showed that SVM is the best predictive model of the ITSR (mean absolute deviation of 0.116, root mean square error of 0.150 and Pearson correlation coefficient of 0.667). The application of a sensitivity analysis indicates that the binder content is the parameter that most influences the water sensitivity of asphalt mixtures (26%). However, this property depends simultaneously on other factors such as the characteristics of the coarse and fine aggregates (24.9%), asphalt binder characteristics (19.3%) and the use of additives (10%).

Keywords: asphalt mixtures; water sensitivity; indirect tensile strength ratio (ITSR); data mining (DM); support vector machines (SVM)

1. Introduction

Asphalt mixtures with hydrocarbon binder stabilised materials, usually asphalt bitumen, form the surface layers of flexible pavements [1]. Water sensitivity is a characteristic that may jeopardise the excellent performance of asphalt mixtures, causing significant losses in terms of strength and durability [2]. The resistance of asphalt mixtures to water action depends on several factors: the aggregates, the binder type and content, the volumetric and grading composition, the layers' thicknesses, and the environmental and traffic conditions [3].

Evaluating the water sensitivity of asphalt mixtures is essential in selecting the type and content of the materials used in the mixtures. Inadequate selection of materials and incorrect consideration of water sensitivity during mix design can lead to premature deterioration of the pavement and excessive maintenance and rehabilitation costs [4]. Therefore, developing an innovative and reliable method that estimates the influence of different parameters on water sensitivity becomes essential, mainly to assist practitioners in selecting the mixture composition.

This method must use extensive data obtained through laboratory tests to increase its reliability. Data mining (DM) aims to capture patterns or models from databases generally with a large amount of data. They use intelligent algorithms that learn with examples or experiences and extract valuable knowledge. Several DM algorithms, such as artificial neural networks (ANN), support vector machines (SVM), regression trees, and multiple regression (MR), can be used for that purpose.

Considerable developments in computing have led to an exponential increase in data storage capacity and, consequently, to an enormous amount of stored information in different fields and activities. Harnessing this information may contain helpful knowledge. Therefore, the so-called knowledge discovery in databases arose. Data mining is an intermediate step in the discovery process that encompasses five main steps: data selection, pre-processing, transformation, DM, and interpretation. DM applies specific algorithms which extract models from data [5].

The literature review confirmed the successful use of DM in many areas related to road pavements and asphalt materials. Nevertheless, none of the reviewed works assessed the dependence of water sensitivity on several input factors related to asphalt mixture composition. The only reference on using DM techniques (ANN and MR) to model water sensitivity of asphalt mixtures [6] focused on assessing the influence of using nanoparticles (TiO_2) to improve that property.

Some authors used DM techniques (neural network models) to improve the pavement design concerning rutting prediction [7] and optimise rehabilitation procedures [8]. Hsie et al. [9] used machine learning algorithms to improve the rehabilitation of asphalt pavements with overlays.

Flexible pavement performance was assessed by Guo and Hao [10], using a random forest model to predict its lifetime potential damage. Amin and Amador Jimenez [11] used a generalised learning algorithm based on a backpropagation neural network that could model pavement performance without uncertainties. Gu et al. [12] addressed the same topic, which predicted geogrid-reinforced flexible pavement performance using ANN models, while Karballaeezadeh et al. [13] forecasted the remaining service life of a road pavement using an SVM regression model.

The characterisation of flexible pavements is associated with back-analysis procedures, which are essential to understanding the evolution of the structural properties of the different layers and subgrade soil. Several authors found DM techniques valuable to improve this process. Several authors applied ANN [14], SVM regression [15], and an adaptive neuro-fuzzy inference system (ANFIS) [16] to predict the subgrade resilient modulus with good results. Maalouf et al. [17] also studied the resilient modulus of stabilised aggregate bases subjected to seasonal variations with SVM regression techniques. The elastic modulus and Poisson's ratio of different flexible pavement layers were also correctly estimated by applying ANN and MR to falling weight deflectometer data [18, 19]. Gopalakrishnan et al. [20] combined SVM, ANN, decision trees, and meta-algorithms with the same objective.

Several authors successfully applied DM techniques to predict the pavement condition, namely for crack, rutting and pothole detection, and surface characteristics, mainly to predict roughness (IRI). Therefore, regression techniques, ANN, genetic programming models and machine learning algorithms based on pavement age or distress level [21-23] were able to predict the pavement condition index (PCI). Majidifard et al. [24] and Gavilan et al. [25] achieved the same objective using a hybrid model and SVM based on image processing systems. Other authors [26, 27] assessed the general pavement diagnostics and distress classification using specific ANN techniques. Several authors suggested crack detection methods using DM techniques, including RF and a space invariant neural network [28-30], a combination of ANN with deconvolution layers [31] and SVM [32]. Different SVM models could predict pavement rutting [33] and detect potholes [34]. Bashar and Torres-Machi [35] demonstrated the advantages of random forest, ANN, and SVM in studying IRI. The mean texture depth and the long-term skid resistance are other surface properties predicted with a convolutional neural network [36] and ANN combined with genetic algorithms [37].

There are also rigid pavement studies with data mining. Typical and hybrid ANN architectures predicted top-down cracking failure in airport rigid pavements [38], roller compacted concrete pavement flexural and compressive strength [39], and shrinkage and creep performance of concrete mixtures [40].

After presenting the objectives and results of several studies using data mining to predict pavement performance and characteristics at a broader scale, the following paragraphs will focus on the use of DM to estimate the asphalt mixtures' performance. The evaluation of water sensitivity is closer to this level of analysis, demonstrating the applicability of such techniques to discover knowledge on this topic.

Bitumen is the component that most influences the behaviour of asphalt mixtures. Therefore, bitumen modification is currently a common practice to improve its rheological performance. Data mining could optimise the composition of modified asphalt binders and predict their rheological properties. Several authors adequately predicted the dynamic shear modulus and the physical-mechanical properties of base and modified bitumens using ANN techniques [41-43]. Ziari et al. [44] used MR and ANN models to investigate the effects of loading frequency and temperature on the rutting susceptibility of asphalt binders with carbon nanotubes. Other researchers [45, 46] used different machine learning techniques, such as ANN, MR, regression models and fuzzy logic, to optimise the composition of polymer and rubber modified binders and improve their mechanical characteristics (e.g., dynamic shear modulus and viscosity).

The performance of asphalt mixtures is closely related to their mix design, which led some authors to use data mining to improve the composition of the mixtures. Some developed ANN models optimised Marshall [47] and Superpave [48] mix designs and predicted specific properties of the mixtures (air voids content at different gyrations, Marshall stability, flow, and quotient). Air voids were also estimated by Androjić and Marović [49], combining MR and ANN models. Sebaaly et al. [50] developed an optimisation model based on ANN and a genetic algorithm for automatically selecting aggregate gradation and binder content of asphalt mixtures. The permeability of asphalt concrete was also predicted by Tarefder et al. [51] using an ANN model.

Several authors have also successfully predicted the rutting performance of asphalt mixtures using ANN models [52, 53], genetic programming [54], an accurate combination of multi expression programming and ANN [55], a combination of MR and ANN models [56] and ANFIS system [57].

An adequate evaluation of asphalt mixtures' dynamic or resilient modulus is relevant for pavement design. Thus, several authors have used DM techniques to forecast this critical property. With exciting results, SVM, ANN, and deep convolution neural networks, isolated or combined, have predicted the dynamic modulus of asphalt mixtures [58, 59]. ANN was also associated with polynomials to indicate the resilient modulus of emulsified asphalt mixtures with the curing time [60, 61]. Shafabakhsh and Tanakizadeh [62] and Pourtahmasb et al. [63] correctly estimated the resilient modulus of different asphalt mixtures under various loading conditions using the ANFIS technique.

Data mining modelled other properties of asphalt mixtures related to their cracking resistance. ANN and genetic algorithms [64] modelled the fracture energy of asphalt concrete. SVM regressions predicted the indirect tensile strength (ITS) of foamed bitumen-stabilised materials [65], and SVM firefly algorithms [66] predicted the fatigue life of polyethene modified asphalt mixtures.

The literature review showed that DM techniques are adequate to model different properties of asphalt mixtures used in road paving, validating the objective of this work. Thus, using the knowledge discovery in databases through data mining techniques, it was possible to obtain a credible predictive model of water sensitivity of asphalt mixtures and the relative importance of each input parameter of this model in the water sensitivity results. In addition, the lack of previous publications about DM techniques applied to evaluate the relative importance of several input parameters on the water sensitivity modelling of asphalt mixtures confirmed the novelty of this work. The DM algorithms most commonly used in the literature were selected to perform the analysis in this work, as shown in Section 2.

2. Used DM algorithms

The DM algorithms selected to evaluate the influence of different parameters on the water sensitivity of asphalt mixtures were artificial neural networks (ANN), support vector machines (SVM), and multiple regressions (MR). Thus, this work used the mentioned data mining techniques to generate forecast models of the indirect tensile strength ratio (ITSR) and applied sensitivity analysis to obtain the relative importance of each parameter in the water sensitivity of asphalt mixtures.

ANN tries to mimic the functioning of the human brain through an architecture based on neurons linked to each other. Each link has an associate weight, $w_{i,j}$ (i and j are neurons or nodes). An activation function that introduces a non-linear component determines the level of activation of a neuron [67]. This study used the multilayer perceptron architecture composed of an input layer, a hidden layer with H processing units, and an output layer (Figure 1). Furthermore, the calculation process used a logistic activation function *f*, given by $1/(1+e^{-x})$, and the general Equation 1, where x_i are the input parameters or nodes, I is the number of input parameters, and o is the output parameter.

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

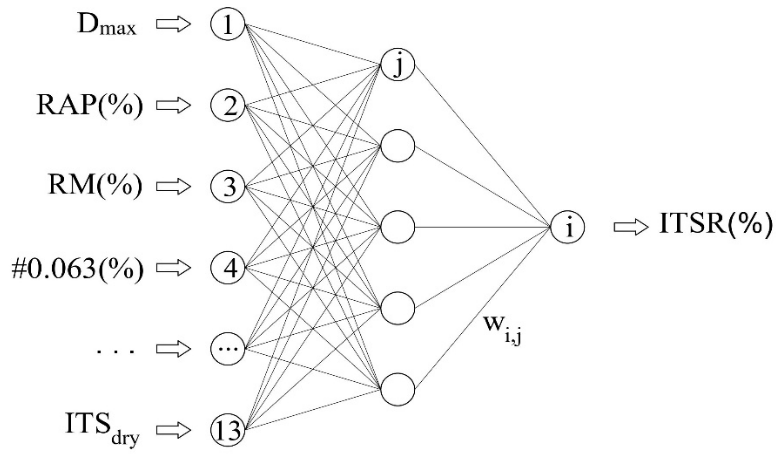


Fig. 1. Multilayer perceptron applied to this particular study case.

Cortes and Vapnik [68] developed the Support Vector Machines for binary classification. The goal was to separate the dataset into two classes or categories using a hyperplane in multidimensional space to separate the samples into sets of the same category. The margin between the closest points of the two classes is maximised, originating the optimal separating hyperplane in the middle of the margin. The support vectors correspond to the points lying in the boundaries, and the points situated on the wrong side are weighted down to reduce their influence [69].

When a linear separator is undetected, there is a transformation via kernel techniques to a higher dimensional space (Figure 2) [69].

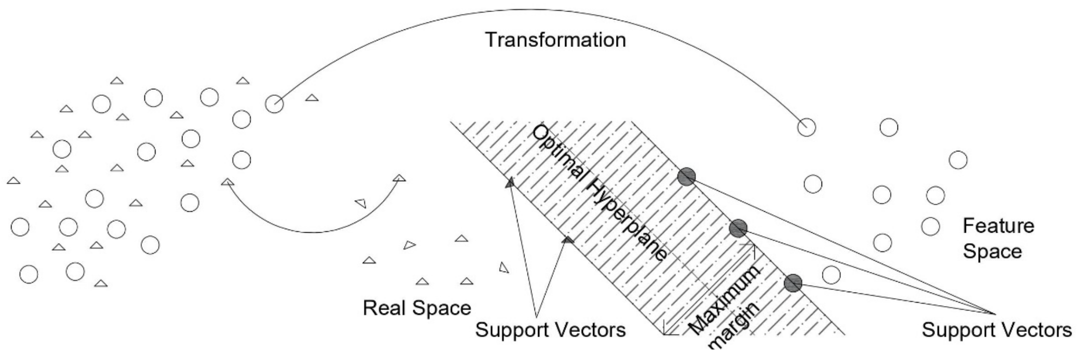


Fig. 2. Example of an SVM transformation.

This study adopted the Radial Basis Function kernel (Equation 2).

$$K(x,x') = exp(-\gamma\|x - x'\|^2)\,, \quad \gamma > 0 \tag{2}$$

The performance of this function is affected by the kernel parameter, γ, the width of the ε-insensitive zone, and a penalty parameter, C. The heuristics proposed in Cherkassky and Ma [70] allowed to set ε and C according to the procedure suggested by Cortez [71] because the standard search intervals for these parameters are significant.

The optimisation of both H and γ parameters used in ANN and SVM techniques followed a grid search according to Hastie et al. [72]: H $\{0, 2, 4, 6, 8, 10, 12, 14, 16, 18, 20\}$ and $\gamma\,\{2^{-15}, 2^{-13}, 2^{-11}, 2^{-9}, 2^{-7}, 2^{-6}, 2^{-5}, 2^{-4}, 2^{-3}, 2^{-2}, 2^{-1}, 2^{0}, 2^{1}, 2^{2}, 2^{3}\}$.

3. Database construction and modelling methodology

3.1. Database construction

The database for this study assembled sixty records obtained from water sensitivity tests performed in the Highways Laboratory of the Civil Engineering Department of the University of Minho [73-91]. The remaining hundred records derive from other published works on the water sensitivity of asphalt mixtures [2, 92-101].

Water sensitivity is a property determined by the EN 12697-12 standard and is suitable for almost all asphalt mixtures specified in the EN 13108 family of standards. This work used the results obtained by method A of the mentioned standard for six specimens prepared with the impact compactor. Then, they are volumetrically characterised and divided into two groups. One is immersed in water (applying a vacuum pressure of 6.7 kPa for 30 minutes) and then left in a water bath at 40 °C for 72 hours. The other is kept dry at 20 °C. After this procedure, all the specimens are conditioned at 15 °C for 2 hours and then subjected to an indirect tensile strength test, according to EN 12697-23 standard. Finally, the main water sensitivity parameter (indirect tensile strength ratio, ITSR) assesses the ratio between the mean indirect tensile strength of the group of wet specimens (ITS_w) and that of the group of dry specimens (ITS_d). For several years, method A was the only one specified in the European Standards for assessing this property. For this reason, ITSR is the main water sensitivity parameter evaluated in several European countries.

The database assembled one hundred and sixty asphalt mixtures to apply the DM techniques. Thirteen input parameters related to the composition of the mixtures and the characteristics of their components, described in the following section, were used to predict the output variable ITSR.

3.2. Input and output variables

The thirteen input variables of the database were the aggregate type (AT), maximum aggregate size (D_{max}), filler type (F), percentage of reclaimed asphalt pavement (%RAP), the percentage of recycled material (%RM), the percentage of aggregate passing through the sieve size of 0.063 mm (% #0.063), the bitumen penetration test value (BPT), the softening temperature of bitumen obtained by the ring and ball method (R&B), the percentage of bitumen (%Bit), the percentage of polymer modifying the bitumen (%Pol), the percentage of other additives incorporated in the bitumen (%Ad), the mean air void content of the compacted mixture (Vv) and the Indirect Tensile Strength of the dry group of specimens (ITS_d). The output parameter was the Indirect Tensile Strength Ratio (ITSR).

The distinction between reclaimed material and recycled material, used as part of the aggregate in the mix design, is because they have different origins. The reclaimed material results from milling one or more asphalt layers from distressed pavements undergoing rehabilitation. The recycled material is associated with construction and demolition wastes or other industrial by-products [94, 98] other than reclaimed material.

The tensile strength reduction (ITSR) evaluated in the water sensitivity tests of asphalt mixtures is a complex phenomenon resulting from adhesive failure in the interface between aggregates and asphalt binder or mastic [102]. Water has easy access to weak interfaces (caused by low bitumen-aggregate compatibility) when mixtures have lower binder contents (%Bit) to cover the aggregates and higher air voids contents (Vv) that allow easier access of water into the mixture [103]. The other input variables were selected because the interfacial strength depends on the characteristics of coarse aggregates (AT, D_{max}) [103], fine aggregates (F, % #0.063) [104] and asphalt binder (BPT, R&B, %Pol) [105]. Moreover, some additives (%Ad) [106] can improve the aggregate-binder bond (e.g., anti-stripping agents). The alternative reclaimed and recycled materials (%RAP, %RM) currently used to increase the sustainability of paving works [107] were included as input variables to assess their possible influence on the water sensitivity and durability of asphalt mixtures. The last input variable used was the tensile strength of asphalt mixtures before being conditioned in water (ITS_d) to check possible relations between the cohesive and adhesive strength [108] of asphalt mixtures.

Table 1 presents the basic statistics of the input and the output parameters.

Table 1. Basic descriptive statistics of the input and the output parameters.

Parameter		Min.	Mean	Max.	Std Dev.	CV (%)
Inputs	D_{max} (mm)	11	17.27	22	4.13	23.89
	%RAP	0	2.94	50	10.97	373.30
	%RM	0	9.72	69	17.49	179.95
	% #0.063	1.5	5.83	10	1.65	28.24
	BPT (0.1 mm)	15	46.56	106	14.37	30.86
	R&B (°C)	21.5	57.59	109	9.98	17.33
	%Bit	3	5.10	10.5	1.12	22.02
	%Pol	0	1.97	21	5.02	254.95
	%Ad	0	0.735	10	2.01	273.62
	%Vv	1.2	4.88	20.7	2.98	61.06
	ITS_d (kPa)	680	1953.27	5148	636.71	32.60
Output	ITSR (%)	42	77.64	113	14.35	18.48

The coefficients of variation indicate medium to high dispersion around the mean, which shows that the data are very heterogeneous. In particular, the %RAP, %RM, %Pol, and %Ad are the parameters with a higher coefficient of variation because the use of these solutions is not standard, and most of the asphalt mixtures in the database do not use these components. Therefore, the percentages of these materials used in asphalt mixtures are significantly different from their mean values. On the other hand, the parameters with a lower coefficient of variation are D_{max}, %#0.063, R&B, %Bit, and ITSR, with values below 30%. This statistic results from a limited range of specified values imposed for these parameters when producing asphalt mixtures.

The type of aggregate and type of filler are categorical variables. There are seven different types of aggregates in the database (basaltic, limestone, pelitic cornean, granitic, ophite, steel slag, and sienitic-limestone) and five types of filler (basaltic, limestone, cement, granitic, and nano clays).

3.3. Modelling and Evaluation

This study used the DM process to predict ITSR and, consequently, the water sensitivity of asphalt mixtures. This process ran in the R environment with the help of the RMiner library developed by Cortez [71], which uses a set of functions that make the data mining algorithms easier to use.

The database parameters showed a significant difference in their values' order of magnitude. Thus, Equation 3 normalised these values between 0 and 1 to allow consistent use of all parameters when applying the DM techniques.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{3}$$

A 10-fold cross-validation process divided the data into ten sets of an equal number of registers [109]. Then nine sets (train data) were used to create a model, using the remaining set (test data) for validation. The developed model was tested with the remaining set, calculating the errors with the predicted and measured values and repeating this process ten times to use every set as a validation set. Then, the average errors after those ten repetitions measured the quality of the DM algorithms. The errors used in this study are the mean absolute deviation (MAD) and the root mean square error (RMSE) given by Equations 4 and 5. Furthermore, the Pearson correlation coefficient (R) was also evaluated by Equation 6.

$$\mathrm{MAD} = \frac{1}{\mathrm{N}} \times \sum_{\mathrm{i}=1}^{\mathrm{N}} |\mathrm{y_i} - \hat{\mathrm{y}}_\mathrm{i}| \tag{4}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{\mathrm{i}=1}^{\mathrm{N}} (\mathrm{y_i} - \hat{\mathrm{y}}_\mathrm{i})^2}{\mathrm{N}}} \tag{5}$$

$$\mathrm{R} = \frac{\sum_{\mathrm{i}=1}^{\mathrm{N}} (\mathrm{y_i} - \bar{\mathrm{y}}_\mathrm{i}) \times (\hat{\mathrm{y}}_\mathrm{i} - \bar{\hat{\mathrm{y}}}_\mathrm{i})}{\sqrt{\sum_{\mathrm{i}=1}^{\mathrm{N}} (\mathrm{y_i} - \bar{\mathrm{y}}_\mathrm{i})^2 \sum_{\mathrm{i}=1}^{\mathrm{N}} (\hat{\mathrm{y}}_\mathrm{i} - \bar{\hat{\mathrm{y}}}_\mathrm{i})^2}} \tag{6}$$

Where *N* denotes the number of examples, y_i the desired value, $\hat{y}_i$ the estimated value for the model concerned, $\bar{y}_i$ the average of the desired values, and $\bar{\hat{y}}_i$ the average of the estimated values.

These metrics compared the three DM techniques' performance, and the best one showed minor errors (MAD and RMSE) and the highest R.

Finally, a sensitivity analysis evaluated each input parameter's relative importance in the ITSR prediction models [110]. Therefore, each input parameter was changed from its lowest to its highest value while keeping the remaining parameters with their mean values. This process was repeated for all DM models used and is essential to identify the most relevant parameters affecting the water sensitivity of asphalt mixtures. The more relevant the parameter, the greater the variance it causes in the model response.

4. Results and discussion

4.1. Performance of the different water sensitivity models

The performance measures MAD, RMSE, and R, obtained with all DM techniques in the cross-validation process, are presented in Table 2.

Table 2. Mean values of the metrics obtained in the cross-validation process.

DM technique	MAD	RMSE	R
MR	0.129	0.164	0.607
ANN	0.130	0.165	0.601
SVM	0.116	0.150	0.667

The SVM algorithm presented minor errors and had the highest correlation coefficient when using the selected database to predict the water sensitivity of asphalt mixtures. Therefore, SVM had the highest predictive capacity, while ANN presented a slightly lower performance than MR in the cross-validation process. This result means that neural networks fail to grasp the complex relationships between the variables that control the asphalt mixtures' non-linear water sensitivity performance.

The efficiency of the different DM models in predicting the water sensitivity of asphalt mixtures was also analysed by comparing the predicted versus measured normalised values of the output variable ITSR. Figure 3 presents those results for the MR, ANN, and SVM models, demonstrating the best performance of SVM in the cross-validation process.

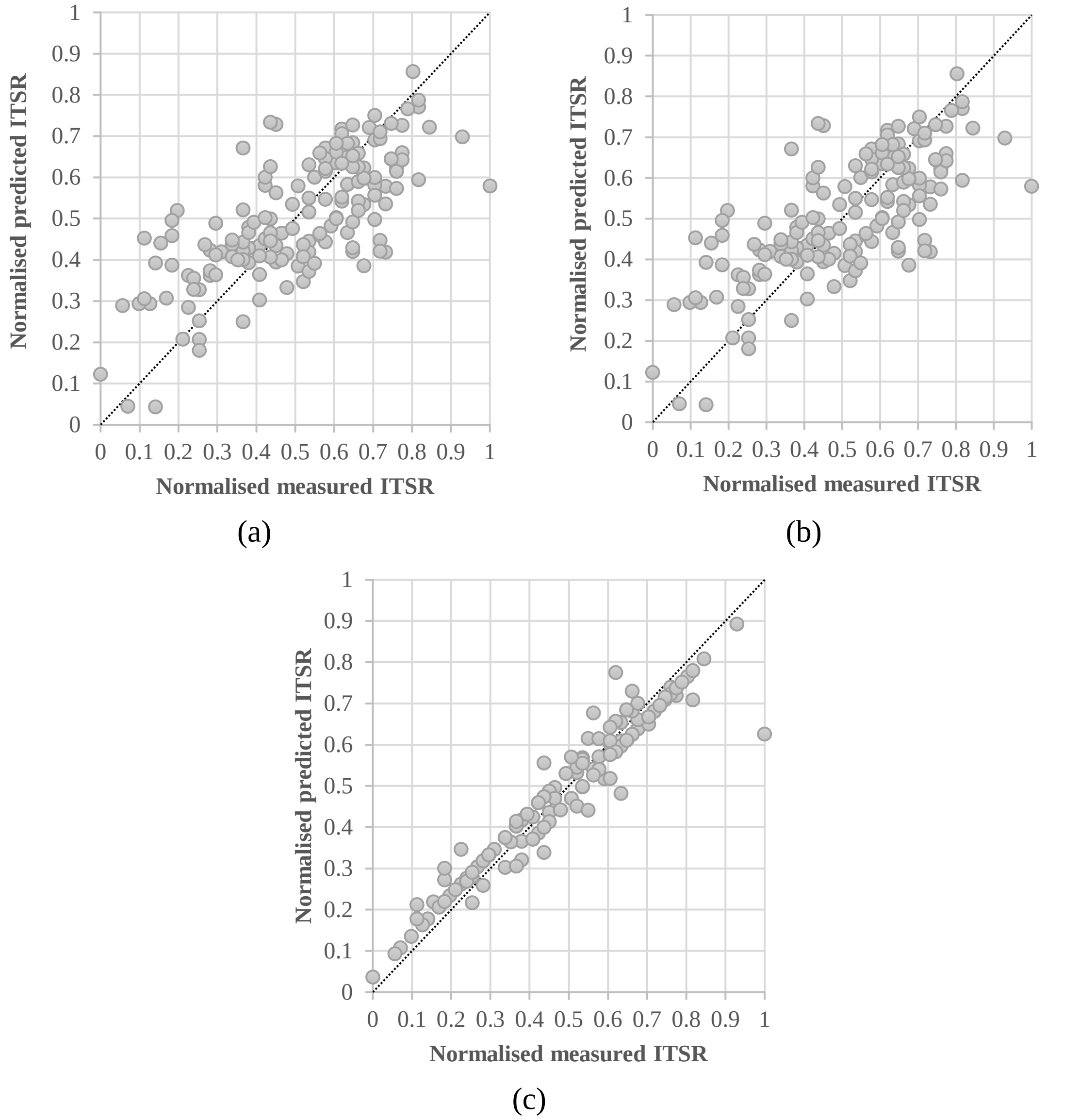


Fig. 3. Performance of (a) MR, (b) ANN, and (c) SVM models.

The adequate performance of the SVM model and the inferior performance of the other models become evident when comparing the predicted versus measured values. The predictions of SVM are similar to the normalised measured ITSR values, while ANN and MR presented a high dispersion. This observation highlights the lower capacity of ANN and MR to translate the non-linearity relation between the variables governing the water sensitivity of asphalt mixtures.

4.2. Relative importance of the input variables to the predicting models

After assessing the performance of the different DM techniques, a sensitivity analysis evaluated the relative importance assigned by each model to the thirteen input variables.

This step is essential to demonstrate which variables should be controlled more carefully during the design of asphalt mixtures to assure a better water sensitivity performance. Figure 4 presents the importance given by MR, ANN, and SVM models to the input parameters. The importance given by the SVM model to the input parameters is different from the other models and may justify its better predictive performance.

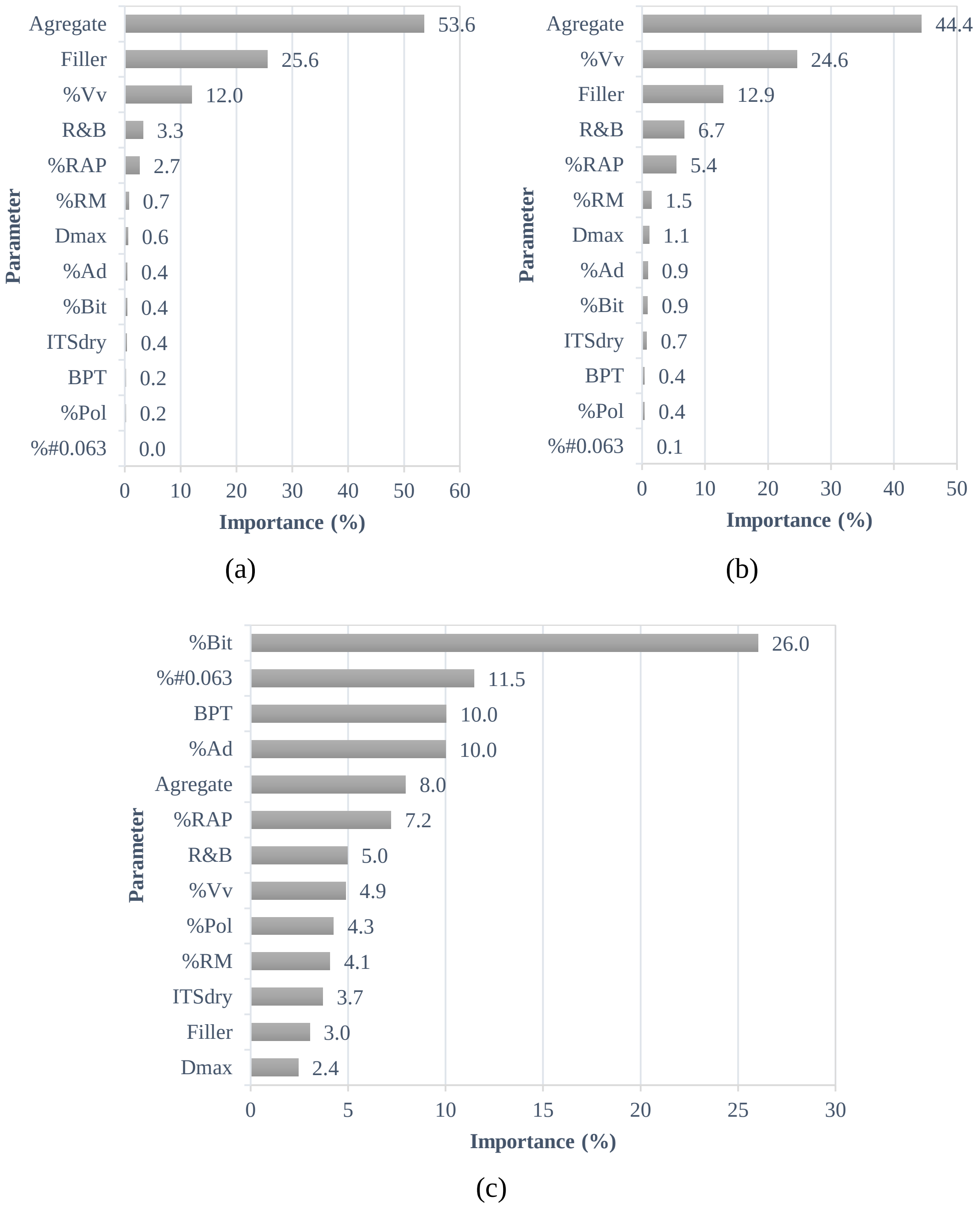


Fig. 4. Importance of the variables in evaluating ITSR using the (a) MR, (b) ANN, and (c) SVM models.

MR and ANN algorithms attribute about half the importance to the aggregate type. The five most important parameters for these models were the same, namely the aggregate type (aggregate), the filler type (filler), the air void content (%Vv), the bitumen softening point temperature (R&B), and the amount of reclaimed asphalt incorporated (%RAP) in the mixture. These input variables account for more than 90% of the total relative importance of all input parameters. Moreover, the only two categorical variables used in this work have cumulative importance of 79% and 57%, respectively, in MR and ANN. However, given the weak predictive capacity of the MR and ANN models, the importance of the several parameters obtained in these models has a limited meaning.

SVM distributes the relative importances more evenly by the different variables and gives the bitumen content the utmost importance (26.0%). This result stresses the importance of strict control of asphalt binder content in asphalt plants to obtain resilient mixtures that are less sensitive to moisture and climate changes. In order to reach the previously mentioned 90% cumulative importance, it is necessary to gather up to ten input parameters. Therefore, the SVM model was able to catch adequately the most relevant parameters that control the water sensitivity of asphalt mixtures. Therefore, the bitumen content is the most relevant parameter that influences the ITSR of asphalt mixtures. Using the same criterion mentioned for the other models, the remaining four parameters with higher relative importance are the percentage of filler (passing the 0.063 mm sieve), bitumen penetration (BPT), the percentage of additives (%Ad) included in the mixture, and the aggregate type (aggregate).

Conventionally, the water damage in asphalt mixtures increases when exposing the aggregate surfaces to moisture, thus justifying the importance of increasing the bitumen content to fully cover the aggregate surface and improve the water sensitivity performance [103, 111]. The filler percentage is also significant since it forms an asphalt mastic with bitumen that influences the bond between coarse aggregates, reducing water access to the aggregate surface [84]. Bitumen penetration or consistency can influence its ability to cover the aggregates or present adhesive failure (instead of cohesive failure) at lower temperatures, thus influencing the moisture resistance [108]. Finally, the percentage of additives can also significantly improve the water sensitivity of asphalt mixtures because some specific additives are anti-stripping agents used to improve the ITSR values [112].

Surprisingly, the relative importance of the air voids content (%Vv) of asphalt mixtures (4.9%) was lower than expected because these voids may facilitate the water access to the aggregates, reducing the water sensitivity performance. Nevertheless, that parameter may be less relevant when bitumen adequately covers the aggregates (e.g., in porous asphalt mixtures), explaining the lower importance given to the aggregate type in the SVM model. Despite this, the model's cumulative importance of coarse and fine aggregate input parameters (%#0.063, aggregate, filler, D_{max}) is significant (24.9%) [111]. When modelling the water sensitivity with SVM, the importance of asphalt binder modification (%Pol) was only 4.3%. However, the physical-mechanical properties of the asphalt binders (BTP and R&B) and their modification correspond to cumulative importance of 19.3% in the SVM model, emphasising the importance for the paving industry of carefully selecting the type of bitumen when producing asphalt mixtures that should be resistant to weather agents [113].

Thus, this work demonstrates that the water sensitivity depends simultaneously on several factors such as the bitumen content (26%), characteristics of coarse and fine aggregates (24.9%), asphalt binder characteristics (19.3%) and use of additives (10%) that can improve the aggregate-binder bond. Thus, asphalt mixture producers need to control all these parameters to ensure adequate resistance to water damage.

The evaluated reclaimed and recycled materials showed a low influence in the water sensitivity models (7.2% and 4.1%, respectively), demonstrating that using these alternative materials in asphalt mixtures does not compromise their durability [114, 115]. The ITSR value does not significantly rely on the ITS value, which demonstrates that the sensitivity to water is not very dependent on the stiffness of the mixture.

4.3. Accuracy of predicting models with a reduced number of input variables

Considering that the models gave low importance to some input parameters, it was essential to evaluate redundant variables that are statistically correlated. Thus, Table 3 shows the correlation between all doubly input parameters used in this work. Recognising that R values higher than ±0.80 are considered statistically significant at 95% confidence [116], there are no significant correlations between the input parameters since all R^2 values are below 0.64. These results mean that the models should discard none of the input parameters used in this work.

Table 3. Coefficient of determination (R^2) values between all doubly parameters

Parameter	D_{max}	%RAP	%RM	%#0.063	BPT	R&B	%Bit	%Pol	%Ad	%Vv	ITS_d
D_{max}	1.00										
%RAP	0.01	1.00									
%RM	0.41	0.02	1.00								
%#0.063	0.01	0.00	0.02	1.00							
BPT	0.00	0.01	0.00	0.08	1.00						
R&B	0.08	0.00	0.05	0.01	0.04	1.00					
%Bit	0.06	0.00	0.00	0.02	0.14	0.04	1.00				
%Pol	0.11	0.00	0.05	0.01	0.10	0.13	0.63	1.00			
%Ad	0.03	0.02	0.04	0.06	0.10	0.13	0.00	0.00	1.00		
%Vv	0.00	0.01	0.02	0.09	0.03	0.00	0.07	0.02	0.02	1.00	
ITS_d	0.11	0.03	0.06	0.01	0.12	0.01	0.00	0.02	0.10	0.04	1.00

Finally, additional analyses were performed, reducing the number of input parameters when running the DM models to assess the changes in their predictive performance when some parameters are missing. Different attempts removed the parameters with lower relative importance in the SVM model. This model was selected since it could catch the most relevant parameters that control the water sensitivity of asphalt mixtures. Thus, three additional models with fewer input parameters were developed and labelled as M1, M2, and M3, as follows:

- M1 is a model developed by removing the D_{max} input;
- M2 is a model developed by removing the D_{max} and filler inputs;
- M3 is a model developed by removing the D_{max}, filler, and ITS_d inputs.

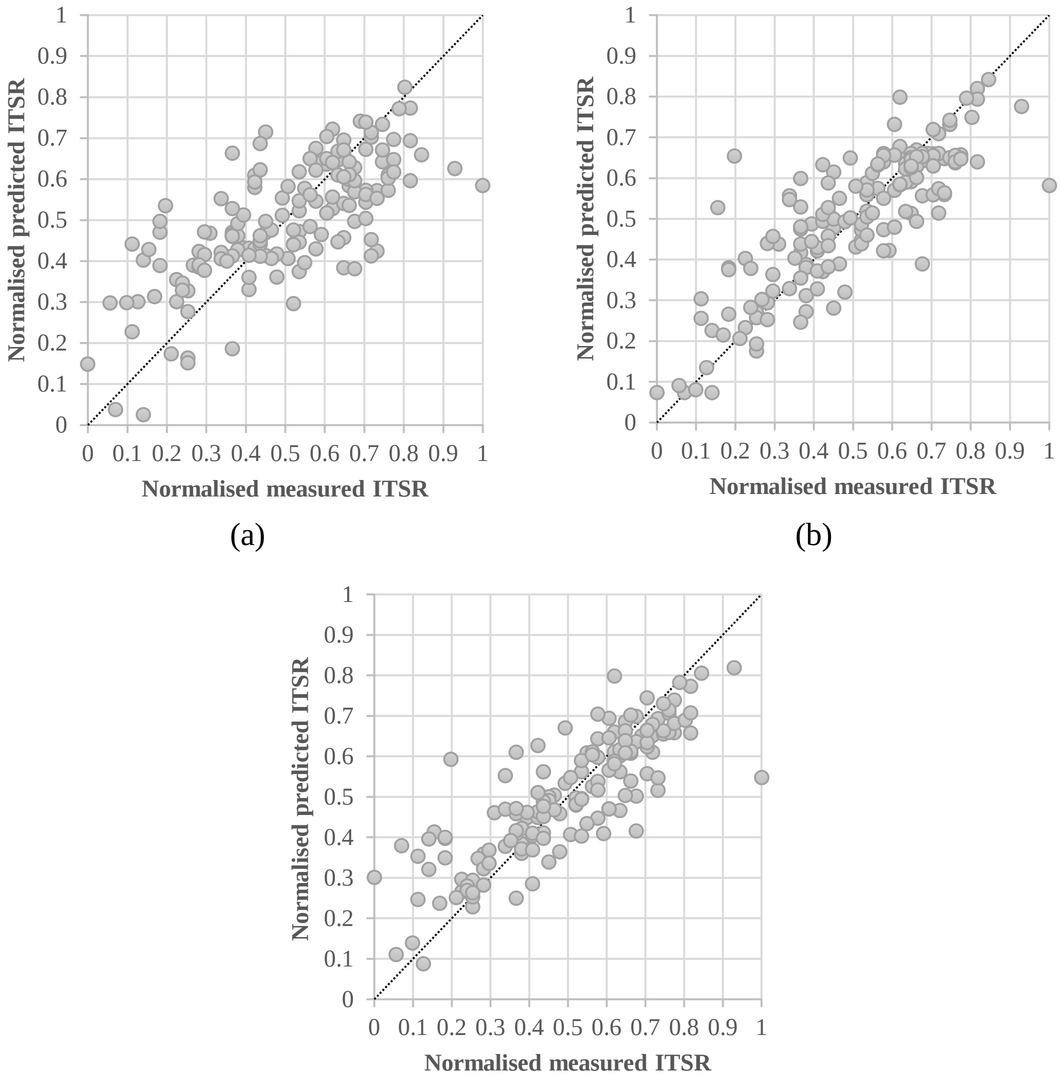
Table 4 presents the mean values of the metrics obtained in the cross-validation process for these models with fewer input parameters.

Table 4. Mean values of the metrics obtained in the cross-validation process for models M1 to M3 with fewer input parameters.

Model	M1			M2			M3		
DM technique	MR	ANN	SVM	MR	ANN	SVM	MR	ANN	SVM
MAD	0.128	0.127	0.118	0.127	0.128	0.119	0.125	0.124	0.115
RMSE	0.163	0.162	0.153	0.160	0.164	0.156	0.159	0.157	0.152
R	0.611	0.615	0.653	0.621	0.605	0.637	0.627	0.638	0.661

The metrics show that the SVM model's performance with fewer input parameters degenerated compared to the previous model with all input parameters. This result demonstrates the importance of all input parameters used in this work to explain the water sensitivity performance of asphalt mixtures. However, the metrics (MAD, RMSE, and R) obtained for MR and ANN techniques did not significantly alter when running the M1 to M3 models with fewer input parameters, showing no evident influence of those missing parameters on ITSR prediction.

Figure 5 shows the relationship between the measured and predicted normalised ITSR for the models with fewer input parameters (M3).



(a) (b) (c)

Fig. 5. Performance of (a) MR, (b) ANN, and (c) SVM algorithms for M3 models using ten input parameters.

The predictive performance degradation of the SVM model becomes evident when comparing the predicted versus measured normalised ITSR values. In addition, the low performance of the other models was not significantly affected compared to that obtained for the models with all input parameters. All M3 models with ten input parameters presented a high dispersion.

5. Conclusions

Resilient road infrastructures with circular materials demand predictive methods with improved performance. Data mining algorithms can be the solution for that need. Water sensitivity is a critical design property for sustainable mixtures and durable pavements. Thus, it is imperative to research DM algorithms for water sensitivity prediction to test their accuracy and find the main parameters that control this behaviour.

This study demonstrated the significant influence of the selected data mining model on the water sensitivity forecast results. The SVM algorithm emerged as the most accurate method, assigning the importance of the several input parameters more equitably. The DM models should discard none of the thirteen input parameters due to the complex water sensitivity behaviour. The performance mainly depends on the binder content, the characteristics of the coarse and fine aggregates, the asphalt binder characteristics, and the use of additives. The use of reclaimed and recycled materials in durable asphalt mixtures is feasible due to their low influence on water sensitivity.

Data mining algorithms can be a powerful tool for predicting the water sensitivity of asphalt mixtures. The research on this topic should continue to improve the accuracy of DM models further. Asphalt mixture producers must control several mix design parameters mentioned above to develop new solutions resistant to water damage.

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