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Rail pad stiffness estimation based in machine learning algorithms

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Abstract

Rail pads are interposed between the steel rails and the concrete sleepers on the railway lines to protect the latter from the impacts induced by the passage of the trains. They provide compliance to the track and play a fundamental role to maximize its durability and minimize the maintenance costs. Rail pads can be fabricated with different polymeric materials that display a non-linear mechanical behavior which strongly depends on the external conditions. Therefore, it is extremely difficult to estimate its mechanical properties, in particular its dynamic stiffness. In this work, several machine learning algorithms (multilinear regression, K nearest neighbors, regression tree, random forest, multi-layer perceptron and support vector machine) have been optimized to determine the dynamic stiffness of rail pads manufactured in EPDM, TPE or EVA, depending on the in-service conditions (temperature, frequency, axle load and toe load). A dataset consisting of 720 stiffness tests under different combinations of these variables was available for the training and testing of the models. The optimal algorithms for EPDM, TPE and EVA were, respectively, multi-layer perceptron (R2 of 0.990 and mean absolute percentage error of 6.51%), multilayer perceptron (0.994 and 2.32%) and random forest (0.968 and 4.91%).

Keywords: Rail pad, Machine learning, operational conditions, dynamic stiffness.

1 Introduction

Rail pads are elastomeric elements that are placed between the rail and the sleeper or the slab track and whose purpose is to provide flexibility to the track, for which reason rail pads are key elements in the durability and maintenance of the railway superstructure [1–5]. Because of their great importance, nowadays there are several types of commercial rail pads, and they can be made of different materials such as EPDM, TPE or EVA.

These elements are not only highly non-linear and depend on a large number of variables such as temperature, test frequency or load values, but these variables also interact with each other, modifying the properties of the rail pads [6–9]. In addition, after a bibliographic review, it was concluded that each material has significantly different mechanical properties, which may vary even by an order of magnitude between different rail pads, although, while operating conditions affect all rail pads similarly, the degree to which each rail pad is affected may be substantially different.

For the reasons explained above, it is extremely difficult to develop an empirical model capable of estimating the properties of these rail pads as a function of the operating conditions. Therefore, a machine learning model was developed capable of predicting the dynamic stiffness of the seat plate as a function of its operating conditions. The use of machine learning algorithms to predict behavior is something that is established and positioned in some branches of knowledge, such as medicine, finance, weather forecasting and in all pioneering technology companies such as Amazon or Google.

In this paper we have developed a machine learning model trained with experimental results, that is not only capable of predicting the equivalent properties of a rail pad under the respective conditions of use, also it can be combined with a finite element model that modifies the properties of the different elements depending on operational conditions.

2 Methods

To train and calibrate the machine learning models, a large amount of data is required. 720 laboratory tests were performed, varying the material of the rail pad (EPDM, TPE and EVA), temperature (-35, -20, 0, 20 and 52 ºC), load amplitude (15.5, 21 and 31.5), toe load (1, 9, 18 and 25) and frequency (2.5, 5, 10 and 20 Hz). Once all these tests were performed, 80% of the data, randomly selected, was used to train the machine learning model and the remaining 20% was used to test it.

Dynamic stiffness (kdyn) tests have been conducted in the laboratory. The procedure followed to determine kdyn is based on the standards UNE-EN 13481-2 [10] and UNE-EN 13146-9 [11]. The procedure consists of applying 1000 sinusoidal load cycles between the maximum and minimum defined values. Ten cycles of the last 100 cycles are selected and the dynamic stiffness value is calculated through Equation 1.

$$k_{dyn} = \frac{\overline{F_{max}} - \overline{F_{min}}}{\overline{D_{max}} - \overline{D_{min}}} \qquad (1)$$

The Machine Learning models have been developed and evaluated in Python using the libraries Numpy, Pandas, Scikit-learn, Matplotlib and Seaborn. The dataset consists of 720 instances and five features: Material, frequency, load amplitude, toe load and temperature. The first variable, material, is categorical, i.e., it contains labels (‘EPDM’, ‘TPE’, ‘EVA’) rather than numeric values. Many ML algorithms cannot operate on categorical data but require all variables to be numeric. For categorical variables where no ordinal relationship exists, one-hot encoding is recommended. For this reason, the feature corresponding to the material was one-hot encoded before any calculation.

Six different machine learnign algorithms were used to determine the model that best fits the rail pads behavior: Multilinear regression (MLR), K-Nearest Neighbors (KNN), Classification and Regression Trees (CART), Support Vector Machines (SVM), Random Forest (RF) and an artificial Neuronal Networks specifically a Multi-Layer Perceptron (MLP).

Permutation importance and feature importance techniques were used to identify the critical variables for each of the materials.

3 Results

The results are organized in two sections. First, the accuracy of the models is shown to determine the optimal. Then, an analysis of the importance and influence of each variable is carried out.

Defining the best model

The coefficient of determination, R2, was selected as the regression score function for the optimization of the hyperparameters of the algorithms. The results of R2 for each of the models and each of the materials are shown in Table 1. For EPDM and TPE R2 is over 0.99 while for EVA it is higher than 0.96.

Algorithm	EPDM	TPE	EVA
MLR	0.452	0.759	0.928
KNN	0.628	0.872	0.927
RT	0.923	0.969	0.922
RF	0.965	0.977	0.968
MLP	0.990	0.994	0.927
SVM	0.060	0.545	0.56

Table 1: Statistical score (R2) in the test dataset provided by each model and material.

The data represented in Figure 3, Figure 4 and Figure 5 illustrate the ability for prediction of the different ML algorithms for EPDM; TPE and EVA, respectively. The experimental values of stiffness are represented in the X-axis and the predictions of each of the regressors are shown on the Y-axis. Each graph includes a 1: 1 line (corresponding to a perfect fitting) as well as two confidence bands separated from the center line by a distance equal to the RMSE.

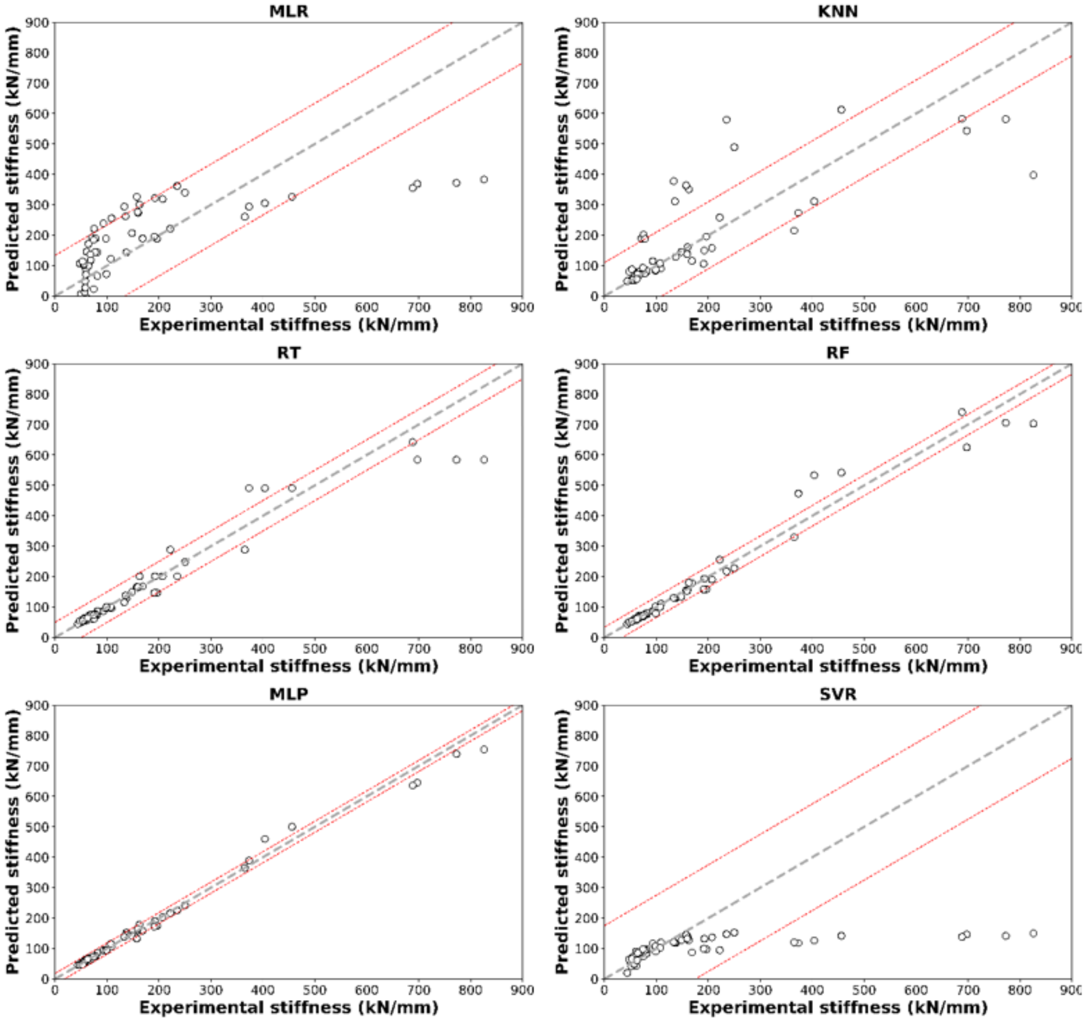

Figure 1: Comparison between the experimental and the predicted stiffness for each of the ML models optimized for the EPDM rail pad.

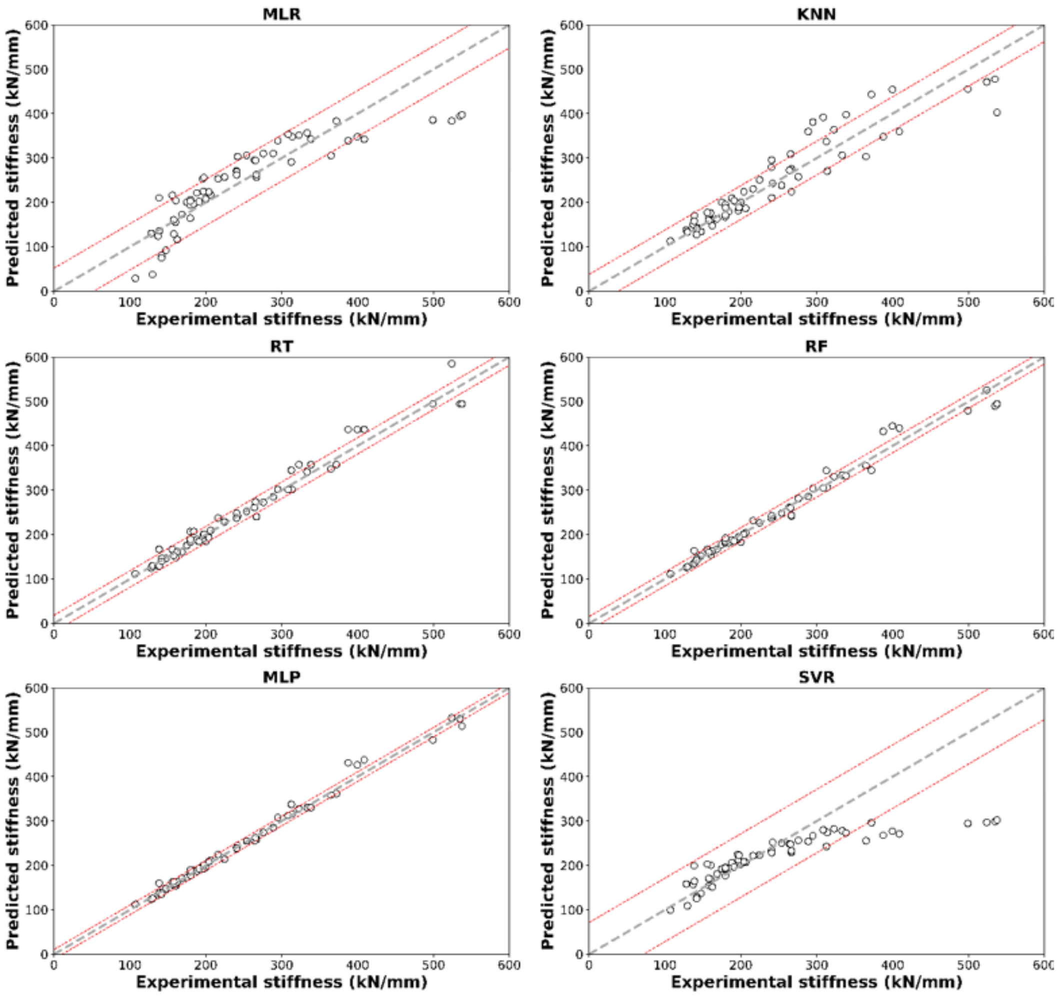

Figure 2: Comparison between the experimental and the predicted stiffness for each of the ML models optimized for the TPE rail pad.

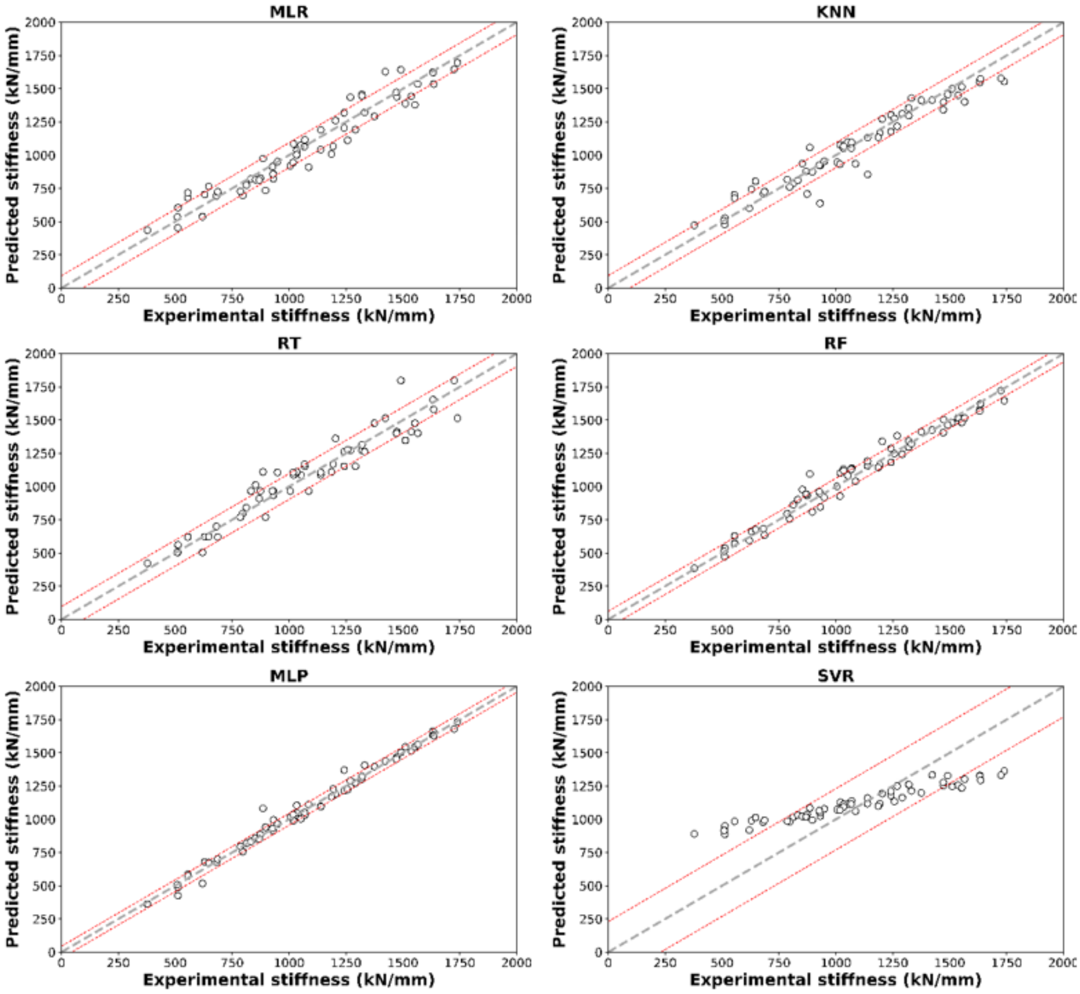

Figure 3: Comparison between the experimental and the predicted stiffness for each of the ML models optimized for the EVA rail pad.

Feature and permutation importance

The results obtained with FI and PI are summarized in Table 2.

	Feature importance			Permutation importance		
	EPDM	TPE	EVA	EPDM	TPE	EVA
Temperature	0.63 ± 0.07	0.69 ± 0.04	0.042 ± 0.009	1.43 ± 0.37	1.44 ± 0.19	0.088 ± 0.009
Toe Load	0.31 ± 0.07	0.27± 0.04	0.81 ± 0.04	0.71 ± 0.09	0.62 ± 0.07	1.78 ± 0.21
Frequency	0.0412 ± 0.0009	0.031 ± 0.011	0.061 ± 0.016	0.10 ± 0.05	0.07 ± 0.02	0.124 ± 0.002
Amplitude	0.0160± 0.0016	0.011 ± 0.007	0.08 ± 0.03	0.028 ± 0.004	0.016 ± 0.006	0.15 ± 0.02

Table 2: Quantitative relevance analysis parameter for each of the rail pad.

4 Conclusions and Contributions

There is not a model at present time capable of predicting the mechanical properties of the rail pads according to its in-service conditions. This is not only because rail pads are highly non-linear elements that depend on a large number of variables such as temperature, axle load, toe load or frequency, but also because these variables interact with each other, making it difficult to build an analytical model that represents the behaviour of these rail pads. In this work, for the first time, a model based on machine learning algorithms has been developed, capable of predicting the dynamic vertical stiffness of three types of rail pad as a function of their operating conditions.

- It has been possible to develop a model that predicts the vertical stiffness of three types of material rail pads better than any model previously proposed.
- It has been proved that in all cases MLP and RF are the models that obtain the best correlations in the test data.
- Both permutation importance and feature importance identify the same parameters as critical parameters.
- In the case of EPDM, it has been found that the conditions that most influence the dynamic vertical stiffness are temperature and toe load.
- Like EPDM, for TPE, the operating conditions that most influence the dynamic vertical stiffness are temperature and toe load.
- In the case of EVA, the operating condition that most influences the dynamic vertical stiffness is toe load.
- In general, the variables that most influence the vertical behavior of the rail pads are temperature and toe load, which are the two parameters analyzed that do not depend on the vehicle running on the track.
- As a general rule, toe Load is the parameter that most influences the dynamic vertical stiffness of rail pad. This parameter is a parameter that the standards do not propose as a variable, so the standard should be revised.

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