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Machine learning algorithms for the prediction of the mechanical properties of railways' rail pads

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Abstract. Train operations generate high impact and fatigue loads that degrade the rail infrastructure and vehicle components. Rail pads are installed between the rails and the sleepers to damp the transmission of vibrations and noise and to provide flexibility to the track. These components play a crucial role to maximize the durability of railway assets and to minimize the maintenance costs. The non-linear mechanical response of this type of materials make it extremely difficult to estimate their mechanical properties, such as the dynamic stiffness. In this work, several machine learning algorithms were used to determine the dynamic stiffness of pads depending on their in-service conditions (temperature, frequency, axle-load and toe-load). 720 experimental tests were performed under different realistic operating conditions; this information was used for the training, validation and testing of the algorithms. It was observed that the optimal algorithm was gradient boosting for EPDM (R^2 of 0.995 and mean absolute percentage error of 5.08% in test dataset), TPE (0.994 and 2.32%) and EVA (0.968 and 4.91%) pads. This algorithm was implemented in an application, developed on Microsoft .Net platform, that provides the dynamic stiffness of the pads characterized in this study as function of material, temperature, frequency, axle-load and toe-load.

1. Introduction
Rail transport is expected to increase in forthcoming years, especially for freight. This evolution requires a mature rail transport system to ensure a transport as economic and efficient as possible. In order to achieve this objective, one of the main milestones to be reached is to implement a set of tools to allow predictive maintenance, which will result in minimising both, maintenance costs and problems during its useful life. In order to understand the influence of train operations on the response of the infrastructure, several studies have been developed [1,2].

One of the key elements in the maintenance of the railway superstructure are the rail pads [3–8], which are elements placed between the rail and the sleeper and whose main functions are to absorb impacts and provide track flexibility. At present, these rail pads can be made of different elastomeric materials, the most common being EPDM, TEP or EVA. These components have a highly non-linear behaviour and, moreover, it depends on the test conditions. While the influence of each of the operational conditions depends on the material, different authors have defined common trends which are described in the literature. There are a number of effects that increase stiffness, such as an increase in axle-load [12], toe-load [10] or frequency [9–11], while other factors like the increase on temperature reduces it [11]. Despite the great importance of these components, due to their complex behaviour, there is currently no model capable of predicting the stiffness of the component as a function of the operating conditions.

Nowadays, and increasingly, in those cases where a highly complex problem is faced, it is possible to use machine learning algorithms to predict some behaviour. These techniques commonly used by companies such as Google or Amazon can be applied to other branches of knowledge such as material mechanics, and later, these linked to finite element models [13].

In this research, dynamic stiffness tests have been carried out on rail pads, varying test conditions. Subsequently, a series of machine learning algorithms were applied to the dataset created. It was found that these algorithms were capable of predicting with great accuracy the dynamic stiffness of rail pads as function of test conditions. Once this model was generated, beyond being able to predict the rail pad behaviour as a function of the test conditions, it is possible to obtain additional information such as identifying suitable working ranges or critical variables.

2. Materials and experimental tests

2.1. Materials

Due to the great influence that the material used has on the behaviour of the rail pads, it was decided to use three of the most commonly used materials for this type of element; EPDM (ethylene-propylene copolymer), TPE (Polyester elastomer thermopolymer) and EVA (Ethylene-vinyl acetate), see Figure 1.

- (a) A solid EPDM 7 mm thick rail pad.
- (b) A TPE rail pad 7 mm thick with protrusions
- (c) A solid EVA 6 mm thick rail pad.

(a) (b) (c)

Figure 1. Different rail pads studied: EPDM (a); TPD (b); EVA (c),.

2.2. Experimental campaign

Dynamic stiffness tests were performed according to European standards EN 13146-9 and EN 13481-2. The procedure consists in applying 1000 load cycles on the rail pad, obtaining the k_{dyn} as the ratio between the load variation and the displacement variation in 10 of the last 100 cycles. The load cycles are sinusoidal waves and are defined by 4 parameters; test temperature, test frequency, load amplitude and minimum load value. 720 tests have been performed modifying each of these 4 parameters within their usual range in order to be able to analyse the interaction of each of the variables with the others [14]. Tests were conducted at 5 temperatures, the values were decided as the maximum and minimum values expected in Spain (-35 and 52), environmental temperature (20) and two additional temperatures

(-20 and 0) to have approximately constant intervals. Four different frequencies were used, this parameter is related to the train speed and the distance between bogies, three of them were defined by the standard (5, 10 and 20 Hz) and an additional one (2.5 Hz) was added based on bibliography [15]. Three values of load amplitude were used), this parameter is related to the train axle load, based on the standard (15.5, 21 and 31.5 kN). Finally, four different minimum loads were used, this parameter is the toe load, which is the load that the fastening system applies to the rail pad, the theorical one (18 kN), the possibility that the fastening system is broken (1 kN), and the two other values analysing the possibility of an over and under torque (9 and 25 kN).

2.3. Machine learning methods

The application of the machine learning algorithms was developed using the programming language Python. Some of the Python open access libraries were used, specifically: Numpy [16], Pandas [17], Scikit-learn [18], Matplotlib [19] and Seaborn [20]. As previously mentioned, the dataset consists of 720 instances, each of them has six features, the k_{dyn} (output) and the tests conditions (inputs); material, test temperature, test frequency, load amplitude and minimum load value. All the variables are numerical except "material", a dumpy variable was used to transform it into a numerical one.

At the beginning of the model calibration the whole dataset was divided in two groups; training and testing data, furthermore, each of these groups was separated into inputs and outputs. The training data are used to fit the regression models and the testing are used to analyse how good is the model.

The following seven regression algorithms have been employed: Linear Regression (MLR), KNN, Regression Trees (RT), Ensemble methods (Random Forest (RF) and Gradient Boosting (GB)), SVM, and Artificial Neural Networks (ANNs). Before the application of these algorithms' features were standardized using the StandardScaler.

The objective of the feature importance and the permutation importance is to evaluate which of the inputs has greater relevance in output. Both of them are implemented in Scikit-Learn and can be used once the model is properly fitted.

Partial Dependence Plot (PDP) were used to analyse the relationship between each feature and the response of the model. In this kind of plots the x-axis shows the feature value, and the y-axis its dependence.

3. Results

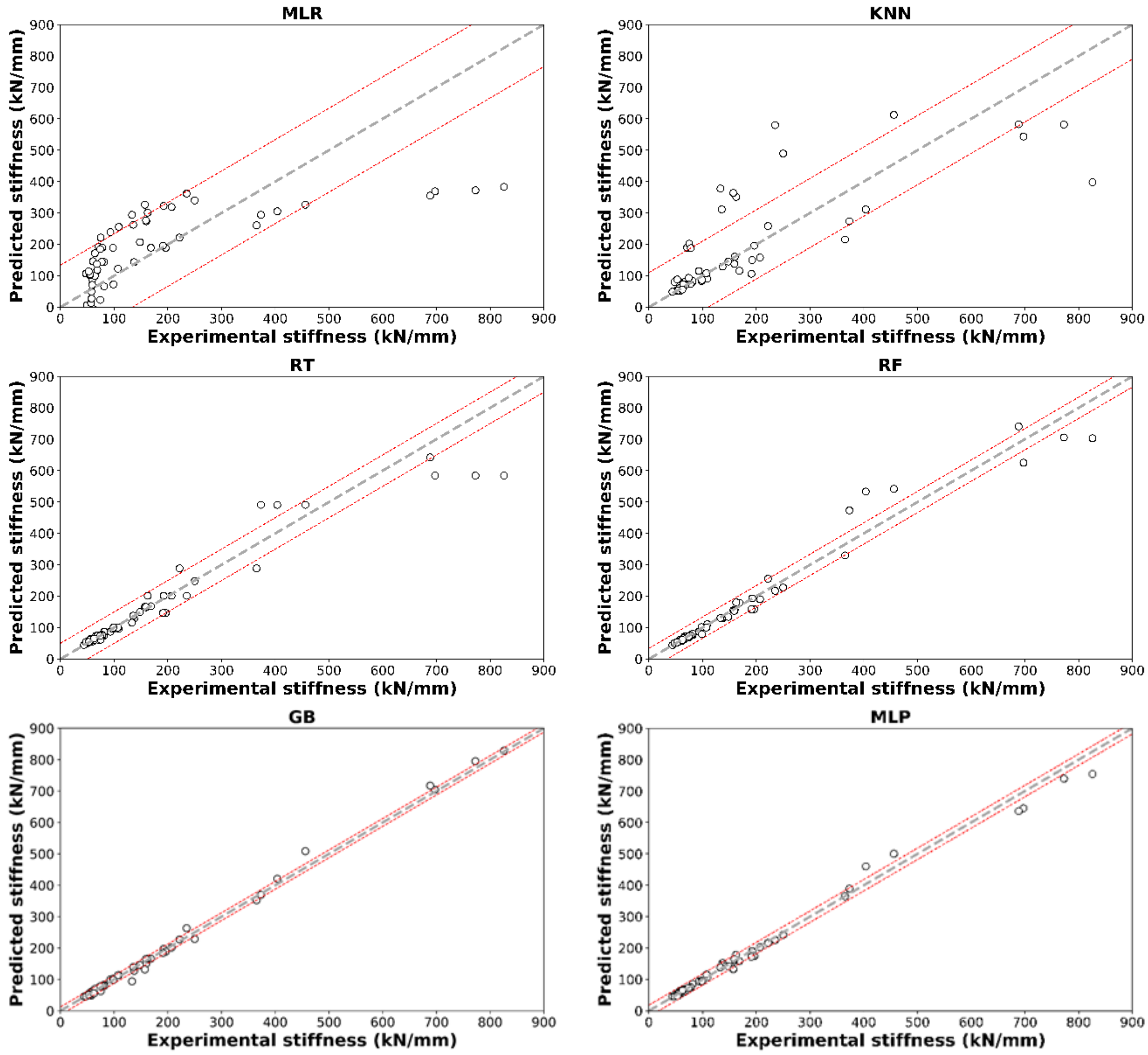
3.1. Optimal model definition

All the hyperparameters of each of the models were optimized, after which, a number of quality parameters were determined (R^2, RMSE, Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE)) in the testing dataset. Table 1 shows the statistical scores in testing dataset provided by each model for each material. Figure 2 shows a comparison between the testing data output (never seen by the regression algorithms) and the value predict by each of the algorithms with the testing data inputs. Figure 2 shows just the results obtained by the EPDM rail pads, but similar figures could be obtained for the other rail pads.

Table 1. Algorithms quality comparison.

Coefficient	MLR	KNN	RT	RF	GB	MLP	SVM
				EPDM			
R^2	0.452	0.628	0.923	0.965	0.995	0.99	0.06
RMSE (kN/mm)	100.39	61.58	22.75	16.45	12.36	10.23	81.28
MAE (kN/mm)	133.67	110.14	50.07	33.66	7.39	17.96	175.13
MAPE (kN/mm)	88.78	34.76	9.24	6.18	5.08	6.51	30.44
				TPE			
R^2	0.759	0.872	0.969	0.977	0.995	0.994	0.545
RMSE (kN/mm)	40.18	27.73	12.48	9.86	7.79	5.8	42.2

MAE (kN/mm)	52.02	37.99	18.52	16.18	5.41	8.02	71.49
MAPE (kN/mm)	17.83	10.18	4.72	3.45	2.25	2.32	13.99
EVA							
R^2	0.928	0.927	0.922	0.968	0.988	0.927	0.56
RMSE (kN/mm)	76.62	67.93	75.15	50.23	37.36	78.3	188.92
MAE (kN/mm)	93.24	93.64	97.02	62.52	20.37	93.72	230.44
MAPE (kN/mm)	7.88	7.04	7.17	4.91	2.38	7.97	22.85



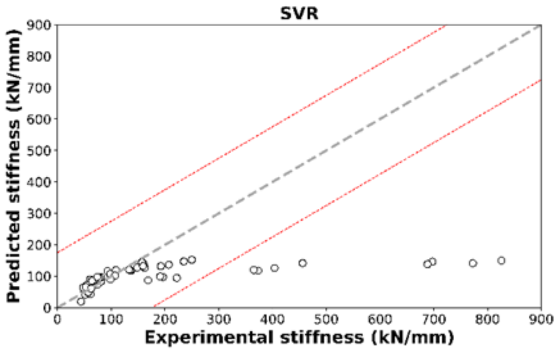


Figure 2. Experimental Vs. predicted stiffness for de different ML algorithms (just the EPDM results are shown).

3.2. Partial dependence plots.

The influence of each of the variables (temperature, frequency, toe load and amplitude) on the k_{dyn} is well known; as the temperature increases, the stiffness decreases, while as the frequency, toe load or amplitude increases, the stiffness increases. Figure 3 shows the PDPs of each the variables over each material. These PDPs not only provide information on how each variable influences the output, they also tell us how much. Figure 3 shows the results just for EPDM, but similar plots could be obtained for the other kinds of rail pads.

Figure 3 shows the evolution of the stiffness of EPDM rail pad as function of the four analysed parameters. It can be seen that the relationship between the increase in amplitude and frequency and the stiffening of the rail pad is approximately constant in the range studied. In the case of the temperature, two clearly different phases can be seen. A great change in behaviour can be seen if the temperature is below -20 ºC, while it remains approximately constant if it is above this temperature. In the case of toe-load, there are also two clearly different behaviours. If it is below 12 kN, which is almost constant. Above this toe-load value, a significant stiffening effect can be observed.

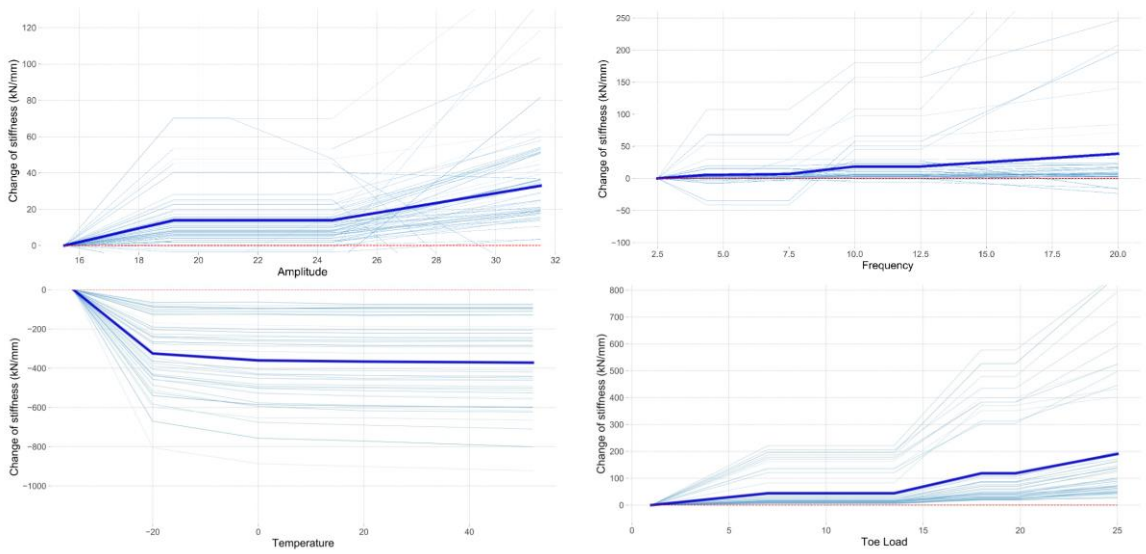


Figure 3. Partial dependence plots (just the EPDM results are shown).

3.3. Feature importance and permutation importance.

Figure 4 shows the results of both, feature importance and permutation importance for each of the materials. Form this figure it can be appreciated the similar results provided by both methods. Moreover, it can be appreciated the high influence of temperature and toe load over EPDM and TPE and the great influence of toe load over EVA rail pads.

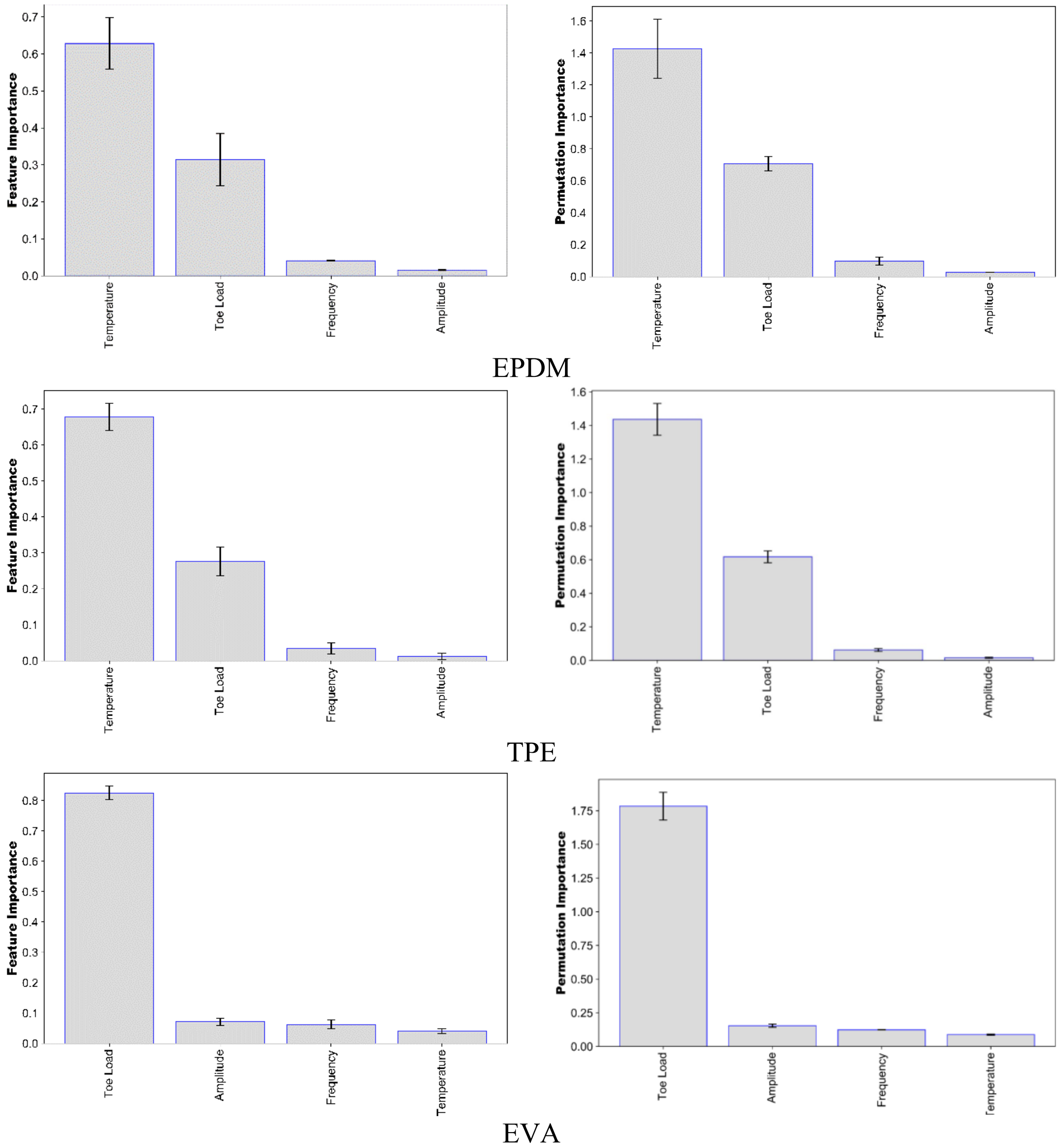


Figure 4. Feature importance and permutation importance for each rail pad material.

4. Conclusions and future developments

Rail pads are not only highly non-linear elements, their mechanical behaviour depends on a large number of variables which interact with each other. This extremely complex behaviour is the reason why until now, there is no model, either analytical or numerical, capable of predicting the behaviour of these elements under different conditions of use. From this work the following conclusions could be extracted:

- A model capable of predicting the dynamic stiffness depending on the operational conditions have been generated and calibrated with great accuracy.
- It has been found that the influence of each variable seriously depends on the rail pad material.
- For EPDM and TPE rail pads temperature and toe-load shows a great influence on the dynamic stiffness of rail pads. The toe load was defined as the critical parameter for EVA rail pad.
- It has been concluded that the track conditions (temperature and toe load) have greater influence than the kind of train passing (frequency and load amplitude).

A model capable of predicting the mechanical behaviour of the rail pads as a function of the operating conditions opens the door to developing a tool that can be integrated into a train to estimate the remaining life of the rail fastening system.

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