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IDENTIFICATION OF EFFECTIVE SEISMIC PARAMETERS FOR SIMULATING NON-LINEAR STRUCTURAL RESPONSE USING MACHINE LEARNING APPROACH

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Abstract

The present study explores the potential of simulating the seismic response of non-linear structural systems using Machine Learning (ML) methods. The main objective is to identify the seismic parameters of the input excitation that provide the most valuable and predictive insights, thereby selecting the most suitable ones for soft computing methods to predict dynamic response. Different signals and seismic parameters were used in a parametric numerical analysis to compute the dynamic responses of 1,000 distinct non-linear single-degree-of-freedom (SDOF) systems. The results were then analyzed using supervised learning techniques, employing 20 different ML algorithms, including linear regression, decision trees, support vector machines (SVM), boosted and bagged trees, and artificial neural networks (ANNs). A feature selection analysis was conducted to reduce the number of seismic parameters considered; those with the highest importance scores were used as input for each ML algorithm to determine which parameters yield the most effective predictions of structural response.

Keywords: Synthetic seismic records, Seismic parameters, Machine learning techniques, Predictive models, Validation analysis.

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1 INTRODUCTION

Over the last few years, Machine Learning (ML) has experienced tremendous growth in various engineering fields due to its ability to transform traditional solution strategies into data-driven approaches for solving complex problems. Its capability to identify patterns, learn behaviors, and make predictions based solely on available data has made it a valuable tool in structural and earthquake engineering. This growth is driven by the increasing availability of massive datasets and advancements in high-performance computing, which have made ML techniques both viable and effective for addressing engineering challenges. ML encompasses a broad range of algorithms designed to automatically achieve mathematically defined objectives using data. These methods include supervised learning, which analyzes relationships between input and labeled output data; unsupervised learning, which identifies patterns in unlabeled data; and reinforcement learning, where autonomous agents learn to optimize their actions within an environment.

The use of ML in civil engineering began early in the 2000s and incorporated soft computing methods, such as artificial neural networks (ANN), genetic algorithms, and fuzzy logic, into numerical problem solutions [1]. Recent developments are significantly broadening the scope of ML applications in earthquake engineering, particularly in seismic hazard assessment, system identification, damage detection, and structural control for earthquake mitigation issues [2]. Experiments have been conducted to prove the usage of ML in dynamic analysis of structures under linear and nonlinear loading [3]-[7] and for soil-structure interaction issues [8].

The estimation of nonlinear responses of SDOF systems has also been promising with the assistance of ML. ANN-based models have been able to make fast and fairly accurate predictions of dynamic responses, particularly for vibration periods of over 0.5 seconds [9],[10]. Likewise, the support vector machine approach has worked successfully in nonlinear system simulation and prediction issues [11] and tools like Random Forest and Gradient Boosting in decision trees have also been extremely successful in seismic response estimation [12]. Besides structural response prediction, ML has been used in seismic signal characterization, facilitating the selection of data from large earthquake event databases and probabilistic modeling of future events [13],[14]. These advances also demonstrate the increasing role of ML in contemporary earthquake engineering, with new paradigms for predicting structural behavior and enhancing resilience in the built environment.

In terms of modeling the seismic response of a structural system, characterizing seismic signals is a key aspect of vulnerability assessment, especially when the dynamic response is highly non-linear [15],[16]. The mathematical model of the structural dynamic response is typically derived through supervised or unsupervised ML methods, without an initial investigation focused on identifying which parameters effectively describe the characteristics of seismic excitation and, consequently, enable a more accurate modeling of the seismic response. Comparable sensitivity analyses have been performed in [17], though using a conventional numerical method.

This research offers a parametric evaluation for choosing the best seismic parameters that define seismic records in order to simulate the dynamic response of non-linear structural systems through ML methods. In particular, several simulated seismic excitations together with different seismic parameters were used within a numerical analyses to examine the seismic responses of 1000 equivalent elastic perfectly-plastic SDOF systems featuring various mechanical characteristics. In particular, the seismic response was assessed, represented in terms of maximum relative displacement, according to the input values of particular seismic parameters. These data were analyzed using supervised learning methods with 20 ML algorithms:

linear regression, decision trees, SVM, boosted trees, bagged trees, and ANN. A feature selection analysis was conducted to reduce the number of seismic parameters considered; those with the highest importance scores were used as input for each ML algorithm to determine which parameters yield the most effective predictions of structural response.

2 SYNTHETIC SEISMIC RECORDS GENERATION

ML methods rely on algorithms that examine data to identify a correlation between input and output variables; the greater the volume of available data, the more robust the ability to generate a dependable structural response given by the algorithm. From this viewpoint, it is crucial to obtain sufficient data that characterizes seismic demand, selecting input signals according to the site's seismic risk [18]-[23]. Since seismic records from natural events for given sites are rare, synthetic accelerograms are instead created [24]-[26]. Employing Aki's "specific barrier model" [27], factors that can be altered in this specific generation consist of magnitude, Joyner-Boore distance, soil type, and tectonic regime. This model is executed using Seismoartif software [28] and has been validated with a substantial database of response spectra for seismic occurrences in intraplate, interplate, and extensional tectonic environments.

In this study, the parameters chosen to characterize site seismic hazard are: a far field earthquake with a moment magnitude of 8, a Type A design spectrum as per Eurocode 8 part C, an importance factor of 1, a target PGA of 0.24 g, linear site effect, and a distance from the epicenter to the site randomly selected from a uniform distribution between 15 and 25 km. In this manner, 400 artificial seismic disturbances have been created randomly. In Figure 1(a), one generated signal's time-history is displayed, while the elastic pseudo-acceleration spectra for all artificial seismic records along with the reference spectrum related to Eurocode 8 – ground type A, are shown in Figure 1(b).

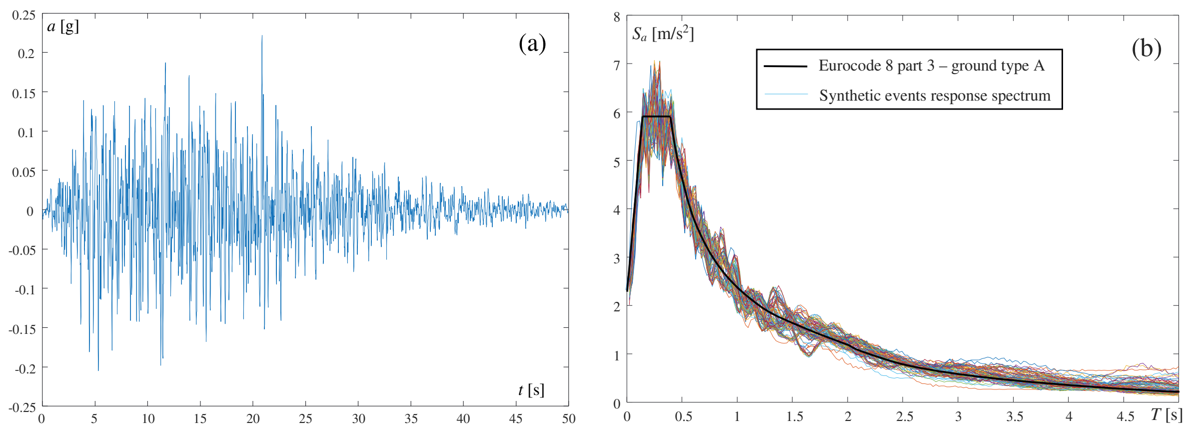

Figure 1: (a) artificial seismic signal; (b) elastic pseudo-acceleration spectra of the 400 artificial seismic records.

The present investigation is focused on studying soft computing prediction of structural response to seismic records by evaluating 16 seismic parameters (S_p) for every single synthetic seismic signal. These seismic parameters are listed in Table 1.

3 DYNAMIC RESPONSE OF NON-LINEAR SDOF SYSTEMS

An elastic perfectly-plastic SDOF model has been adopted for evaluating the seismic response in terms of displacement. This model, introduced by Shibata and Sozen [29] and widely used in both scientific literature and design provisions [30] is characterized by three parameters: the elastic stiffness (k), yield strength (f_y) and relative displacement capacity (x_m) (Figure 2).

Table 1: Seismic parameters characterizing the signals adopted in numerical analyses.

S_p	Seismic parameter	Description
No. 1	Peak Acceleration	Peak acceleration of the seismic input time-history: $\ddot{u}_{g,peak}$
No. 2	Peak Velocity	Peak velocity of the seismic input time-history: $\dot{u}_{g,peak}$
No. 3	Peak Displacement	Peak displacement of the seismic input time-history: $u_{g,peak}$
No. 4	AV ratio	Peak ground acceleration-to-velocity ratio: $AV = \ddot{u}_{g,peak} / \dot{u}_{g,peak}$
No. 5	Acceleration RMS	Square root of the mean of acceleration squares: $a_{RMS} = \sqrt{\int_0^{T_t} \ddot{u}_g^2 dt \Big/ T_t}$, where T_t is the time duration of the signal
No. 6	Velocity RMS	Square root of the mean of velocity squares: $v_{RMS} = \sqrt{\int_0^{T_t} \dot{u}_g^2 dt \Big/ T_t}$, where T_t is the time duration of the signal
No. 7	Displacement RMS	Square root of the mean of displacement squares: $x_{RMS} = \sqrt{\int_0^{T_t} u_g^2 dt \Big/ T_t}$, where T_t is the time duration of the signal
No. 8	Arias Intensity	Time-integral of the square of the acceleration: $I_A = \frac{\pi}{2g} \int_0^{T_d} \ddot{u}_g^2(t) dt$, where T_d is the time duration of the signal above a threshold equal to $0.05g$
No. 9	Character. Intensity	$I_C = a_{RMS}^{1.5} \cdot t_S^{0.5}$, where t_S is the significant duration
No. 10	Specific Energy Density	Energy of the velocity-time history: $SED = \int_0^{T_d} \dot{u}_g^2(t) dt$, where T_d is the time duration of the signal above a threshold equal to $0.05g$
No. 11	Cumulative Absolute Velocity	Area under the accelerogram over a significant duration: $CAV = \int_0^{Tt} \ddot{u}_g(t) dt$, where T_t is the time duration of the signal
No. 12	Acceleration Spectrum Intensity	$ASI = \int_{0.1}^{0.5} PSA(T,\xi) dT$, where PSA is the pseudo spectral acceleration; T is the natural period and $\xi = 0.05$ is the damping coefficient
No. 13	Velocity Spectrum Intensity	$VSI = \int_{0.1}^{0.5} PSV(T,\xi) dT$, where PSV is the pseudo spectral velocity; T is the natural period and $\xi = 0.05$ is the damping coefficient
No. 14	Housner Intensity	$SI_H = \int_{0.1}^{2.5} S_v(T,\xi) dT$, where S_v is the pseudo-velocity response spectrum; T is the natural period and $\xi = 0.05$ is the damping coefficient
No. 15	Sustained Max Acc.	Third-highest acceleration absolute value peak in the time history record: SMA
No. 16	Sustained Max Vel.	Third largest velocity peak in the time history record: SMV

The dynamic equation governing the seismic response of a non-linear SDOF system with mass m, inherent viscous damping coefficient c and resisting force $f_S(x)$ can be written as follows:

$$\ddot{x} + 2\xi\omega_0\dot{x} + \omega_0^2 x_y \overline{f}_S(x) = -\ddot{u}_g \tag{1}$$

where $\omega_0 = \sqrt{k/m}$, $\xi = c/(2m\omega_0)$ and $\overline{f}_S = f_S(x)/f_y$. In the following, the value of the yield strength has been defined in each case as the product between the peak value of the earthquake-induced resisting force in the corresponding linear system f_0 and the yield strength factor R_y, as follows: $f_y = R_y \cdot f_0$. During the elastic response, $\overline{f}_S(x)$ represents the restoring force and depends on the stiffness *k*. The corresponding elastic vibration period is denoted as T_0.

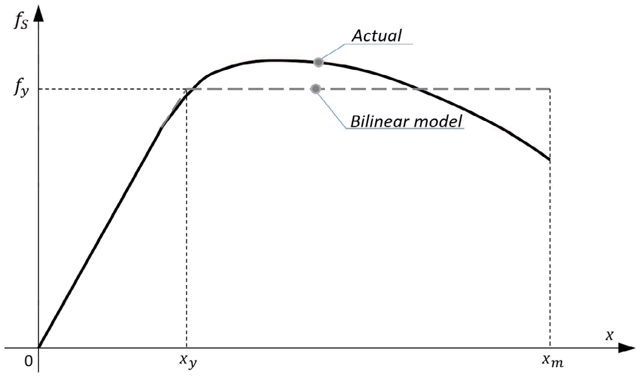

Figure 2: Force-relative displacement curve: actual response compared with the elastic perfectly-plastic model.

A comprehensive parametric analysis, aimed at determining the seismic demand and, thus, the maximum ductility for the 400 generated seismic excitations, has been carried out. Specifically, for each seismic excitation, 1000 different elastic perfectly-plastic SDOF systems have been considered. The initial stiffness k has been modified such that T_0 varies in the range $[0.05\text{ s}, 3.00\text{ s}]$. Similarly, the yield strength has been varied so that R_y ranges from a minimum value of 0.05 to a maximum value of 1, corresponding to a linear dynamic response of the system. In the following, the peak relative displacement is the response variable of the non-linear SDOF systems to predict through ML models [31]-[34].

4 SUPERVISED MACHINE LEARNING MODELS AND FEATURES SELECTION

The previous results representative of the non-linear response of the considered SDOF systems have been utilized as input and output data in an extensive numerical analysis involving 20 ML algorithms (Table 2). The aim is to study the relationship between the mechanical properties characterizing SDOF systems, the characteristics of the seismic excitations and the seismic responses in terms of peak relative displacement. Specifically, the two properties characterizing the system, namely k and R_y, together with the 16 seismic parameters, representing the seismic signal, have been provided as input data for the specific ML algorithm defining the corresponding ML model. The aim of the numerical analysis is to identify an optimal set of seismic parameters to model the non-linear dynamic response of several structural systems using supervised ML techniques.

As a first step, a statistical analysis of the available data allows for a reduction in the numerical complexity of the problem and a more effective interpretation of the results [35]-[40]. In particular, a feature selection analysis was performed using the F-test technique. The F-test is a powerful statistical tool widely used in feature selection procedures to enhance machine learning model performance [41]. It measures the relationship between features and the target variable by comparing variances, making it highly effective in identifying the most relevant predictors [42]. It is particularly beneficial in high-dimensional datasets due to its computational efficiency [43] and, additionally, its ability to identify features with high discriminative power makes it particularly useful in scenarios where interpretability is a priority. The advantages of the F-test extend beyond its statistical rigor and computational efficiency; it also serves as a valuable tool for improving model robustness. By eliminating irrelevant features, it reduces the risk of overfitting, ensuring that the model generalizes well to unseen data [44]. In Figure 3, the F-test results in terms of importance scores are shown for the 16 considered seismic parameters. Results highlight that seven parameters exhibit a stronger correlation with the nonlinear response of the SDOF system (Peak Velocity, Peak Displacement, AV Ratio, Velocity RMS, Displacement RMS, Specific Energy Density, Sustained Maximum Velocity), allowing subsequent analyses to focus on these parameters and determine which algorithm provides the most effective modeling of the obtained numerical results. The selected seismic parameters involve velocity and displacement, as well as integral-based energetic factors. In contrast, parameters directly related to acceleration or time are less effective in this context.

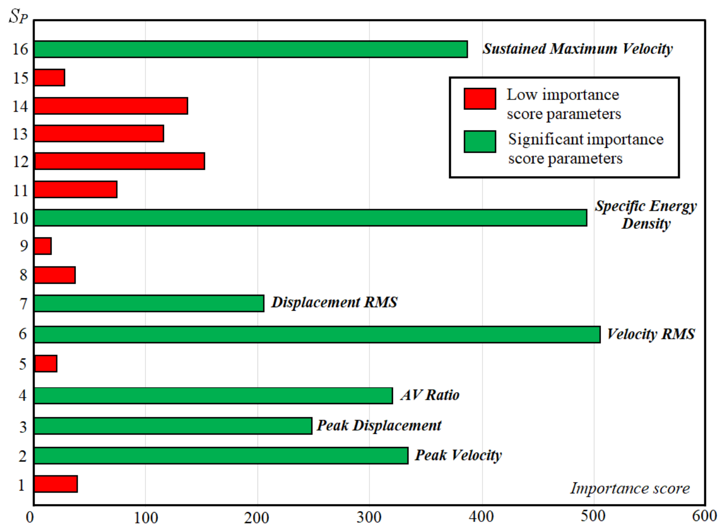

Figure 3: Feature importance score using F-Test algorithm.

Therefore, 20 different algorithms have been analyzed with respect to the seven selected seismic parameters (input features) to model the responses of the 1000 non-linear SDOF systems to the 400 artificial records. As for the ML model validation, the method called "N-fold cross-validation" has been employed. This implies to divide the original dataset, composed of the 400000 cases, into N equal parts, denoted as "validation folds". The training and validation process is repeated N times, each time using a fold as validation set and the remaining $N-1$ folds as the training set. This way, each observation in the dataset has the opportunity to be in both the training and validation sets. During each iteration, the model is trained on the $N-1$ training folds and evaluated on the basis of the single validation fold. In this study, N was set to 5, dividing the dataset into 5 subsets for each analyzed case. Two evaluation metrics are then computed: specifically, the root mean squared error (RMSE) and the Mean Absolute Error (MAE). The RMSE provides a measure of the dispersion between the model-predicted values and actual values in the validation dataset, as expressed by Eq.(2):

$$RMSE = \sqrt{\frac{1}{N}\sum_{s=1}^{N}(x_{s,true} - x_{s,pred})^2} \quad (2)$$

in which N represents the total number of observations in the validation dataset (i.e., N=400000), $x_{s,true}$ is the target parameter value for the non-linear SDOF system, represented by the peak relative displacement obtained from the parametric analysis and $x_{s,pred}$ is the predicted value by using the considered ML model.

Table 2: Considered Machine Learning algorithms.

ML Algorithm Group	#	Algorithm	Algorithm Description
Linear Regression [44]	1	*Linear*	Minimizes the sum of squared differences between predicted and observed values.
	2	*Interaction Linear*	Introduces interactive terms capturing non-linear relationships or conditional dependencies between independent parameters
	3	*Robust*	Introduces a loss function to mitigate the impact of outliers during training, ensuring reduced sensitivity to errors from anomalous values.
	4	*Stepwise*	Sequentially adds or removes parameters based on statistical criteria, simplifying the model by considering only the most significant parameters.
Tree [45]	5	*Fine Tree*	Uses decision trees with a high number of terminal nodes, capturing more details from input data but increasing the risk of overfitting.
	6	*Medium Tree*	Uses decision trees with a balanced number of terminal nodes, maintaining a trade-off between detail capture and overfitting risk.
	7	*Coarse Tree*	Uses decision trees with a low number of terminal nodes, generalizing well but potentially missing finer details.
Support Vector Machine (SVM) [46]	8	*Linear SVM*	Uses a linear kernel function to find the optimal hyperplane for classifying input data.
	9	*Quadratic SVM*	Uses a second-degree polynomial kernel function to transform data into a higher-dimensional space for more complex decision boundaries.
	10	*Cubic SVM*	Uses a third-degree polynomial kernel function for even more flexible decision boundaries.
	11	*Fine Gaussian SVM*	Uses a Gaussian kernel function with a small bandwidth (γ), allowing the model to capture intricate patterns in the data.
	12	*Medium Gaussian SVM*	Uses a Gaussian kernel function with a moderate bandwidth (γ), balancing complexity and generalization.
	13	*Coarse Gaussian SVM*	Uses a Gaussian kernel function with a large bandwidth (γ), making the model more generalized but potentially less sensitive to fine details.
Ensemble [47]	14	*Boosted Trees*	Combines multiple weak learners (often shallow decision trees) iteratively, where each new model focuses on correcting errors made by previous ones.
	15	*Bagged Trees*	Uses bootstrap sampling with replacement to train multiple decision trees on different subsets of data, improving robustness and reducing variance.
Neural Networks (NN) [48]	16	*Narrow NN*	A neural network with a single hidden layer containing 10 nodes, designed for simple pattern recognition tasks.
	17	*Medium NN*	A neural network with a single hidden layer containing 25 nodes, offering a balance between complexity and computational efficiency.
	18	*Wide NN*	A neural network with a single hidden layer containing 100 nodes, capturing more complex patterns but requiring greater computational resources.
	19	*Deep NN (2 Layers)*	A neural network with two hidden layers, enabling the learning of more complex hierarchical patterns in data.
	20	*Deep NN (3 Layers)*	A neural network with three hidden layers, enhancing model depth for highly complex pattern recognition tasks.

The MAE is a measure of the accuracy of the prediction model, it is the average of the absolute value of the difference between the model's predictions and the observed actual values, Eq.(3):

$$MAE = \frac{1}{N}\sum_{s=1}^{N}\left|x_{s,true} - x_{s,pred}\right| \tag{3}$$

The combined use of both metrics allows for a more comprehensive evaluation of the model's performance. In fact, while the RMSE reveals the presence of outliers and level of dispersion in the predictions, the MAE provides a simple and straightforward measure of the average error, being less sensitive to high-intensity prediction errors. To show some results of the validation process, Figure 4 and Figure 5 report both the RMSE and MAE values for the 20 algorithms considered, assuming the Peak Velocity as the input feature (Table 1) and the output variable (i.e., peak relative displacement) related to all the 1000 non-linear SDOF systems subjected to the 400 signals.

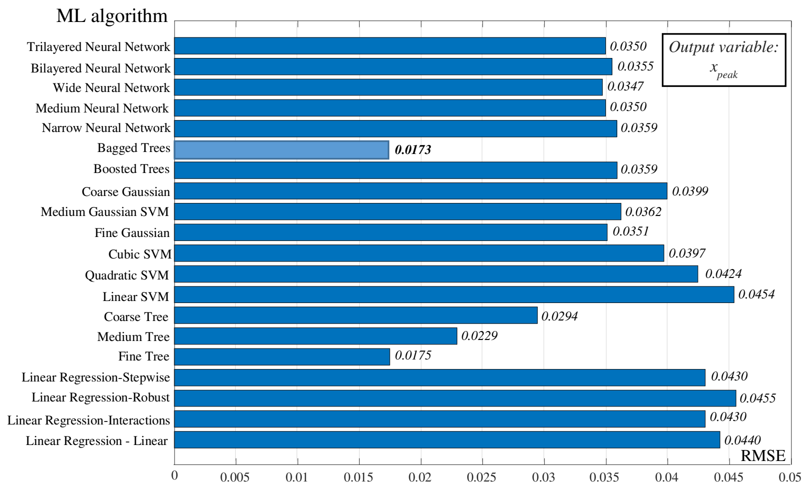

Figure 4: RMSE for each considered algorithm assuming the Peak Velocity as seismic parameter.

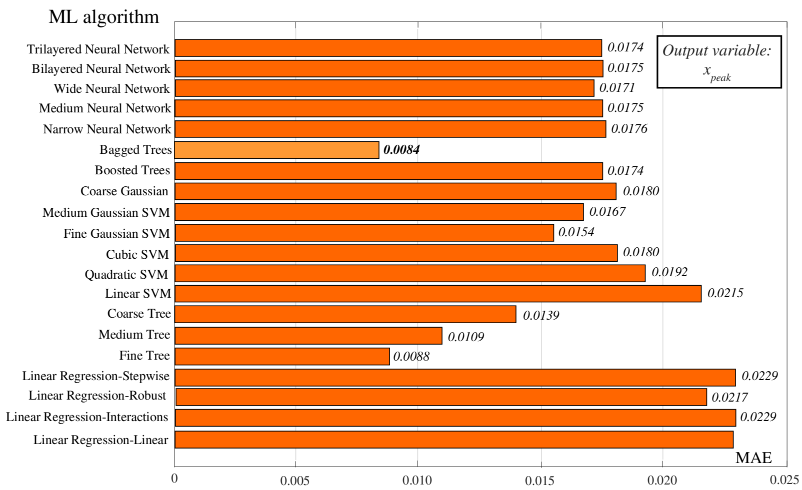

Figure 5: MAE for each considered algorithm assuming the Peak Velocity as seismic parameter.

5 MACHINE LEARNING MODELS COMPARISON

The performance of all the 20 considered ML algorithms has been assessed with respect to the input features through numerical analyses, where a set of seven selected seismic parameters is provided as input data together with the 400 signals and dynamic characteristics of the 1000 elastic perfectly-plastic SDOF systems. For all these models, the effectiveness of the model prediction has been analyzed by using both the RMSE and MAE indices with respect to peak relative displacement output as represented in the Figures 6-8.

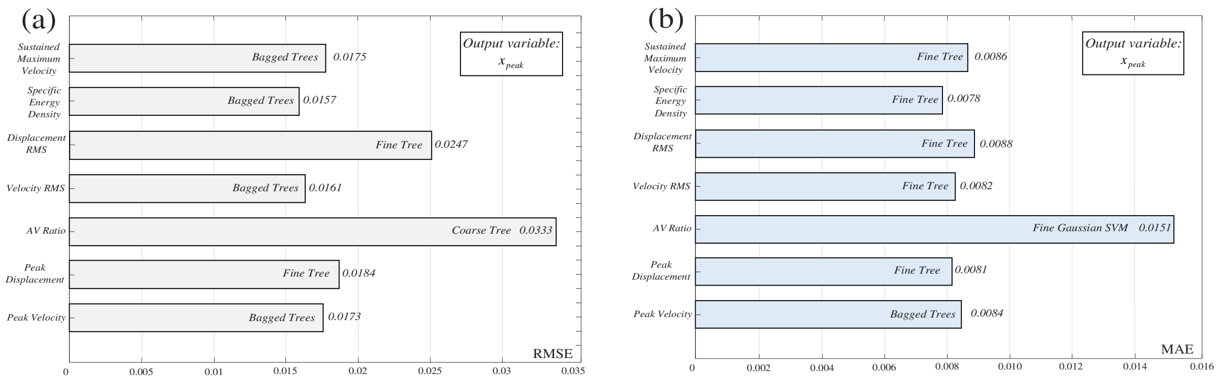

Figure 6: Prediction performance obtained by the most effective ML algorithm.

In Figure 6, for each input feature, the ML algorithm that achieved the best performance is highlighted. Specifically, Figures 6(a) refer to the RMSE index for peak relative displacement, while Figures 6(b) present the results related to the MAE index.

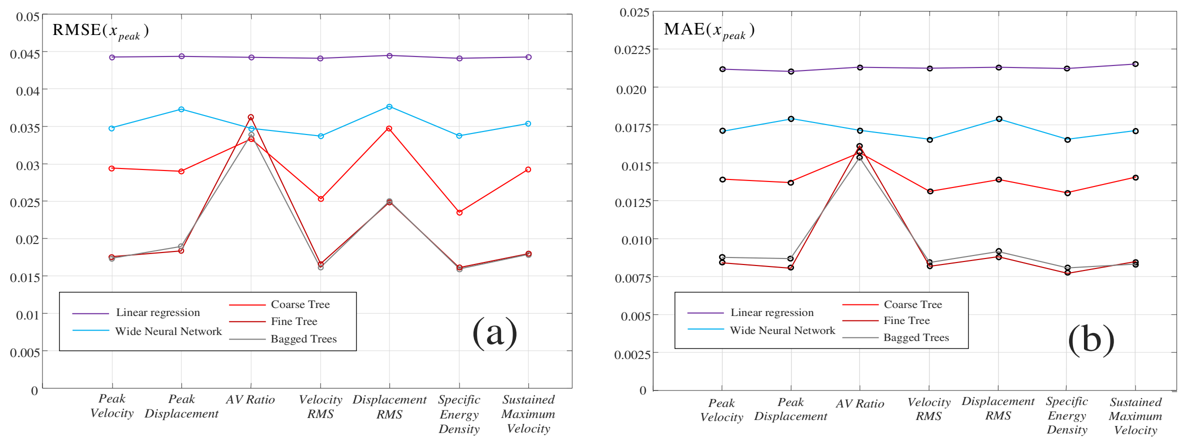

Figure 7: Performance comparison between the different seismic parameters for some ML algorithms.

The results in Figure 6 clearly highlight that the most effective algorithms for achieving the prediction objective are Bagged Trees, Fine Tree, Coarse Tree and Fine Gaussian SVM. Among these, Bagged Trees and Fine Tree stand out as the optimal choices. Generally, algorithms based on decision trees exhibit higher average predictive performance in this case, as shown in Figure 7, for both the metrics considered, with the single exception of the AV ration input feature. This figure shows the performance achievable with some relevant algorithms as the seismic parameters vary, for both the metrics. It highlights how the choice of the seismic parameter plays a significant role. Based on performance predictions in terms of the RMSE index, three input features appear to yield better results, namely Specific Energy Density, Velocity RMS, and Peak Velocity, with their RMSE values being slightly above 1.5%. In terms of MAE, the situation is similar, with the only difference being that Peak Displacement replaces Peak Velocity in the group of three indices achieving the best performance, with values close to 0.75%.

In Figure 8, the actual response in terms of peak relative displacement and the response obtained using the Bagged Trees model (i.e., x_{pred}), for all the signals and non-linear SDOF systems, are represented for Specific Energy Density input feature. This graph highlights the limited error made with the best model in the evaluation of peak displacement.

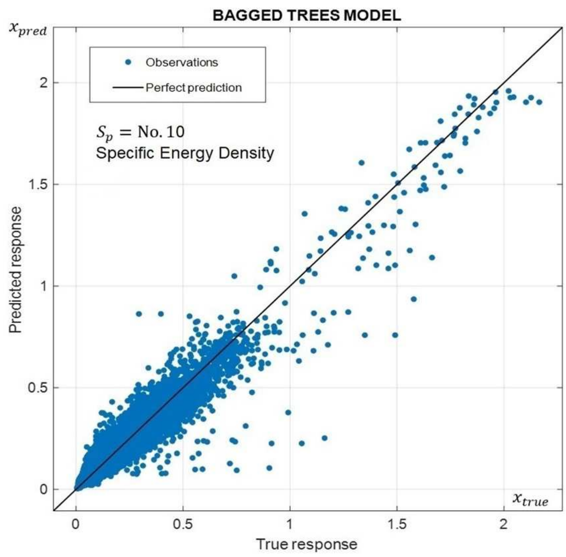

Figure 8: Predicted and true response in Bagged Trees models for Specific Energy density input feature

Figures 9-11 show partial dependence plots to highlight the relationships between the structural properties (i.e., the system elastic period T_0 and the yield strength factor R_y), the response predicted by the ML model and the input feature Specific Energy Density (SED) for which the ML model leads to the best predictions.

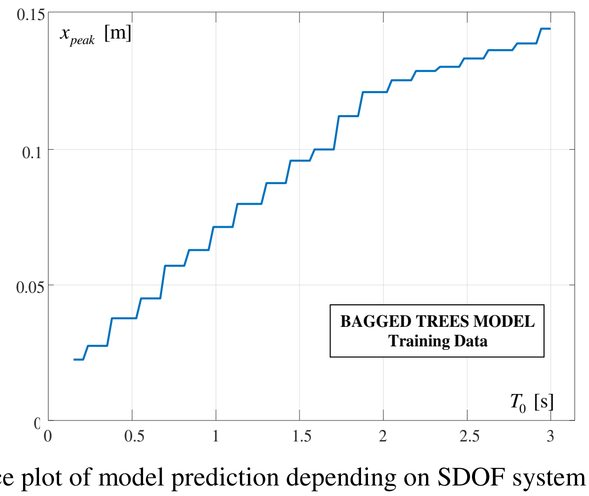

Figure 9: Partial dependence plot of model prediction depending on SDOF system elastic period: peak relative displacement.

Specifically, Figure 9 and Figure 10 respectively show how the elastic period, T_0, of the structural system and the yield strength factor, R_y, influence the peak relative displacement (Figure 9(a) and Figure 10(a)), predicted by the ML model averaging over the 400 signals and other structural characteristics. It is highlighted how the Bagged Trees model, with the knowledge of a single seismic parameter, effectively manages to capture the dependence of the non-linear response on the mechanical characteristics of the SDOF systems. In detail, the relative displacement demand is greater in the case of lower stiffness levels (Figure 9), while the trend of the peak relative displacement as a function of the elastic resistance of the equivalent SDOF system is consistent with the formulations defining yield strength factors within the displacement-based design [30].

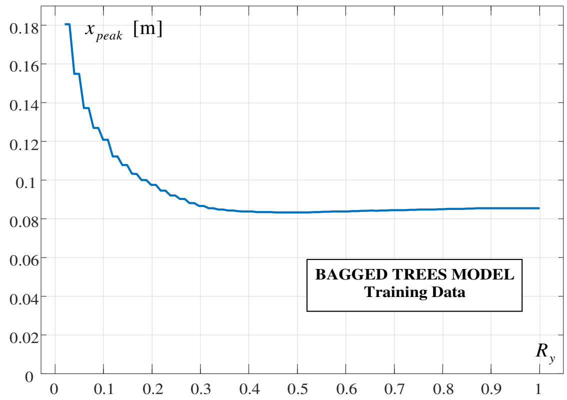

Figure 10: Partial dependence plot of model prediction depending on SDOF system yield strength factor: peak relative displacement.

Figure 11 show how SED input feature is related to the structural response in terms of peak relative displacement predicted by the ML model averaging over both the 400 signals and 1000 SDOF systems. The analysis of this relationship is particularly useful for understanding the physical role that each seismic parameter plays in the non-linear response of the system. In detail, the Bagged Trees model predicts a regular increasing trend, highlighting a significant linear correlation between both the input data and the seismic responses, especially, in the range of feature values where the largest number of examples, used during the model's training phase, is available.

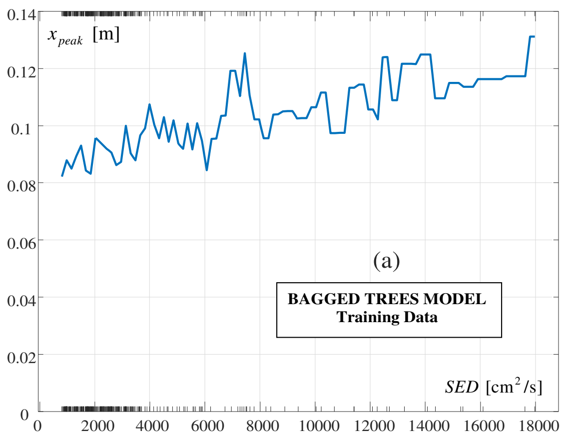

Figure 11: Partial dependence plot of model prediction depending on Specific Energy Density input feature: peak relative displacement.

6 CONCLUSIONS

The use of supervised learning algorithms in the field of structural engineering, and, in general, the potential offered by ML, is a topic that has recently attracted the interest of the scientific community. While these techniques appear to be promising in terms of numerical results, they pose challenges due to being black-box models, compromising the physical understanding of the problem and the control of information necessary for a correct design approach.

This study presents the results of a comprehensive investigation aimed at evaluating machine learning (ML) algorithms that can be effectively applied within the framework of performance-based seismic design procedures. The objective is to identify the ML model with the highest capability to predict the nonlinear responses of structural systems. These seismic parameters are interpreted as the physical quantities providing the most comprehensive information, enabling the model to reliably predict the system's response.

A feature selection analysis based on F-Test demonstrate that seven out of the twenty-three considered seismic parameters, provided as single input data for the ML model, can lead to superior quality of the performance predictions. It is also noteworthy that this input features set is composed of the seismic parameters involving velocity, displacement and parameters with an energetic nature. Instead, the use of seismic parameters directly related to acceleration or time is less effective, highlighting the low effectiveness of the seismic hazard definition if ML models will be considered in the context of performance-based design. Furthermore, the family of algorithms called "Tree", specifically the "Bagged Tree", leads to models capable of making more reliable predictions of the non-linear dynamic response, in terms of peak relative displacement, of a wide class of equivalent SDOF systems.

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