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Machine Learning-Based Prediction of Railway Bridge Vertical Accelerations

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Abstract

This paper presents a comprehensive study on the dynamic response of railway bridges, based on a data collection of over 500 structures and 2000 train passages developed within the InBridge4EU project, funded by Europe's Rail Joint Undertaking under the Horizon Europe programme 2020-2027. Initially, the vertical accelerations due to traffic loads of 509 bridges are computed using numerical models with different levels of complexity. Then, through a statistical procedure the fundamental frequency and structural configuration are identified as the primary parameters responsible for the maximum deck vertical acceleration, highlighting simply-supported bridges as the most susceptible to resonance. While traditional Stepwise Linear Regression (SLR) provides a baseline, it fails to capture the inherent non-linearity of the dynamic problem and its dependence on its governing parameters and on their combinations, achieving coefficient of determination $R\hat{2}$ approximately 0.50. To overcome these limitations, an optimized Random Forest (RF) machine learning model is proposed, enhanced by physical feature engineering through the introduction of design parameters. The RF model significantly outperforms linear methods, reaching an $R\hat{2} = 0.88$ and RMSE of 0.9312 m/s$\hat{2}$ on unseen data. Interpretability analysis through Partial

Dependence Plots reveals that the model successfully reproduces the physical trigger mechanisms of resonance due to railway traffic. The predictive engine is further integrated into a design application that incorporates typology-specific RMSE offsets to provide conservative acceleration estimations to be used in the design stage. These results demonstrate that the proposed framework acts as an accurate surrogate for the preliminary and fast dynamic screening of railway bridges, optimizing resources by limiting complex simulations only to specific cases.

Keywords: railway bridge dynamics, dynamics, modal parameters, resonance, transient analyses, statistical analysis, predictive model, random forest algorithm, machine learning

1 Introduction

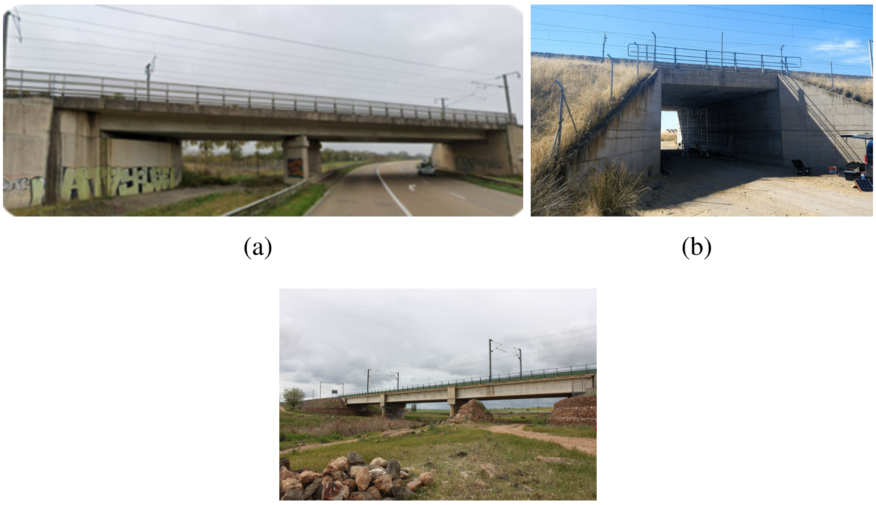
The development of a Single European Railway Area is a key objective of Europe's Rail Joint Undertaking (EU-Rail), aiming to harmonize standards and improve interoperability across Europe. A critical challenge in this initiative is to enhance the structural analysis of railway bridges to optimize capacity, service quality and cost efficiency. Railway bridges play a fundamental role in rail transport networks, yet their dynamic response under operating conditions remains a complex issue requiring advanced methodologies for accurate assessment.

InBridge4EU project `https://inbridge4eu.eu/` started on September 1st 2023. During the first year of the project, with the support of five European Infrastructure Managers, an extensive and representative set of European railway bridges are selected, and including the technical drawings is retrieved and stored in a database: `https://computeruse.us.es/`. Starting from the beginning of the second year, time-step calculation (TSC) transient dynamic analyses are performed over the complete database under the circulation of 26 load trains, selected based on their dynamic signature to be an envelope of more than 300 existing real High-Speed trains across Europe. From the statistical analysis of these results, realistic worst-case combinations of critical parameters leading to the maximum vibrational response of the bridges are identified. Relevant output is also provided in relation to the appropriateness of different model updates and of the use of the classical beam line model for the analysis of certain bridge configurations.

This paper presents a statistical analysis based on the bridge features and on the results of the numerical dynamic analyses conducted on the bridges documented in the database. The objective of this analysis is to identify realistic bridge parameter combinations within the database, determine the most critical parameters and combinations that yield maximum vertical bridge accelerations during train passages, and characterize the statistical distribution of these critical parameters.

2 Data base

A preliminary evaluation of the bridge population reveals that $55\,\%$ of the structures are simply-supported, $15\,\%$ are continuous, and $30\,\%$ are portal frames (Figure 1). Regarding material composition, $28\,\%$ are prestressed concrete bridges, $25\,\%$ are steel-concrete composite structures, and $4\,\%$ are steel bridges, with the remainder consisting of reinforced concrete.The most prevalent deck configuration is the full slab ($40\,\%$), followed by filler beam ($22\,\%$), beam ($9\,\%$), and U-girder decks ($7.5\,\%$). Furthermore, the sample is approximately evenly distributed between single-track and double-track configurations. Finally, $89\,\%$ of the analysed cases feature ballasted tracks.



(a) (b)

(c)

Figure 1: Bridge structural configurations: (a) continuous, (b) closed portal frame and (c) simply-supported.

2.1 Numerical analysis

All bridges within the database are analyzed with either analytical or numerical models. The formers are used in planar analysis, where only longitudinal bending of the bridges is accounted for and the latter for detailed three-dimensional (3D) finite element analysis, which is performed on a subset of the cases. The computational procedure involves determining the structural dynamic response under several train passages in a wide speed interval ranging from 144 to $450\,\text{km/h}$ in $1.8\,\text{km/h}$ intervals, specifically assessing maximum accelerations and displacements at the deck. The selection of the train models for the dynamic analyses is based on the concept of dynamic train signature, introduced by European Rail Research Institute (ERRI) [1].

Given the number of bridges and time-intensive nature of these dynamic simulations, the methodology prioritizes the use for the most computationally efficient models possible. Initially, three fundamental beam configurations are employed across all

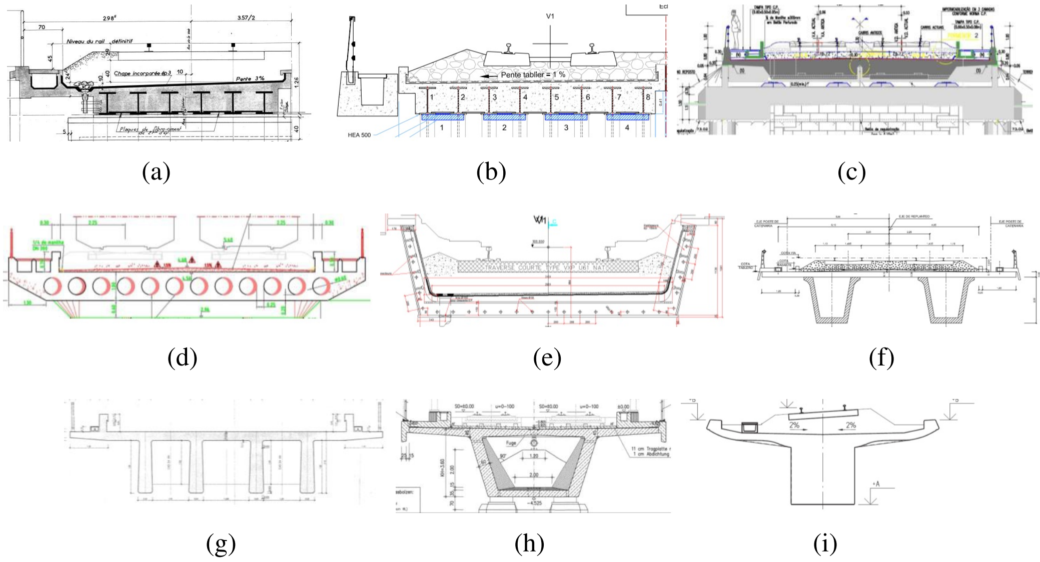


Figure 2: Schematic representation of the most common deck configurations analyzed: (a) filler beam, (b) filler beam reinforced, (c) solid slab, (d) hollow slab, (e) U-type, (f) U-girder, (g) T-beam, (h) box and (i) beam bridges.

typologies of the 509 bridges included in the study: simply supported, continuous, and fixed-end beams. These Euler-Bernoulli analytical models are used to evaluate the serviceability limit state in a first stage in order to roughly differentiate the bridges that exhibit inadequate dynamic behaviour. Accordingly, only the longitudinal bending response of the structures is accounted for. Also, factors such as the deck obliqueness, supports flexibility and interaction with either de soil, the vehicle or the track are disregarded. It should be stressed that despite these simplifications the adopted models and analysis procedure is aligned with the standards recommendations. In instances where the bridge response approaches the established acceleration thresholds, the structures are re-evaluated using more comprehensive models.

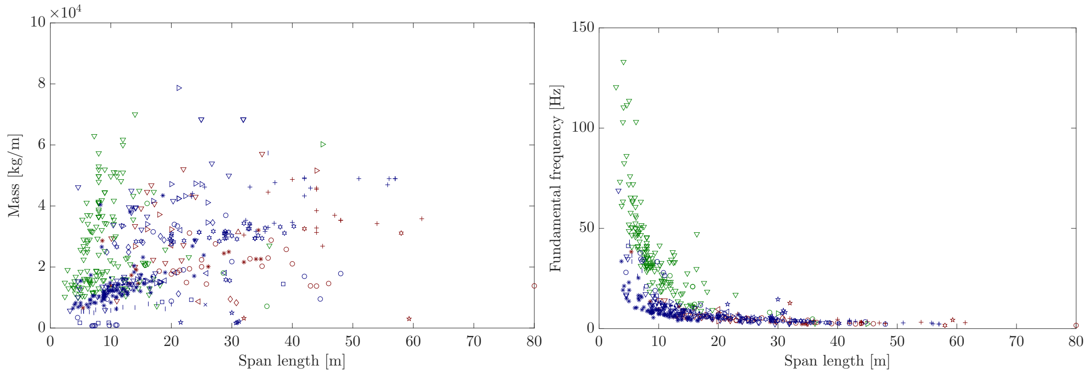
In a second stage, 3D finite element (FE) models are developed for the 94 bridges that failed to meet the acceleration compliance criteria during the initial beam-based analysis. The approach has been to implement detailed models for all non-compliant bridges to perform modal analyses and extract the fundamental natural frequencies and mode shapes along the load paths (rails) and at the response post-processing points. These modal parameters are subsequently utilized in time-step calculation (TSC) dynamic analyses to obtain the bridges dynamic response under train models previously mentioned employing the SINC-Dyn toolbox [2]. In all instances, only the superstructure is modelled; the stiffness and deformation of piers, abutments, and foundations are disregarded.

3 Statistical analysis

This section presents a statistical analysis based on the numerical results. For bridges where vibration levels remained below the established threshold using simplified models, those initial results were retained (415 bridges). Conversely, in cases requiring more complex structural modelling, the computations derived from these advanced models were utilized for the subsequent analysis (94 bridges).

3.1 Data analysis, structural parameters and parameter interdependence

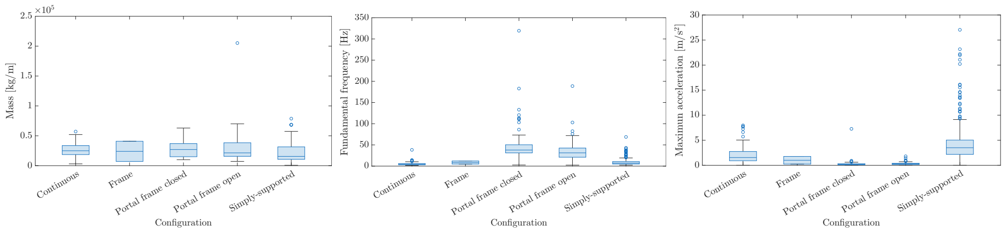
The characterization of the bridge database is summarized in Figure 3. Figure 3a presents the mass per unit length as a function of the maximum span length, showing a general increasing trend where portal frame bridges exhibit higher mass per unit length values. Figure 3b shows the expected inverse relationship between fundamental frequency and span length. Notably, frame structures demonstrate higher fundamental frequencies at shorter spans compared to simply-supported and continuous bridge configurations, reflecting their higher structural stiffness.



(a) (b)

Figure 3: Distribution of (a) mass per unit length and (b) fundamental frequency versus maximum span length: (red) continuous, (green) frame, portal frame open and portal frame closed, and (blue) simply-supported bridge configurations. Markers represent deck configurations: $\circ$: beam, $+$: box, $*$: filler beam, $\cdot$: filler beam reinforced, $\times$: grillage, $\square$: half-through, $\diamond$: multi-girder, $\triangle$: slab beam, $\triangledown$: slab full, $\triangleright$: slab hollow, $\triangleleft$: T beam, $\star$: truss, ✳: U-girder deck, $|$:U-type deck.

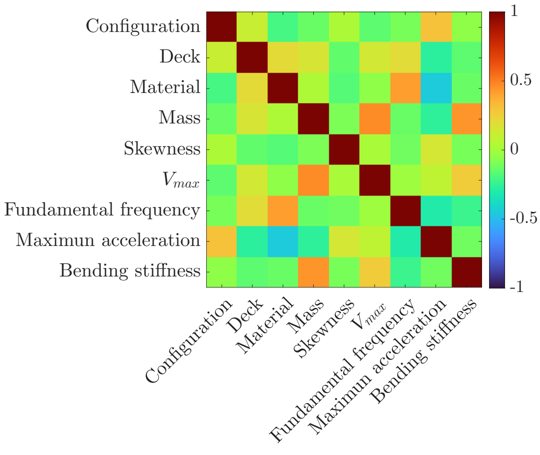
Figure 4 illustrates the variation in the mass per unit length, fundamental frequency, and maximum predicted acceleration across different bridge configurations. In these plots, the horizontal blue line represents the median (50th percentile). The blue box is defined by the 25th and 75th percentiles, while the black whiskers indicate the dispersion outside this central 50% range. Circles denote outliers. While most configurations maintain a similar median mass, a significant outlier is observed in the portal frame open configuration; this specific case corresponds to an exceptional bridge carrying seven tracks. The fundamental frequencies for the frame type configurations are the highest and exhibit the greatest dispersion. Certain atypical values exceeding 100 Hz result from the numerical modelling assumptions, specifically the consideration of fully fixed boundary conditions. Conversely, simply-supported and continuous bridges show lower, more concentrated fundamental frequency ranges. Finally, simply-supported bridges exhibit numerous outliers with accelerations exceeding $10\,\mathrm{m/s^2}$, indicating that this configuration is more susceptible to exhibiting substantial vibration levels associated to resonance phenomena.



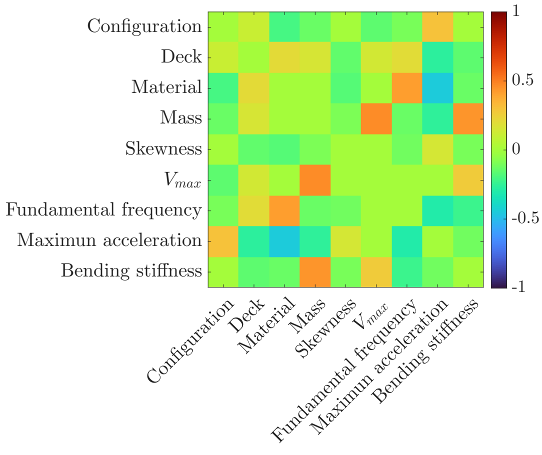
(a) (b) (c)

Figure 4: Statistical distribution of structural and dynamic parameters grouped by bridge longitudinal configuration: (a) linear mass, (b) fundamental frequency, and (c) maximum vertical acceleration. Boxes represent the interquartile range, the horizontal line denotes the median, and circles indicate statistical outliers.

The interdependence between structural parameters and the resulting maximum acceleration is now evaluated through a Pearson correlation analysis. To ensure the reliability of the observed trends, a significance test is performed, masking all correlations with a p-value exceeding 0.05 (Figure 5). The analysis reveals several critical insights. A statistically significant negative correlation is observed between the fundamental frequency and the maximum acceleration. This confirms that higher structural stiffness -and the consequent shift to higher frequency ranges- effectively reduces the susceptibility to resonant vibration under train passages. A strong, significant positive correlation exists between mass and bending stiffness. This dependency is physically consistent with bridge engineering, where larger cross-sections required for higher load-bearing capacity inherently increase both linear mass and the cross-section inertia. The significant positive correlation between the operational maximum velocity V_{max} and mass/bending stiffness suggests that lines designed for higher operational speeds are typically associated with more robust structural typologies. While the full matrix (Figure 5.(a)) suggests minor interactions for all variables, the filtered matrix (Figure 5.(b)) clarifies that configuration and material are the primary categorical drivers of the fundamental frequency, whereas parameters like skewness show a less significant impact on the global peak acceleration. It should be indicated that the skewness is not included in the simplified analyses due to their planar nature but it is included in the ones performed with 3D FE models. Fundamental frequency and longitudinal configuration are the primary drivers of peak acceleration, with the highest values concentrated in simply-supported bridges and those exhibiting natural frequencies below 10 Hz.



(a)



(b)

Figure 5: Correlation analysis of structural and dynamic parameters: (a) Full Pearson correlation matrix (R) illustrating global interaction trends and (b) statistically significant correlation matrix, retaining only coefficients with a p-value < 0.05. Non-significant relationships are masked (set to zero) to highlight robust structural dependencies.

The categorical analysis reveals that while fundamental frequency remains the universal driver for all typologies, the impact of structural mass and stiffness is highly configuration-dependent, with simply-supported spans showing the greatest sensitivity to resonance-induced accelerations. Therefore, a category-specific correlation analysis was performed to isolate the mechanical drivers of peak acceleration for each bridge configuration, revealing that the influence of structural parameters is highly dependent on the longitudinal configuration.

3.2 Stepwise linear regression model

Following the data analysis, a Stepwise Linear Regression (SLR) model is implemented to quantify the influence of the identified structural parameters. The model follows an approach based on the Bayesian Information Criterion (BIC), ensuring that only statistically significant variables are retained to prevent overfitting. The performance of the SLR is initially evaluated using the entire dataset (Figure 6(a, b). This global model yielded an R^2 of 0.3948 and a Root Mean Square Error (RMSE) of $2.8380\,\text{m/s}^2$. To ensure the robustness of the baseline linear model, a diagnostic analysis is conducted using studentized residuals and Cook's distance. Observations with $|r_{stud}| > 3$ are flagged as outliers, while influential points are identified using a Cook's distance threshold of $4/n$, where n is the total number of observations. Figure 6 reveals several bridges exceeding this limit. By removing these anomalous data points (Figure 6(c, d), the performance of the model significantly improved, reaching an R^2 of 0.5017 and the RMSE reducing to $1.7599\,\mathrm{m/s^2}$. To ensure a valid comparison between the different stages of the model, the residual distributions are presented as Probability Density Functions (PDF). In these plots, the area under the histogram is normalized to unity, making the distributions comparable regardless of the number of observations in each subset. This diagnostic phase is useful, as it filters out noisy data -such as bridges with very high mass-to-stiffness ratios or resonant peaks- that could otherwise bias the subsequent machine learning models.

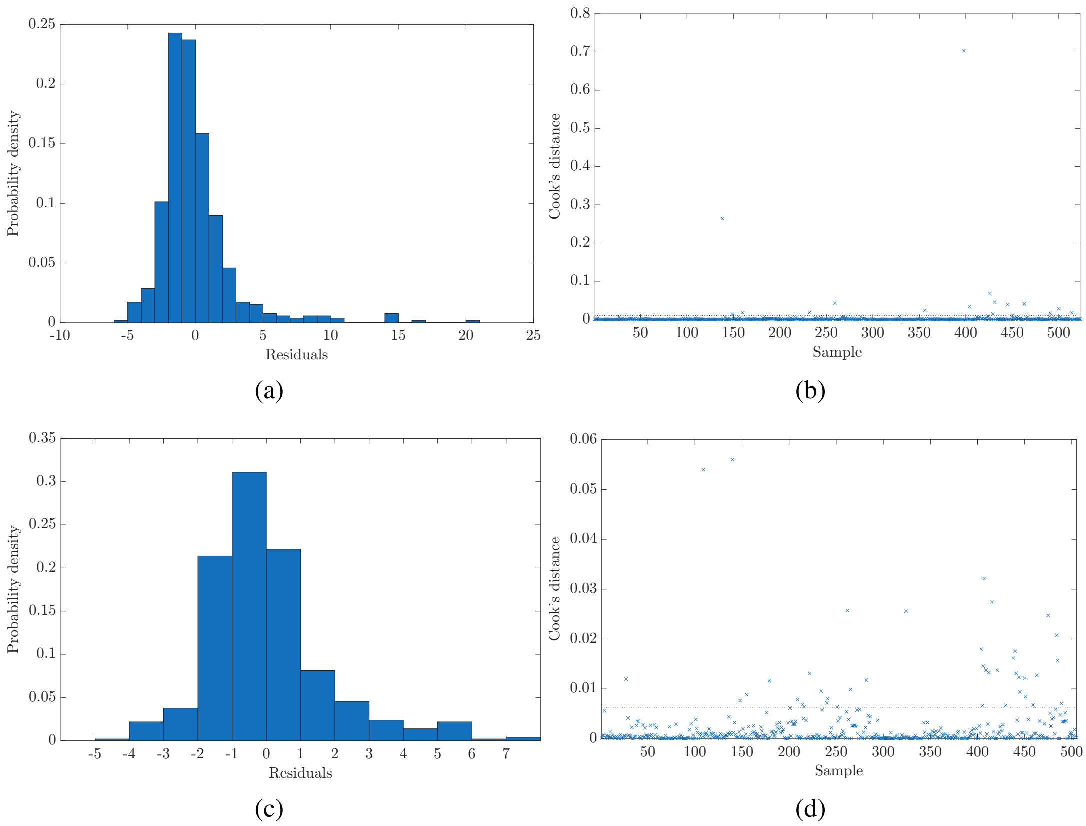


Figure 6: Diagnostic analysis of the global linear model using (a,b) the full dataset ($R^2 = 0.3948$ and $RMSE : 2.8380\,\mathrm{m/s^2}$) and (c,d) after removing identified outliers and influential points ($R^2 = 0.5017$ and $RMSE : 1.7599\,\mathrm{m/s^2}$): (a,c) histogram of raw residuals showing the initial error distribution and (b,d) Cook's distance plot identifying influential observations (The Cook's distance threshold is plotted by dashed lines).

3.3 Random forest regression model and machine learning

To overcome the inherent non-linearity of resonance phenomena that linear models fail to capture, a Random Forest (RF) regression model is developed using a Gradient Boosting approach (LSBoost). Unlike standard black-box models, the RF is enhanced through physical feature engineering, introducing two synthetic parameters to the predictor set: i) Resonance factor = $\frac{V_{max}}{2Lf_{fund}}$ (an non-dimensional parameter relating maximum operational velocity (V_{max}), span length (L), and fundamental frequency (f_{fund}) to quantify the characteristic speed-frequency ratio), and ii) Stiffness Index = $\log(EI)$ (a logarithmic transformation of bending stiffness to linearize its relationship with acceleration and improve convergence).

The model is trained on 80% of the dataset, leaving 20% for independent testing. To ensure robustness and prevent overfitting, Bayesian Optimization is employed to fine-tune the hyperparameters using a 5-fold cross-validation scheme. The search space is constrained to a minimum leaf size of 5 to ensure that the model learned general physical trends rather than memorizing individual bridge samples. The RF model achieved high predictive accuracy, with an R^2 of 0.8832 and a Root Mean Square Error (RMSE) of $0.9312\,\mathrm{m/s^2}$ on the unseen test set (Figure 7). As shown in Figure 7.(a), most observations fall within a $\pm 20\%$ interval, indicating a strong capture of the dynamic response. The Residual Probability Density (Figure Figure 7.(b)) shows a zero-centered distribution with a high concentration of errors near zero. The fat-tailed nature of the distribution (where the theoretical normal curve is wider than the central histogram peak) highlights that while the model is highly accurate for the majority of the population, a few cases, physically complex to predict, account for the largest errors.

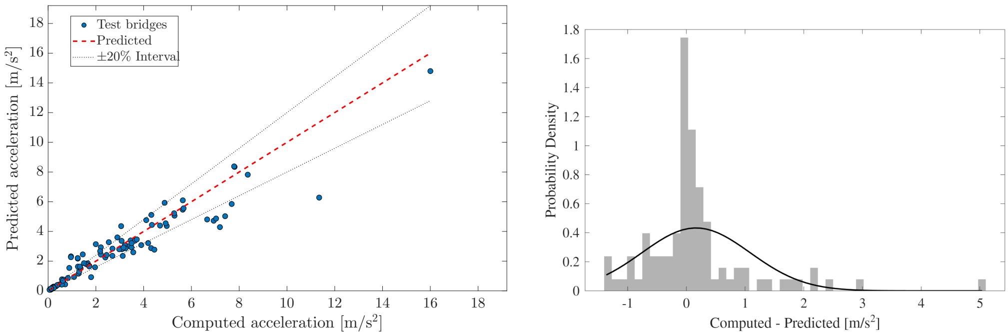


Figure 7: Performance of the optimized Random Forest model on the test set: (a) Predicted vs. computed acceleration with $\pm 20\%$ confidence intervals and (b) probability density of residuals.

To evaluate the contribution of each structural and operational parameter to the dynamic response of the bridge, a predictor importance analysis is performed (Figure 8). Furthermore, the complex non-linear relationships captured by the random forest model are visualized using Partial Dependence Plots (PDP) and Individual Conditional Expectation (ICE) curves (Figure 9). The importance analysis reveals that the configuration of the bridge is the most influential factor, followed closely by the Dimensionless speed ($V_{max}/(2Lf_{fund})$). This hierarchy indicates that the model successfully prioritizes the structural typology and the dimensionless ratio that governs the dynamic interaction regime over individual variables like mass or stiffness. The high ranking of the dimensionless speed summarizes the interaction between geometry, frequency, and speed. Mass and bending stiffness show moderate importance, acting as secondary parameters of the acceleration amplitude. Figure 9 provides a detailed view of the physics learned by the model. Regarding the maximum operational speed, the standard PDP shows a stepped increase in acceleration, while the ICE curves reveal that for certain bridges, there are sharp jumps at specific speeds, indicating that the model has identified individual resonant situations. The Dimensionless speed analysis shows a clear upward trend as the factor approaches values associated with resonance. The Partial Dependence Plots reveal non-linear staircase increments in acceleration as the factor approaches critical thresholds. This behaviour, observed in individual ICE curves, represents the physical transition to resonant amplification, a phenomenon that the random forest model captures without an explicit closed-form dynamic equation. The stabilization of the median (blue line) below the mean (black line) suggests that while most bridges follow a steady trend, a subset of high-acceleration cases (outliers) increases the average. The model correctly identifies that increasing the mass or bending stiffness of the bridge reduces the expected vertical acceleration, following an inverse non-linear relationship. Finally, for the fundamental frequency, the sensitivity is higher in the low-frequency range, where the highest accelerations are obtained, becoming almost neutral for very stiff structures.

An observation in the interpretability analysis is the presence of non-linear jumps or steps in acceleration at specific dimensionless speed values. While the dimensionless speed is calculated using the maximum operational velocity (V_{max}), the structural resonance does not necessarily occur exactly at that peak speed. High accelerations are triggered when any of the excitation frequencies, produced by the periodic passage of axles or bogies, coincide with the bridge's natural frequencies. Since the dataset records the maximum acceleration reached across the entire speed range $[0, V_{max}]$, a bridge will exhibit a high response if a critical resonant speed with relevant amplitude is less than or equal to V_{max}. In this context, V_{max} acts as a scanning envelope; if the resonant threshold is within the operational range, the peak acceleration is captured. The specific steps observed at sub-multiples of the main resonance peak suggest that the random forest model is identifying multiple resonance orders (harmonics). The model's ability to identify these jumps at specific factor values demonstrates that it has not only learned a statistical correlation but has effectively mapped the spectral limit states and the underlying dynamic behaviour of the structures.

The limitations of traditional statistical methods for predicting complex dynamic responses are evident when comparing the linear regression results with the random forest model. As shown in Figure 6, the global linear model achieved a modest $R^2 = 0.3948$ with a significant error (RMSE = $2.8380\,\mathrm{m/s^2}$). Even after removing outliers, the linear model only reached $R^2 = 0.5017$. In contrast, the optimized RF model (Figure 7) achieved an $R^2 = 0.8832$ and an RMSE of $0.9312\,\mathrm{m/s^2}$ on unseen data. The SLR residuals (Figure 6(a)) show a wide, asymmetrical distribution, indicating that the model systematically fails to capture high-acceleration events. However, the RF residuals are centred around zero, demonstrating that the ensemble approach significantly reduces both bias and variance compared to the linear approach. The performance of the Random Forest model was further scrutinized by segmenting the dataset into structural configurations (Table 1).

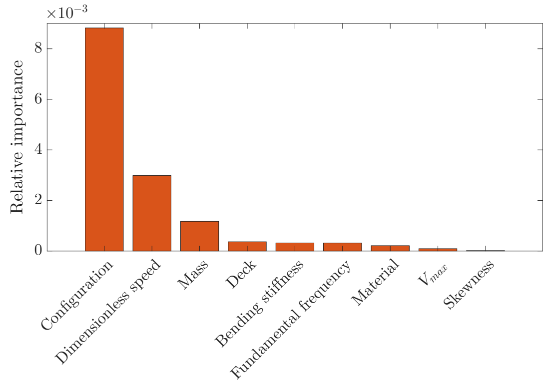


Figure 8: Relative importance of predictors.

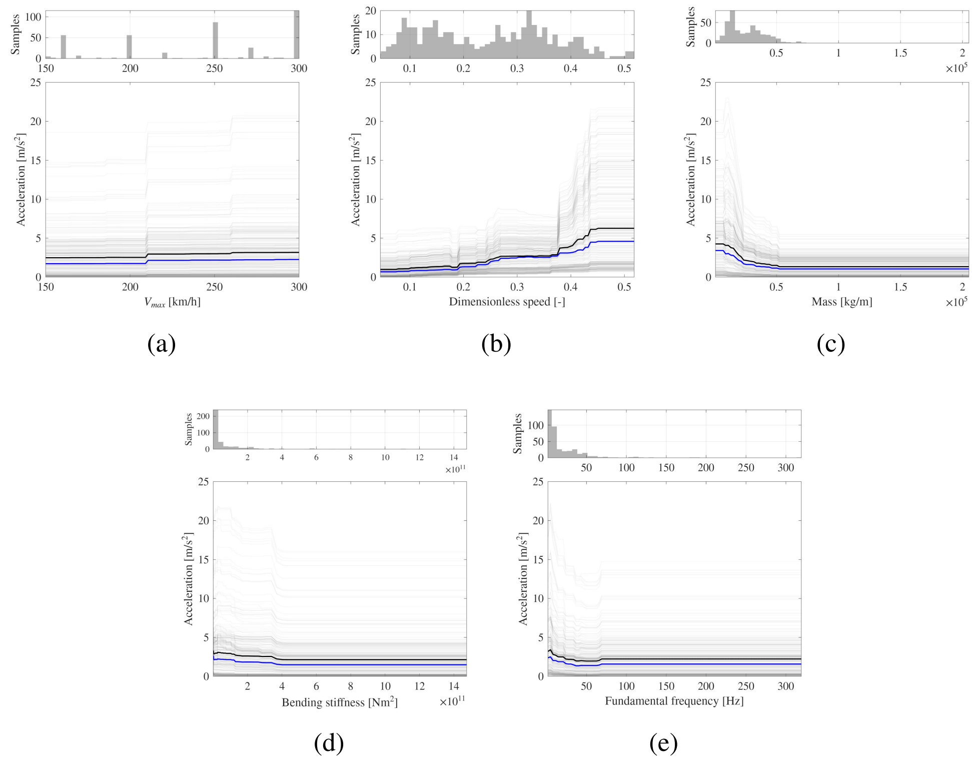


Figure 9: Interpretability analysis of the random forest model. (a-e) Partial Dependence Plots (PDP) and Individual Conditional Expectation (ICE) curves for key predictors. The thick black line represents the average global trend (mean PDP), the blue line indicates the median response (robust trend), and the grey lines show individual bridge sensitivities (ICE). Top histograms illustrate the sample density across the training range.

Based on the developed RF LSBoost regression model, a design application has been implemented to translate predictive results into structural engineering practice. It is important to emphasize that the predictive engine uses a single global model

Table 1: Performance metrics of the Random Forest model disaggregated by structural configuration.

Configuration	**RMSE** (m/s^2)	R^2
Simply-supported	2.8855	0.6052
Continuous	0.7903	0.8090
Frame	0.1375	0.3075
Global Model	0.9312	0.8832

trained on the entire dataset, encompassing all structural configurations. This approach ensures that the algorithm captures the shared underlying physical behaviour across different bridge typologies while maintaining high generalization capabilities. To transform the raw predictions into a reliable engineering value, a conservative margin is incorporated by adding the RMSE specific to each structural configuration. This allows the tool to provide a design acceleration (a_{design}) that accounts for the historical uncertainty of the model for each specific category: $a_{design} = a_{pred} + RMSE_{config}$ (Table 1).

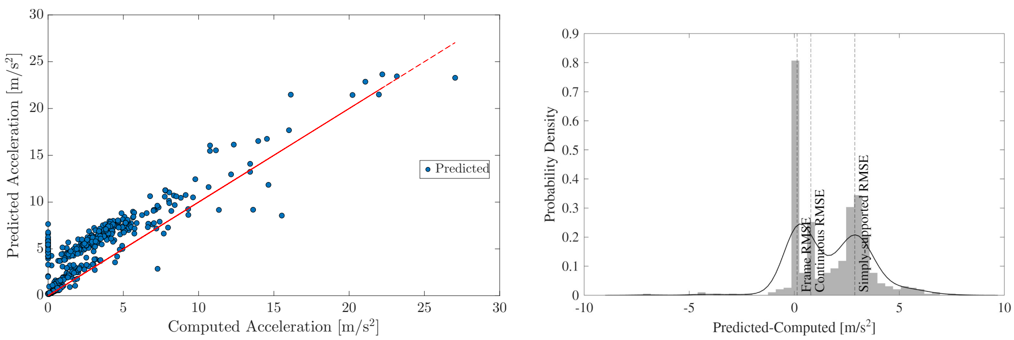


Figure 10: Performance evaluation of the proposed structural design tool: (a) scatter plot comparing the calculated design acceleration against the real computed acceleration. The red line represents the 1:1 identity line, and (b) the probability density function of the design errors. The RMSE offsets for different bridge configurations are indicated by the vertical dashed lines.

Figure 10(a) shows the relation between the computed accelerations and the design accelerations calculated by the tool. By integrating the configuration-specific RMSE, the data points exhibit a deliberate positive shift. This shift effectively establishes a conservative envelope, ensuring that for more than 95% of the considered bridges the predicted design value equals or exceeds the computed acceleration, thereby minimizing the risk of underestimation in structural assessments. Figure 10(b) shows the probability density function of the design errors (defined as $a_{design} - a_{pred}$). The distribution shows a multimodal profile, a direct result of applying discrete RMSE offsets across different structural typologies. The concentration of the probability in the positive region provides empirical evidence of the tool robustness. This statistical distribution indicates that the proposed methodology effectively provides a quantifiable safety buffer, shifting the model uncertainty towards a conservative, safe design range.

4 Conclusions

The integration of statistical analysis and machine learning applied to the prediction of the dynamic response of a vast railway bridge population has led to the following conclusions:

- The preliminary statistical assessment confirms that peak vertical accelerations are highly dependent on structural typology and fundamental frequency. Simply-supported bridges exhibit the highest susceptibility to resonance whereas continuous and frame structures show more controlled responses due to structural redundancy and high stiffness, respectively.
- Linear regression models are insufficient for precise acceleration prediction ($R^2 \approx 0.50$). Their failure to account for non-linear jumps in acceleration near resonant speeds makes them unreliable for railway bridge engineering applications.
- The optimized RF model achieved a high predictive accuracy ($R^2 = 0.88$). The inclusion of the dimensionless speed as a top-ranked predictor proves that physical feature engineering is essential for allowing black-box models to capture the underlying spectral limit states of the structures.
- Categorical analysis reveals that while the RF model is extremely precise for frame structures ($RMSE = 0.1375\,\text{m/s}^2$), simply-supported spans remain the most challenging to predict due to their higher probability of experiencing significant response amplification.
- The proposed model may serve as an efficient screening tool for infrastructure managers. It allows for the rapid identification of at-risk bridges within large networks, enabling a predictive maintenance strategy.
- The design application transfers the RF model by incorporating typology-specific RMSE offsets to derive conservative design accelerations (a_{design}). This implementation transforms the predictive output into a safety-oriented envelope, providing a quantifiable margin that minimizes the risk of underestimation in real infrastructure assessments.

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