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Prediction of Dynamic Load Factor in Curved Box-Girder Bridges under High-Speed Trains using ANN

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Forecasting the dynamic behavior of curved thin-walled box-girder bridges subjected to high-speed train loads is computationally demanding yet crucial for evaluating structural integrity. This study seeks to assess the Dynamic Load Factor (DLF) through a comprehensive framework that ensures high precision while markedly decreasing computing demands. A detailed coupled dynamic model was created, including a 38-degree-of-freedom train system, a three-layer slab track, and a thin-walled box-girder bridge. The system addressed rail irregularities through power spectral density (PSD) and wheel-rail interactions based on Hertzian contact theory. The resultant data trained a feedforward artificial neural network (ANN) employing the Levenberg-Marquardt algorithm. The model utilized span length and bridge damping as input variables to forecast essential structural responses, such as shear force, bending, torsion, and distortion. The ANN model attained exceptional prediction accuracy, with regression coefficients (R) above 0.99 and negligible mean squared error (MSE) across all datasets. The results illustrate the model's capacity to precisely identify intricate nonlinear correlations between structural factors and dynamic outputs. This research presents a unique method for the rapid evaluation of bridge behavior by combining a robust finite element framework with a data-driven surrogate model and particularly suitable for real-time structural optimization in high-speed rail engineering.

Keywords: Artificial Neural Network**,** Box-girder Bridge, Dynamic load factor, Finite Element Method, High Speed train.

1. Introduction

Curved alignment bridges were uncommon in the past. Yet new bridges and traffic separation systems are commonly built on a horizontal curve due to developments in technology. This has been influenced by the geometric limitations of the urban landscape, higher traffic volumes and speeds, and better structural forms that accommodate curved buildings. One type of long-distance structural component is the box girder. Among the advantages of curved box-girder bridges are their cost-effective and aesthetically pleasing structural designs, higher stiffness-to-mass ratios, enhanced stability and serviceability, better flexural and torsional rigidity, and decreased dead load due to thinner sections. The dynamic relationship between automobiles and bridges has long piqued the interest of structural engineers. Vibrations that could reduce the bridge's lifespan and jeopardize the occupants' safety and comfort are given special consideration. One crucial issue is figuring out how a bridge would respond dynamically when fast-moving vehicles are crossing it. It is particularly challenging to assess dynamic response when there are problems with the interaction between cars and bridges, and precise dynamic loading estimates over a structure are crucial to its structural design. Due to the development of stronger, lighter, and more resilient building materials as well as recent improvements in analytical and design methodologies, lighter railway bridge construction has grown in popularity. The merging tendencies of lightweight bridges supporting heavy and fast-moving trains necessitate a deeper knowledge of the coupled dynamic interaction of fast-moving trains and rail bridges. Every time a train crosses a bridge, it splits in half. The third section is the vehicle bridge interaction or coupling component, which controls the dynamic forces applied to the entire system. The train and the bridge are the first two sections. The dynamic interaction between a vehicle and a bridge is a complex phenomenon that involves a number of vehicle and bridge characteristics, including axle count, spacing, and loads, spring damping and friction, bridge shape, support conditions, vehicle speed, and so forth, as well as their reciprocal effects on one another. The strains and deformation caused by a moving vehicle crossing a bridge are often greater than those caused by the same vehicle loads applied statically. For design purposes, the static loads are usually increased to an impact factor or dynamic load factor (DLF) to account for the dynamic impact of loads. In most bridge-related codal requirements, the dynamic load factor is calculated using a formula that depends on the bridge's length. This design method virtually ignores the effects of several variables, such as the type of bridge, the vehicle's velocity, bounce, pitch, roll, sway, surge, and yaw motions, mass distribution, suspension characteristics, and rail surface unevenness profile. Therefore, to determine the design coefficients of different stress resultants for a curved box-girder bridge, the coupled vehicle-bridge dynamics must be investigated. The dynamic interaction between vehicles and bridge structures has been extensively investigated using various analytical and numerical approaches. Existing studies can broadly be categorized based on the level of modeling complexity and the representation of vehicle–bridge interaction. To track the non-linear dynamic behavior of the vehicles and supporting structure, a mathematical model should be created for interaction systems.

Early studies primarily employed simplified low-degree-of-freedom (DOF) models to represent vehicle dynamics and bridge interaction. Javed et al. (2011) used the finite element approach to study the dynamic interaction between a moving vehicle and a curving bridge. The vehicle was represented as a six-degree-of-freedom half-car planner system that travels across the bridge steadily. In contrast, the bridge was represented by a curved beam that adhered to Timoshenko beam theory. Vincenzi et al. (2012) conducted a case study to demonstrate the outcomes of the dynamic interaction between trains and bridges. The authors utilized a vehicle model with three degrees of freedom and one with fifteen degrees of freedom to determine the impact of a train crossing a bridge. Zakeri et al. (2014) carried out a sensitivity analysis of a train-bridge-track structure for a number of dynamic railway parameters. The railway car was mathematically represented using an 11-degree-of-freedom system with independent equations of motion for the wheel sets, bogie, and car body. To assess the track's behavior during the deterioration phenomenon, Vale and Calçada (2014) offered a dynamic vehicle-track interaction prototype. Because the vertical component predominates, a one-dimensional model was employed even though track settlement is a three-dimensional phenomenon. The vehicle and quarter bogie prototype was shown in a two-dimensional form. Zeng et al. (2016) determined the dynamic behavior of curved bridges exposed to fast trains under resonance conditions. The train model consisted of a car body, bogies, and wheel sets coupled by suspension systems. The bridge was simulated using Euler Bernoulli beam elements, which have six degrees of freedom at each node. It was discovered that the train's acceleration increased when the bridge was put into resonance. Although these studies improve the representation of bridge behavior, they are generally limited to planar responses and may not fully capture the coupled bending–torsion–distortion interaction inherent in curved box-girder bridges.

More advanced studies have attempted to incorporate three-dimensional modeling and coupled interaction effects using detailed finite element frameworks and commercial software tools. Amara and Mazzilli (2017) developed a dynamic analytical approach for the vibrations caused by a moving passenger train in railroad bridges. A 15 degree of freedom approach was to be used to model the car's heave, pitch, roll, sway, and yaw motions. A finite element-based program called ADINA was used to simulate the vehicle, bridge, and the dynamic interaction between the rail and train. Time domain analysis was utilized by Ling et al. (2017) to investigate the dynamic response characteristics of an implanted railway track while a tram carriage was operating. The authors used the finite element methodology to develop a dynamic three-dimensional prototype of an integrated tram vehicle and railway track system. The dynamic characteristics of box-girders under high vehicle forces were documented by Abbas et al. (2018). The finite element program ABAQUS was used to create a three-dimensional model of the bridge. The objective of the dynamic study was to ascertain the effects of truck velocity on the stress, displacement, and maximum acceleration of the bridge's bottom flange. Using a macro modeling technique, Kumar and Pallav (2021) carried out a dynamic examination over a masonry tower. The authors used a number of techniques, including the commercial software ANSYS, to create a model based on the finite element methodology. The acceleration and displacement responses of the tower were recorded. Using empirical regional and worldwide correlations among various magnitudes, Das and Meneses (2021) created a time-varying dynamic earthquake database for an area. The authors developed a technique for converting various magnitudes to moment magnitudes. In order to conduct the dynamic response study in a coupled bridge-train-track system subjected to earthquake and wind loads, Gong et al. (2021) created a real-time solution based on finite element software MATLAB and ANSYS. Nguyen et al. (2022) created a quarter-car prototype to investigate tire-road separation from a wider perspective. A two-degree-of-freedom model was used to predict the vehicle's vertical vibration. The Dynamic Load Factor (DLF) is a crucial parameter for evaluating the structural performance of railroad bridges, particularly thin-walled box-girder bridges, under high-speed train loads. The additional dynamic effects caused by the interaction between moving trains and bridge structures cannot be measured by static analysis alone. Numerous studies have focused on accurately calculating DLF using analytical models, field data, and numerical simulations. Moghaddam et al. (2024) presented an improved structural health evaluation method for cable-stayed bridges utilizing phase space dynamics. The framework assessed structural performance amid varying load patterns, effectively detecting deterioration patterns to enhance the accuracy of ongoing infrastructure surveillance. However, such approaches rely on simplifying assumptions and empirical relationships, which may not accurately represent the complex vehicle–track–bridge interaction under varying operational conditions. Verma et al. (2026) developed a regression-based model that predicted dynamic response parameters including shear force and distortional moments with a good accuracy rate ($R^2 = 1$).

In recent years, data-driven approaches, particularly artificial neural networks (ANN), have gained significant attention for predicting structural responses of bridge systems. Artificial neural network has become an important tool in analysing the behaviour of box-girder bridges. Li and Zhang (2022) integrated a genetic algorithm to optimize a BP neural network (GA-BP), enhancing prediction of deflection risk in steel box-girder bridges. Wang et al. (2022) applied a whale-optimization algorithm to initialize a BP neural network (WOA-BPNN) to predict temperature induced stress in three-curved steel box girders and achieved high R^2 (~0.99) and faster convergence compared to conventional BPNN. Bhattacharya et al. (2024) observed ANN maps bridge deck thermal response to bearing support stiffness. Trained on FE simulations and validated in the field, they identified bearing conditions—e.g. frozen, corroded—to aid maintenance decisions. Luo et al. (2022) employed Gated Recurrent Unit (GRU) neural networks to detect and quantify cracks in steel box girders using acceleration-response signals. The GRU outperformed wavelet-MLP models, demonstrating robustness to noise. Neves et al. (2021) investigated how signal frequency content affects ANN outcomes in bridge damage detection. Simulating different train speeds and damage cases on box-girder bridges, it revealed the optimal frequency bands and sampling rates to maximize detection accuracy. Zhao et al. (2023) utilized feed-forward artificial neural networks to forecast solitary wave forces on box-girder bridge decks. The network correlated wave parameters with structural reactions, providing nearly instantaneous force estimates that matched the precision of comprehensive fluid dynamics models. Zhu et al. (2024) employed sophisticated deep learning architectures to analyze the transient dynamic behavior of high-speed railway bridges. The model effectively monitored intricate vehicle-bridge interactions and accurately forecasted structural responses at different train velocities. Li et al. (2022) employed a trained neural network methodology to evaluate the dynamic load factors of urban rail transit bridges. This methodology efficiently circumvented redundant numerical procedures, expediting the assessment of safety margins for intensively trafficked transit routes. Kim et al. (2021) utilized machine learning frameworks to forecast the coupled dynamic responses of curved box-girder bridges subjected to moving vehicles. The model created precise correlations between strain measurements and continuous displacement fields, facilitating non-invasive structural health monitoring. Wang et al. (2025) introduced a machine learning-based methodology to assess dynamic impact factors for multi-span curved box-girder bridges. The improved network swiftly assessed intricate geometry and track layout variables, minimizing overall processing durations throughout the preliminary structural design stages.

From the above review, it is evident that although significant progress has been made in modeling vehicle–bridge interaction, most existing studies either rely on simplified low-DOF models or adopt two-dimensional representations that fail to capture the full three-dimensional behavior of curved thin-walled box-girder bridges. Moreover, the combined influence of key structural and vehicle parameters on dynamic load factor (DLF) has not been comprehensively investigated within a unified framework. In addition, although artificial neural networks have shown strong potential in structural response prediction, their application in modeling complex, coupled vehicle–track–bridge interaction systems, particularly for predicting torsional and distortional responses, remains limited. Therefore, the present study aims to bridge these gaps by developing a detailed three-dimensional finite element model integrated with an ANN-based predictive framework. Therefore, there exists a clear need for a comprehensive, ANN-based predictive model that incorporates a 3D, high-DOF train system and simulates the complete coupled interaction with a thin-walled curved box-girder bridge. Such a model would bridge the gap between numerical simulation and real-world design conditions by accurately predicting dynamic response behaviors that conventional approaches cannot effectively capture.

The objectives of the study are as follows:

1. To develop a comprehensive coupled dynamic simulation model that accurately represents the interaction between a high-speed train modelled with 38 degrees of freedom, slab track sub-system, and a curved thin-walled box-girder bridge.
2. To analyse and quantify the influence of key structural and vehicle parameters such as bridge span length, damping ratio, secondary suspension system stiffness, and bogie mass on the dynamic load factor.
3. To implement and validate an Artificial Neural Network model capable of predicting dynamic load factor using span length and bridge damping as inputs, with the aim of reducing computational time compared to conventional finite element simulations while maintaining high prediction accuracy.

2. Theoretical Framework of the Coupled Vehicle-Bridge Interaction System

To obtain precise estimations of the dynamic response of horizontally curved bridges under high-speed rail traffic, a sophisticated modeling technique is required that considers the interactions among the bridge, track, and train system. In contrast to linear bridge designs, curved box-girders exhibit intricate interaction forces, wherein vertical, lateral, and torsional vibrations are inherently interconnected. This paper presents a computational model of a high-speed train that simulates the essential primary and secondary suspension characteristics required to achieve a realistic stress history, incorporating 38 degrees of freedom resolved at high velocity. The bridge was modeled with thin-walled box beam finite elements, incorporating 9 degrees of freedom at each node to account for torsional and distortional warping, which are essential for the behavior of curved structures and are not considered in Euler-Bernoulli or Timoshenko beam finite elements. The interaction was presumed to adhere to Hertz contact theory, with surface imperfections of the rail represented by a power spectral density (PSD) function, identified as the primary source of dynamic stress amplification. The comprehensive mathematical modeling, equations of motion, and iterative solution methodology for this interacting system are meticulously formulated and validated based on prior research conducted by Verma and Nallasivam (2023).

3. Numerical Validation

The finite element model used in this study has been previously validated by the Authors through experimental and analytical investigations (Verma and Nallasivam, 2021). In that work, a scaled thin-walled curved box-girder bridge model made of Perspex was tested under impact excitation to determine its modal characteristics. The experimentally obtained natural frequencies were compared with the numerical predictions from the developed model.

Table 1 Validation of natural frequencies of curved box-girder bridge

Mode	Description	FEM (Hz)	Experimental (Hz)	Difference (%)
1	Vertical bending mode	59.17	61.50	3.93
2	Lateral bending mode	116.20	121.00	3.96

As summarized in Table 1, the comparison shows very good agreement, with deviations less than 4% for the first two modes, confirming the accuracy of the model in capturing the fundamental dynamic behavior of the bridge. Additionally, the model was benchmarked against established analytical studies, further verifying its capability to predict bending, torsional, and distortional responses. This validated framework forms the basis for the present vehicle–track–bridge interaction analysis. The finite element model developed in this study is implemented within the MATLAB computational environment using a custom-coded formulation. The bridge structure is discretized using appropriate beam elements capable of capturing bending, torsional, and distortional responses, while the train is modeled as a multi-degree-of-freedom system. The track subsystem is represented through spring-damper elements to simulate rail-vehicle interaction. The coupled equations of motion for the vehicle-track-bridge system are assembled in matrix form and solved in the time domain using the Newmark-β integration method. This framework enables efficient simulation of the dynamic response under moving train loads, while accurately capturing the interaction effects among the system components.

4.Parametric study of dynamic load factor

To quantitatively evaluate the amplification of structural response due to dynamic effects, the Dynamic Load Factor (DLF) is defined in this study as the ratio of the maximum dynamic response to the corresponding maximum static response, expressed as:

$$DLF = \frac{R_{dyn}^{max}}{R_{stat}^{max}} \qquad \text{Eq. (1)}$$

where R_{dyn}^{max} represents the peak dynamic response obtained from the coupled vehicle–track–bridge interaction analysis, and R_{stat}^{max} denotes the maximum static response under equivalent loading conditions. The dynamic response is computed using the fully coupled finite element model incorporating train–track–bridge interaction, including inertia effects, damping, and rail surface irregularities, solved using the Newmark-β time integration scheme.

The static response is determined by applying the same train axle loads as equivalent static loads on the bridge model, while neglecting all dynamic contributions such as inertia forces, damping effects, and track irregularities. This approach ensures a consistent baseline for assessing the dynamic amplification of various structural response parameters, including shear force, bending moment, torsional moment, and distortional effects. Indeed, a variety of bridge and vehicle factors influence the dynamic interaction between a vehicle and a bridge, making it a complex phenomenon. As a result, a parametric study is conducted to identify the different factors affecting the dynamic load factor of the box-girder bridge. Some of the important factors are as follows:

4.1 Effect of span length (L)

Table 2 illustrates how the dynamic load factor changes with span length. As the span expands, it is seen that the dynamic load factor associated with all stress resultants decreases. The observed reduction in DLF with increasing span length can be attributed to the change in dynamic characteristics of the bridge system. As the span length increases, the overall stiffness of the structure decreases, resulting in lower natural frequencies. Consequently, the likelihood of resonance between the moving train excitation frequency and the bridge natural frequency is reduced. Additionally, longer spans lead to an increase in the load traversal time, allowing the induced vibrations to dissipate more effectively before reaching peak amplitudes. This increased interaction duration promotes energy redistribution and reduces peak dynamic amplification. Therefore, the combined effect of reduced stiffness, lower excitation compatibility, and enhanced energy dissipation results in a decrease in DLF with increasing span length.

Table 2 Dynamic load factor (DLF) change with span length

Length (m)				
Response Parameter	**15**	**20**	**25**	**30**
Q_y(N)	1.70	1.61	1.54	1.45
M_z(N-m)	1.85	1.70	1.61	1.52
M_x(N-m)	1.91	1.84	1.70	1.62
B_1(N-m^2)	2.11	2.02	1.91	1.82
M_d(N-m)	1.71	1.64	1.52	1.40
B_{11}(N-m^2)	1.82	1.78	1.63	1.51

4.2 Effect of bridge damping (ξ)

Table 3 displays the variation of the dynamic load factor with radius for each stress resultant. It is clear that all of the dynamic load factors (DLF) decrease as the radius increases. The reduction in DLF with increasing damping is primarily due to the enhanced energy dissipation capacity of the system. Damping mechanisms act to absorb and dissipate vibrational energy generated by the moving train, thereby reducing the amplitude of dynamic oscillations. It is also observed that damping has a more pronounced effect on certain response parameters, particularly torsional and bending moments, compared to distortional components. This behavior can be explained by the fact that global vibration modes (such as bending and torsion) are more sensitive to damping, as they involve larger structural participation and energy exchange. In contrast, distortional responses are governed by localized cross-sectional deformations, which are less influenced by global energy dissipation mechanisms. As a result, damping is more effective in reducing global dynamic responses than localized distortional effects.

Table 3 Dynamic load factor (DLF) variations with damping

Bridge Damping (%)						
Response Parameter	**0**	**1**	**2**	**3**	**4**	**5**
Q_y(N)	1.80	1.72	1.65	1.57	1.51	1.45
M_z(N-m)	1.90	1.84	1.72	1.63	1.57	1.52
M_x(N-m)	1.85	1.82	1.75	1.70	1.66	1.62
B_1(N-m^2)	1.88	1.86	1.85	1.83	1.83	1.82
M_d(N-m)	1.46	1.45	1.43	1.43	1.41	1.40
B_{11}(N-m^2)	1.57	1.56	1.56	1.54	1.52	1.51

4.3 Effect of secondary suspension system

The dynamic load factor variation with secondary suspension system for all stress resultants is shown in Table 4. As primary suspension values increase, it is found that the dynamic load factors (DLF) associated with shear force, bending moment, and torsion moment decrease while the others stay constant.

Table 4 Dynamic load factor (DLF) variations in relation to the secondary suspension system

Secondary suspension system			
Response Parameter	**0.5**	**1**	**1.5**
Q_y(N)	1.49	1.45	1.41
M_z(N-m)	1.58	1.52	1.46
M_x(N-m)	1.64	1.62	1.61
B_1(N-m^2)	1.82	1.82	1.82
M_d(N-m)	1.40	1.40	1.40
B_{11}(N-m^2)	1.51	1.51	1.51

4.4 Effect of mass of bogie (M_b)

Table 5 also displays the dynamic load factor fluctuation with Bogie mass for all stress resultants. It's noteworthy to see that when mass grows, the dynamic load factors (DLF) associated with shear force, bending moment, and torsion moment drop while the others stay unchanged.

Table 5 Dynamic load factor (DLF) variations in relation to bogie mass

Mass of bogie			
Response Parameter	**0.5**	**1**	**1.5**
Q_y(N)	1.51	1.45	1.41
M_z(N-m)	1.59	1.52	1.45
M_x(N-m)	1.64	1.62	1.60
B_1(N-m^2)	1.82	1.82	1.82
M_d(N-m)	1.40	1.40	1.40
B_{11}(N-m^2)	1.51	1.51	1.51

5. Training and Architecture of Artificial Neural Networks

A multilayer feedforward neural network was constructed in this paper to forecast the dynamic behaviour of the curved thin-walled box-girder bridge. The architecture and the details of training mechanics are described below:

5.1 Network Topology

A three-layer feedforward artificial neural network consisting of input, hidden, and output layers was developed. The input layer contains neurons that reflect important physical parameters of the bridge-track system namely the span length and the damping of the bridge, where the hidden layer is being used with 10 neurons using a Hyperbolic Tangent Sigmoid (tansig) activation function, which was chosen after experimentation, to best represent the non-linear relationships between bridge geometry and dynamic load factors. Lastly, neurons of the structural responses like shear force, bending moment, torsional moment and distortional effects are placed in the output layer, using a Linear (purelin) transfer function to allow the prediction of the values over a continuous range beyond the standardized interval of -1 to 1.

5.2 Levenberg-Marquardt (LM) Training Algorithm.

The Levenberg-Marquardt (LM) backpropagation algorithm was used to train the network because it is recommended as a way of training the network based on its excellent convergence speed and accuracy in the case of medium-sized network in structural engineering.

LM algorithm fills the gap between the Gauss-Newton and the Gradient Descent methods in an adaptive manner. The network weight update rule, which involves the weights of the network (w), is represented as:

$$w_{k+1} = w_k - [J^T J + \mu I]^{-1} J^T e \qquad \text{Eq. (2)}$$

Where J is the Jacobian matrix of the first derivatives of the network errors with regard to the weights, e is the network error vector and μ is the combination coefficient (damping factor). The algorithm will resemble the Gauss-Newton method when μ is small (around zero) to achieve faster convergence towards a local minimum. With a large μ, it acts as a gradient descent with a small step, and guarantees that the Mean Squared Error (MSE) is steadily decreasing in the early stages of training.

5.3 Pre-processing and validate data.

To avoid the saturation of neurons and to have the same weight of input features all input and target data were brought to the range $[-1, 1]$ prior to training, and then the dataset was randomly split into three separate subsets. A training set (70% of the data) was used to compute the gradient and update the network weights and 15% of the data was used in a validation set to check for over-fitting and to early stop the training when the validation error started to rise. The rest 15 percent was a testing set that was independent to give a clear gauge of predictive power of the model on previously unknown data.

5.4 Data Generating and Partitioning.

The ANN model was developed based on the dataset formed by through numerical simulations of the vehicle-track-bridge system. Two primary data collections were designed to make sure that the network would be able to generalize to a large selection of structural conditions:

Geometric Collection (Span Variation): The effect of bridge stiffness and mass were investigated by simulating the effect of change in span length between 15 m and 30 m. This gave a set of data points that characterize the dynamic load factor at various fundamental frequencies of the bridge.

Damping Collection (Energy Dissipation Variation): The damping of the bridge was varied in the range of 0 to 5 percent to take into consideration the different materials and structure conditions. This set enables the network to get to know how torsional and distortional resultants are sensitive to the energy dissipation properties.

The overall sample size was 200 simulation cases. This pool was further divided into three groups, 70% (140 cases) to train the network weights and biases; 15% (30 cases) to overfitting by tracking the error throughout the training process; and the remaining 15% (30 cases) to test. The testing collection remained completely independent during the learning phase to be used as an independent measure of the predictive accuracy of the model on unexplored structural configurations.

5.5 Model selection and Architecture optimization.

In order to make the surrogate model robust and to avoid the risks of underfitting and overfitting, a systematic comparative analysis of different network architectures was carried out. Since the model takes two inputs and six complex structural outputs as its outputs, the hidden neurons and layers were varied to find the best trade-off between learning capacity and generalization. The same set of training parameters and data were used to evaluate five architectures. The testing dataset was used to measure the performance in terms of the Mean Squared Error (MSE) and the Regression Coefficient (R) of the testing dataset, which is unseen data. Table 6 summarizes the results of this comparison.

Table 6 Performance comparison of different ANN architectures.

Architecture (Inputs-Hidden-Outputs)	**Training MSE**	**Testing MSE**	**Testing R-value**	**Remarks**
2-5-6	4.22×10^{-4}	6.83×10^{-4}	0.986	Evidence of slight underfitting
2-10-6	2.06×10^{-5}	3.13×10^{-5}	0.998	Optimal convergence and accuracy
2-20-6	1.89×10^{-5}	9.46×10^{-4}	0.991	Signs of minor overfitting
2-5-5-6 (Two layers)	3.56×10^{5}	5.13×10^{-4}	0.993	Increased complexity, no gain
2-10-10-6 (Two layers)	1.13×10^{-5}	1.03×10^{-3}	0.987	Overfitting due to high parameter count

The architecture with single hidden layer of 10 neurons had the lowest testing MSE and the highest R-value as indicated in Table 12. Although the 20-neuron and two-layer models had lower training errors, their error on the testing set increased, which showed that the higher complexity caused the model to memorize noise instead of learn the underlying structural physics (overfitting). In contrast, the 5-neuron model did not have enough degrees of freedom to model the non-linear interaction between torsion and distortion (underfitting). Therefore, the most effective and efficient architecture was chosen to be the 10-neuron configuration.

5.6 Selection of Input Variables.

The choice of the input features is of great importance to the efficacy of a surrogate model since they must be the features reflecting the physical behavior of the system. Though the original parametric test assessed six variables, it was found that span length and bridge damping were the two most important factors to determine the Dynamic Load Factor. In particular, span length was found as the most crucial geometric variable since it directly determines the basic natural frequencies of the bridge, thus determining the resonance occurrence during the passages of high-speed trains. On the other hand, the bridge damping ratio was established to be the most critical mechanical parameter in the energy dissipation aspect, which had a great impact on the maximum levels of the torsional resultants and distortional resultants. The high predictive reliability of the model with the two major parameters isolated as ANN inputs is thus attained at a high computational efficiency and without the curse of dimensionality that may arise with the inclusion of less sensitive variables.

5.7 Neural Network implementation using span length as input

The performance evaluation of the artificial neural network (ANN) model trained using MATLAB reveals a highly accurate and efficient predictive framework for structural response parameters based on span length input. The ANN was developed with a single hidden layer consisting of 10 neurons, optimizing the model using the Levenberg-Marquardt backpropagation algorithm. The mean squared error (MSE) and regression coefficient (R) were employed as primary indicators of model performance. As shown in the training record and performance plots, the training phase achieved an MSE of 7.0195e-6 with a near-perfect regression coefficient of R = 0.9999, signifying an excellent fit between predicted and actual output values. Validation and test results further support the generalizability of the model, with MSE values of 1.4415e-4, 4.9943e-4 and R values of 0.9997 and 0.9911, respectively. The high R values across all data subsets affirm that the model exhibits strong correlation and minimal deviation from true outputs. The gradient and Mu plots provide insight into the convergence behavior of the network. A consistent decline in the gradient, culminating in a final value of 5.88e-6, indicates effective learning and optimization. The Mu parameter, which governs the step size in the Levenberg-Marquardt algorithm, reduced from an initial value of 0.001 to 1e-9, suggesting smooth convergence without encountering numerical instability. Early stopping occurred at epoch 9 after reaching the maximum number of validation checks (6), a safeguard that prevents overfitting by halting training when validation performance ceases to improve. The performance plot illustrates that the optimal validation MSE of 1.44e-5 was achieved at epoch 3. Beyond this point, validation error showed signs of a plateau or slight increase, while the training error continued to decrease. This divergence typically signals the onset of overfitting; however, the early stopping mechanism effectively mitigated this risk. Figure 1 and Figure 2 depicts Training state plot and Performance plot respectively for this model using span length as input. The error histogram (Figure 3) shows that the vast majority of prediction errors are narrowly distributed around zero, with very few outliers. Most errors lie in the range of ±0.007, which is acceptable considering the complexity of structural response variables being predicted. Furthermore, the regression plots (Figure 4) for the training, validation, test, and overall datasets display a tight clustering of data points around the identity line (Y = T), with minor deviations observed in the test data. This indicates the model's robust predictive capability across all phases. The function fit plot (Figure 5) further confirms the model's accuracy. The predicted outputs closely follow the actual targets for each output element, with negligible errors observed. The alignment across training, validation, and test subsets illustrates the model's ability to generalize well to unseen data.

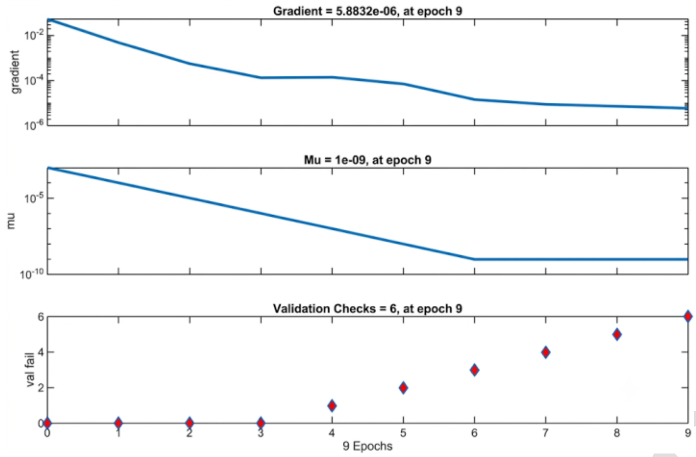

Figure 1 Training state plot (span as input)

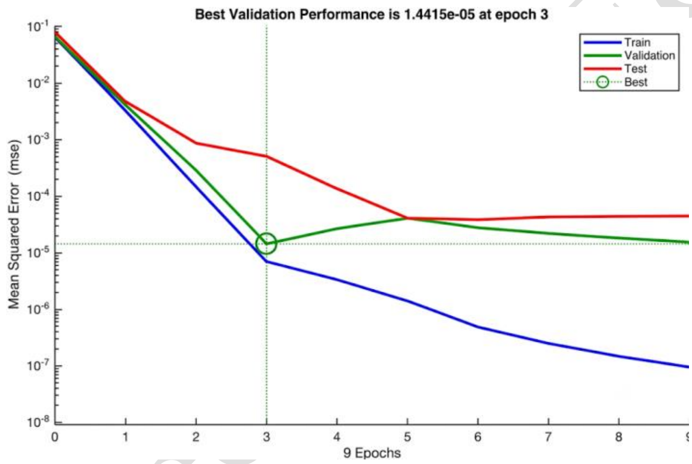

Figure 2 Performance plot (span as input)

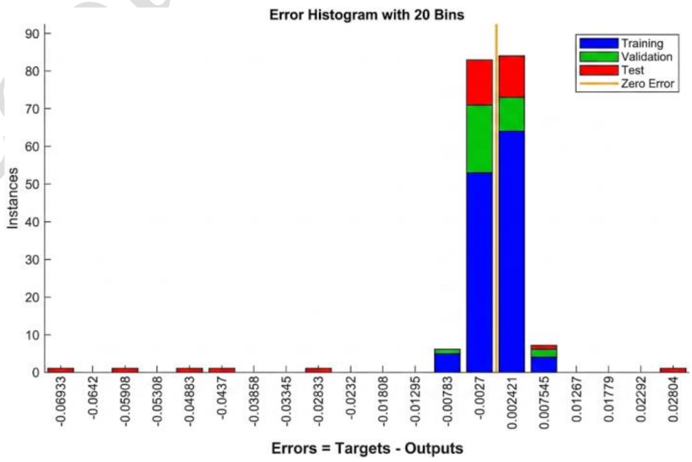

Figure 3 Error histogram plot (span as input)

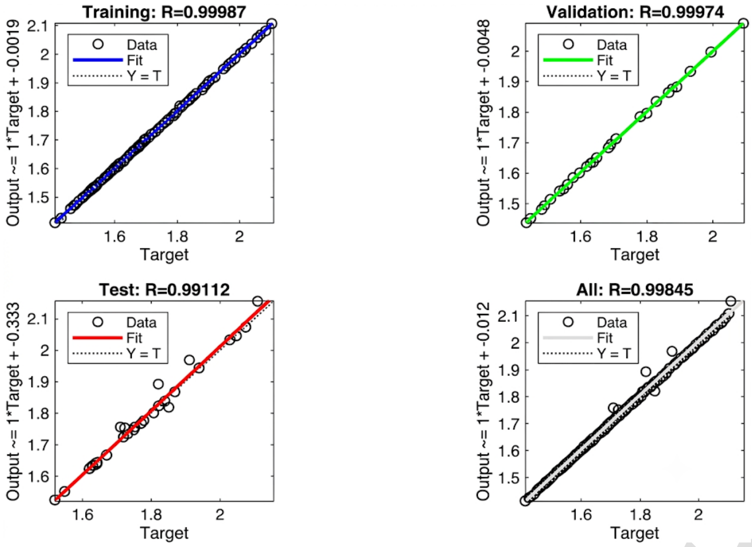

Figure 4 Regression plot (span as input)

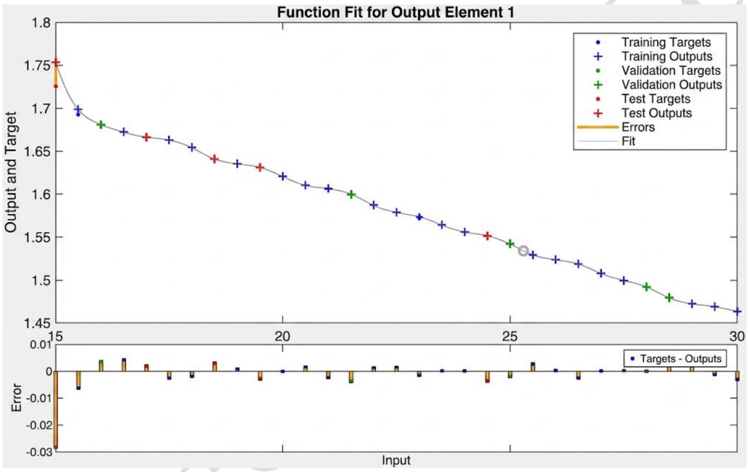

Figure 5 Function fit plot (span as input)

5.8 Neural Network implementation using Bridge's damping as input

The presented Artificial Neural Network (ANN) model was developed to predict key structural response parameters—including Shear Force, Bending Moment, Torsional Moment, Torsional Bi-moment, Distortional Moment, and Distortional Bi-moment, based on a single input variable: Damping. The network architecture employed a single hidden layer with ten neurons, trained using the Levenberg-Marquardt backpropagation algorithm. The training process was rigorously monitored using performance metrics such as Mean Squared Error (MSE), regression values (R), gradient descent behavior, and early stopping through validation checks. The network exhibited exceptional predictive performance across all datasets. The training dataset achieved an MSE of 4.57e-6 with a near-perfect correlation coefficient (R = 0.99991). Validation and test datasets also showed very high accuracy, with respective MSEs of 1.62e-5 and 7.01e-6, and R values of 0.99969 and 0.99984, which can be seen in Figure 6. These results indicate a strong generalization capability and a minimal risk of overfitting. The early stopping criterion was triggered at the 10th epoch due to six successive increases in validation error, preventing overtraining and preserving the model's generalizability. The performance curve (Figure 7) revealed a steady reduction in error for both training and validation sets up to epoch

4, after which the validation error plateaued, signalling optimal convergence. The final performance value dropped significantly from an initial 0.0367 to 1.19e-6, emphasizing the network's ability to learn intricate relationships in the data. The final gradient magnitude of 1.50e-6 and the minimum mu value of 1e-7 further demonstrate that the training process converged smoothly and effectively. The error histogram (Figure 8) and regression plots (Figure 9) provide additional validation of model reliability. Errors were symmetrically distributed around zero, with the majority tightly clustered within narrow bounds (e.g., ±0.0015), indicating that most predictions closely matched the target values. Furthermore, regression plots for training, validation, and testing phases all closely aligned with the ideal diagonal line (Y = T), affirming the accuracy of the model across different data subsets. The functional fit plot (Figure 10) comparing predicted and actual values of output variables as a function of damping showed a strong match across training, validation, and testing groups. The negligible deviations between predicted and true values and the absence of significant systematic errors in the lower subplot (error curve) confirm that the model captures the underlying physical relationships accurately. Given the high fidelity of the ANN predictions, this model serves as a viable surrogate for computationally intensive simulations in structural engineering. It can be particularly useful for real-time analysis or parametric studies where damping effects on shear forces and various moment types are of interest. The ability to predict multiple complex outputs from a single input also highlights the ANN's potential for integrating into optimization or control frameworks in structural health monitoring.

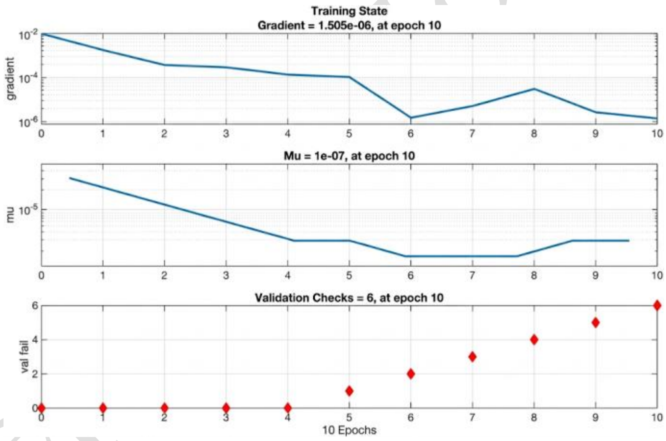

Figure 6 Training state plot (Damping as input)

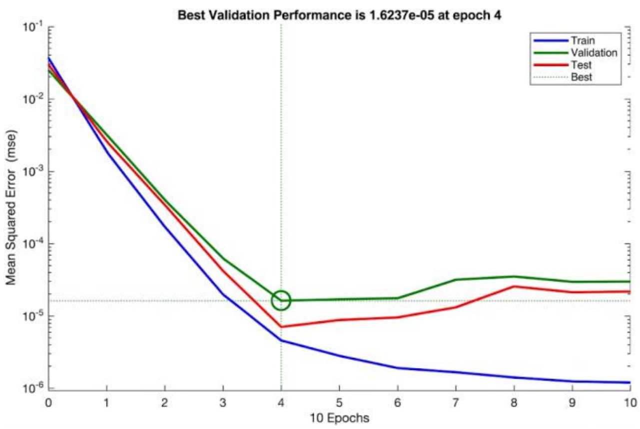

Figure 7 Performance plot (Damping as input)

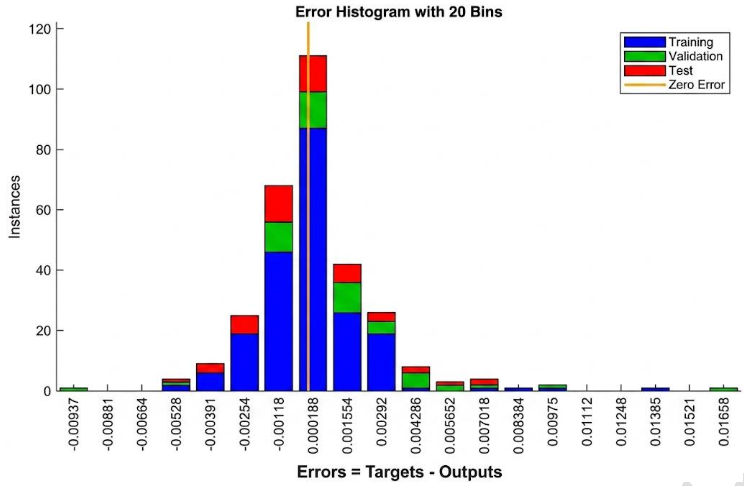

Figure 8 Error histogram plot (Damping as input)

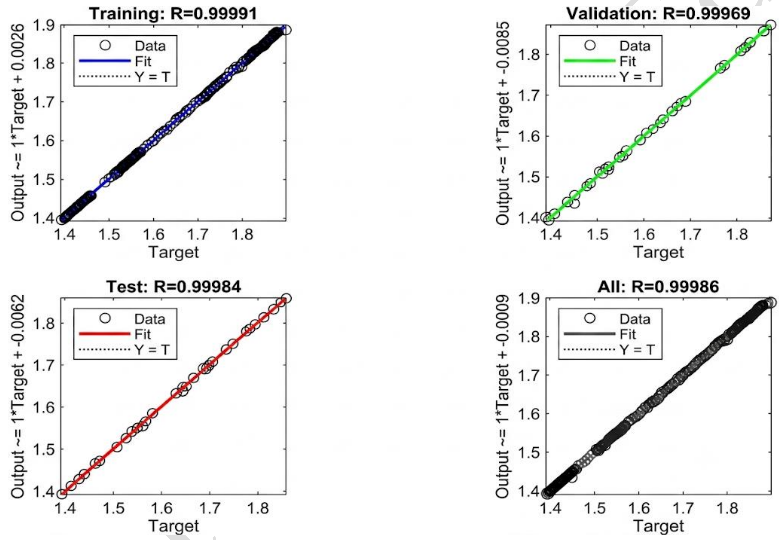

Figure 9 Regression plot (Damping as input)

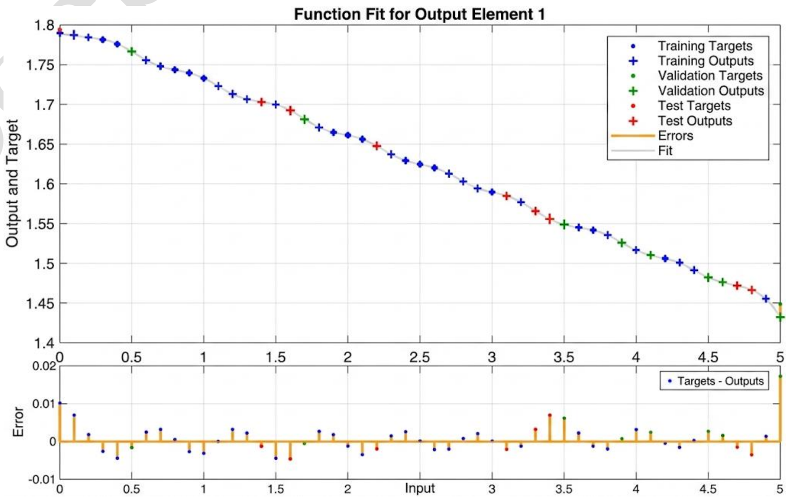

Figure 10 Function fit plot (Damping as input)

6. Conclusion

The study demonstrates that employing a high-fidelity 38-degree-of-freedom train model, along with a more intricate slab-track and thin-walled curved box-girder bridge system, facilitates enhanced simulation of vehicle-bridge interactions. This comprehensive model incorporates dynamic effects, specifically torsional and distortional behavior, frequently overlooked in simplified analytical models. Parametric analysis verifies that the dynamic load factor is significantly influenced by parameters including span length and bridge damping.

6.1 Significance of the Hybrid Modeling

This work's primary innovation is the combination of a verified 3D finite element (FE) framework with an artificial neural network (ANN) to develop a robust surrogate model. The proposed model employs high-fidelity simulation data that explicitly considers cross-sectional distortion and torsional-distortional coupling, in contrast to prior studies that depend on simple 2D models or empirical data for training. The created ANN functions as a computationally efficient surrogate while maintaining the accuracy of a 38-DOF system. This hybrid methodology facilitates swift and precise forecasting of structural responses ($R > 0.99$) while significantly diminishing the computational expenses associated with traditional finite element analyses. Thus, the applied surrogate model represents a substantial enhancement for the initial design and real-time oversight of intricate curved bridge systems.

6.2 Limitations of Study

Although the surrogate model demonstrates high predictive accuracy, several limitations must be acknowledged. The scope of this research is primarily restricted to a single radius of curvature and a single train configuration, which may limit the generalizability of the ANN model to bridges with significantly different geometric configurations. Moreover, while the parametric study includes the effect of train velocity, the ANN model was trained at a constant speed to ensure a focused input space. Consequently, the performance of the surrogate model under a wider range of train speeds and varying rail irregularity profiles has not been fully explored.

In addition, the ANN model has been validated using numerical data generated from a rigorously validated finite element framework. A direct comparison with field measurements from real bridge structures would further enhance confidence in the predictive capability of the model. However, the availability of such comprehensive field data, particularly for curved box-girder bridges under controlled conditions, is limited. Future work will focus on incorporating field monitoring data to further validate and improve the robustness of the proposed approach.

6.3 Future Research Scope

Future Research can be directed towards increasing the ANN input space to feature an extended set of operational parameters (train speed, radius of curvature, and varying profiles of rail irregularities). This will allow the creation of a more universal surrogate model that will be able to evaluate a greater range of infrastructures of railway bridges. Furthermore, it can be intended to test the proposed hybrid framework based on the field measurements of the available high-speed rail lines. It might also be considered to integrate deep learning methods, e.g., Recurrent Neural Networks (RNNs) or Physics-Informed Neural Networks (PINNs), to better reflect the time dependence of dynamic vehicle-bridge interactions.

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