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MACHINE LEARNING APPROACH TO MODELLING WHEEL-RAIL CONTACT FORCES IN HYBRID VEHICLE-STRUCTURE INTERACTION ALGORITHM

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Abstract

Vehicle-structure interaction models are highly complex non-linear dynamic problems used to evaluate the responses of the bridge and the vehicles due to passing traffic. These problems usually require specialized algorithms for their solution and its complexity arises from the need to accurately model the dynamic behaviour of the vehicle and structure as well as the interactions between them. Realistic modelling of these contact forces is essential for simulating vehicle dynamics and ensuring train safety but entails significant computational cost due to the highly nonlinear and high-resolution requirements of traditional methodologies. This paper introduces a machine learning approach to calculate wheel-rail contact forces within a hybrid vehicle-structure interaction algorithm, aimed at enhancing computational efficiency by replacing the costly wheel-rail contact algorithms with a properly trained neural network. Simplified two-dimensional vehicle and structure models are employed to train and validate the hybrid algorithm, with neural networks trained on a comprehensive dataset generated numerically containing diverse track irregularity profiles, multiple train speeds, and various vehicle properties. Numerical comparisons between the hybrid and conventional algorithms are performed, comparing the accuracy of the proposed solution in terms of the dynamic responses of the systems and contact forces. Results demonstrate that the machine learning-based model achieves reliable force predictions with minimal compromise on dynamic response fidelity. This approach offers a scalable solution for rapid vehicle-structure interaction analysis, supporting applications in structural dynamics and safety assessments where computational efficiency is critical.

Keywords: dynamic analysis, vehicle-structure interaction, machine learning, wheel-rail contact.

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1 INTRODUCTION

Train running safety on bridges is a critical concern in railway engineering, as dynamic interactions between vehicles and structures can significantly impact operational performance, track and bridge structural integrity, and ultimately train running safety. Evaluation of this vehicle-structure interactions can often prove challenging, since commercial software used for train-track interaction analyses do not accurately represent bridge structures, and commercial finite element software usually do not include train-track interaction elements. Thus, most research is performed with methods developed specifically for this problem.

Traditionally, train-track-bridge interaction models are based on establishing the compatibility conditions in the contact points, either using uncoupled algorithms where structure and vehicle models are developed separately or coupled methods where the systems' matrices are solved simultaneously [1,2]. Furthermore, vehicle-structure interaction models rely on the complex behaviour of the wheel-rail contact, which has a highly nonlinear nature due to the geometric contact problem and non-conservative forces caused by the relative motion of contact surfaces. Algorithms used to simulate these interactions must solve the geometric problem [3], where the point of contact between wheel and rail occurs is determined, and the normal [4] and tangential problems [5–8], where the contact forces are determined. However, these algorithms often suffer from high computational costs and limited adaptability to varying operational conditions, prompting the need for more efficient and accurate modelling approaches.

Recent advancements in artificial intelligence algorithms have demonstrated the potential of machine learning techniques to replace or augment traditional engineering modelling, with capabilities to learn even strongly nonlinear relationships and create highly accurate predictive models [9]. Authors have developed methodologies to predict contact forces and assess vehicle safety using artificial intelligence methods, predicting entire time histories of wheel-rail forces [10]. Hybrid algorithms were also developed to improve the efficiency of traditional numerical integration algorithms using a surrogate model for the wheel-rail contact problem [11]. Due to the complex nature of wheel-rail contact and the high computational cost of predicting its behaviour in numerical simulations make it a challenging problem to model. Machine learning methods have emerged as powerful tools for addressing this issue. By leveraging carefully designed networks, these methods can effectively map and predict the intricate behaviour of wheel-rail interactions, significantly reducing computational costs and enhancing calculation efficiency.

In this paper, a computationally efficient and accurate hybrid model for the solution of train-track-bridge interaction and evaluation of train running safety is developed. The proposed model uses machine learning algorithms to simulate wheel-rail interactions, offering improved adaptability and performance compared to traditional methods, while still solving the dynamic interaction problem numerically using traditional time integration methods. In Section 2, the train-track-bridge interaction algorithm and models used are described, while Section 3 described the machine learning algorithms implemented. Section 4 described the methodology used to generate the datasets, train the networks and implement them within the conventional vehicle-structure algorithm. Finally, results for the accuracy of networks and hybrid model are given in Section 5.

2 TRAIN-TRACK-BRIDGE INTERACTION MODELS

The methodology employed to solve the train-track-bridge interaction problem in this study is based on a two-dimensional analysis considering a simplified vertical wheel-rail contact model. The dynamic interaction solution method used is the Direct Method [12,13], based on the Lagrange multiplier method, which creates a coupled global matrix of train-track and vehicle systems. The coupling between vehicle and track is represented through additional constraint equations that establish the displacement relations in the contact points, forming a single system of equations described in Equation (1), where $\bar{\boldsymbol{K}}$ is the effect stiffness matrix, $\bar{\boldsymbol{D}}$ and $\bar{\boldsymbol{H}}$ are the transformation matrices that relate the contact forces with nodal forces and the displacements in the structure, and vectors $\boldsymbol{\Delta a}$ and $\boldsymbol{\Delta X}$ are the incremental nodal displacements and contact forces, $\boldsymbol{\psi}$ is the residual force vector and $\bar{\boldsymbol{r}}$ is the vector with irregularities on the contact points.

$$\begin{bmatrix} \bar{\boldsymbol{K}} & \bar{\boldsymbol{D}} \\ \bar{\boldsymbol{H}} & 0 \end{bmatrix} \begin{bmatrix} \boldsymbol{\Delta a}_F^{i+1} \\ \boldsymbol{\Delta X}^{i+1} \end{bmatrix} = \begin{bmatrix} \psi(\mathbf{a}^{t+\Delta t,i}, \mathbf{X}^{t+\Delta t,i}) \\ \bar{\boldsymbol{r}} \end{bmatrix} \quad (1)$$

The vehicles were modelled as simplified half-vehicle models, where an oscillating mass composed of a mass, spring and damper represents half of a typical high-speed vehicle encompassing half of the carbody mass, the bogie and wheelsets masses and an equivalent suspension system. The bridge was modelled along with the track structure using frame elements and springs and dampers representing the ballasted track properties. Both models are described in Figure 1.

The adopted properties for the oscillator were a mass of $16925\ kg$, and spring stiffness and damping of $1200\ kN/m$ and $10\ kNs/m$ respectively. The bridge represents a typical simply supported short-span bridge in high-speed railways, with a span length of $11.5\ m$, equivalent moment of inertia of $0.27951\ m^4$ and modulus of elasticity of $3.61 \cdot 10^{10}\ N/m^2$ for the frame element, equivalent mass of $16462\ kg/m$ and damping of 2%.

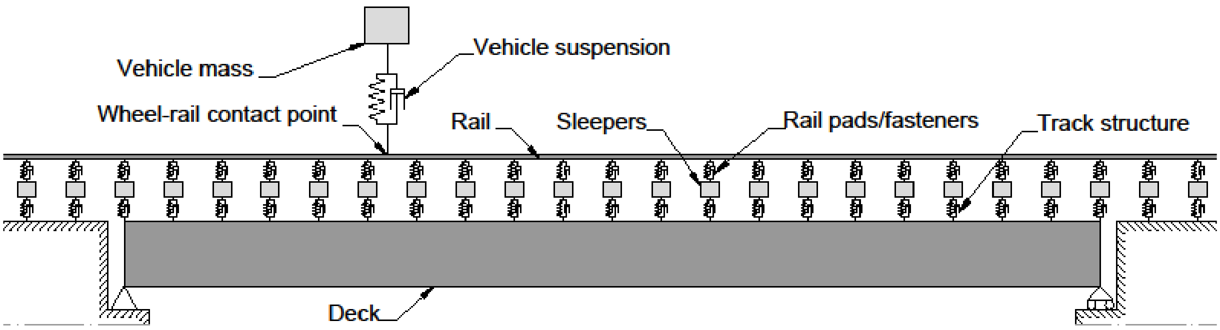

Figure 1: Vehicle and structure models

The track irregularity profile was generated using the spectral representation method [14], where the power spectral density functions of the track irregularities are used to create realistic profiles that reflect the statistical properties of real-world tracks. The German low, medium, and high interference spectra were employed to define the PSD functions [15], representing varying levels of track quality. These spectra were applied to generate irregularity profiles in the vertical direction, disregarding effects of cross-level irregularities due to the two-dimensional nature of the analysis. Multiple samples were generated for each degree of irregularity to ensure significant variability in the results obtained.

3 MACHINE LEARNING ALGORITHMS

Artificial intelligence methods, particularly those designed for regression tasks, have become indispensable tools in modern engineering modelling. These methods, such as neural networks, support vector regression, and Gaussian processes, excel at capturing complex, nonlinear relationships between input and output variables. In engineering applications, where traditional models often struggle with high-dimensional data or computationally expensive simulations, AI-based regression offers a powerful alternative. By learning patterns from data, these algorithms can provide accurate predictions, reduce computational costs, and enable real-time decision-making. Their ability to handle large datasets and adapt to varying conditions makes them particularly valuable for highly nonlinear and computationally expensive applications, where precision and efficiency are critical.

In this study, two artificial intelligence architectures were employed to model the wheel-rail contact dynamics: a simple feedforward neural network (FNN) and a hybrid convolutional-recurrent neural network (CRNN). Both networks described were trained to predict contact forces given different inputs from the dynamic analysis, offering a computationally efficient alternative to traditional wheel-rail contact algorithms.

The FNN was chosen for its ability to capture nonlinear relationships between input and output variables with relatively low computational and implementation complexity. Meanwhile, the hybrid CRNN combines the spatial and temporal feature extraction capabilities of both types of networks making it particularly well-suited for capturing the time-dependent and spatially complex nature of wheel-rail interactions. Convolutional networks can learn local patterns and features, which can be particularly useful for higher frequency changes in the input data. On the other hand, recurrent neural networks are designed to process sequential data by maintaining a hidden state that captures information from previous time steps, making them well-suited for time-series problems. Thus, combining both can be a powerful approach for predicting sequential data.

The general architecture of both networks investigated in this study is given in Figures 2 and 3. The feedforward neural network contains multiple hidden layers of fully connected neurons with rectified linear unit (ReLU) activation functions, which introduce nonlinearity while mitigating the vanishing gradient problem, while the output layer utilized a linear activation function to provide continuous predictions for contact forces. In contrast, the hybrid convolutional-recurrent neural network combined convolutional neural network layers with bidirectional long short-term memory (LSTM) layers. The CNN layers employed ReLU activations and used 1D convolutions to extract spatial features from the input data, with max-pooling applied to reduce dimensionality. The bidirectional LSTM layers, which processed sequential data in both forward and backward directions, used hyperbolic tangent (tanh) activations for the cell states and sigmoid activations for the gate mechanisms. Dropout layers were incorporated in both architectures to prevent overfitting. Both networks were trained using the Adam optimizer was used to efficiently minimize the mean squared error (MSE) loss function during training.

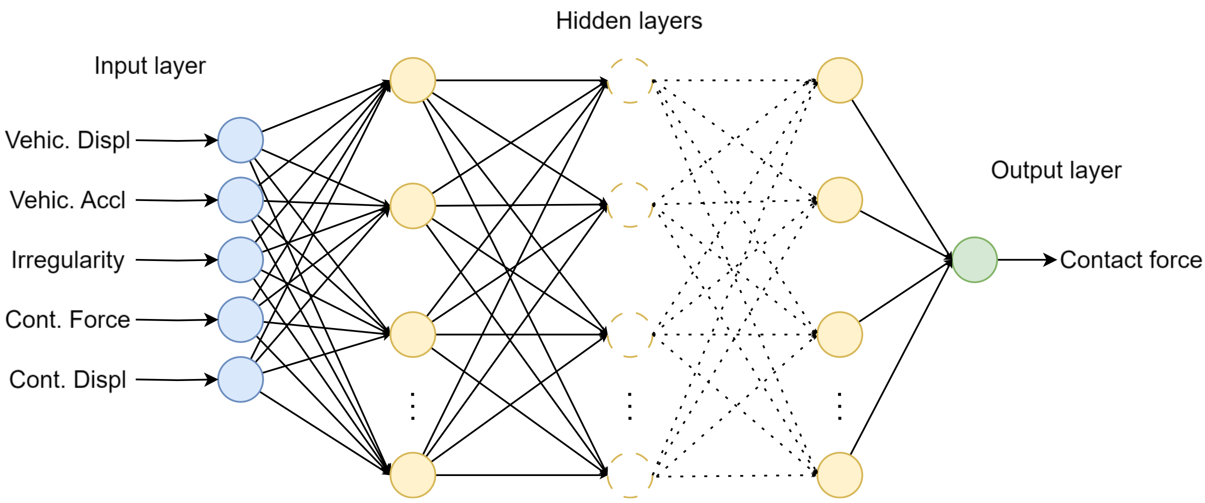

Figure 2: Feedforward neural network architecture

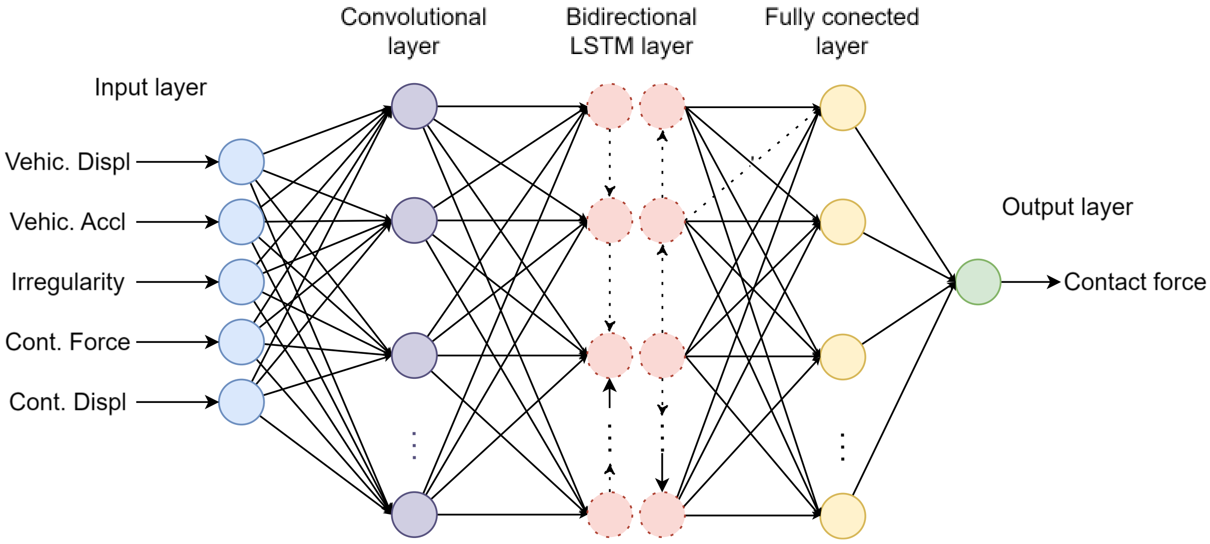

Figure 3: Hybrid convolutional-recurrent neural network architecture

The neural networks were trained using data generated from the dynamic vehicle-structure interaction simulations, which included track irregularity profiles, vehicle and structure dynamic responses, and corresponding wheel-rail contact forces. The dataset was divided into training, validation, and testing subsets to ensure the models' robustness and generalization. During training, the networks learned to map the complex relationships between inputs and outputs by minimizing prediction errors. The simple feedforward neural network focused on capturing nonlinear relationships, while the hybrid convolutional-recurrent neural network leveraged its architecture to model both spatial and temporal dependencies in the data. The training process emphasized achieving a balance between accuracy and computational efficiency, ensuring the models' suitability for real-world engineering applications.

4 METHODOLOGY

The analyses described in this study were developed by first performing dynamic analyses using the previously described train-track-bridge interaction method under a variety of conditions, including different train speeds and track irregularity profiles. These analyses generated a comprehensive dataset of vehicle and structure responses, which served as the foundation for training the neural networks. To enhance the accuracy of the networks, multiple combinations of input features were tested, and hyperparameters were systematically tuned to achieve an optimal balance between computational efficiency and prediction accuracy. Once trained, the neural networks were integrated into a hybrid interaction algorithm, replacing traditional wheel-rail contact models and its efficiency and accuracy was evaluated.

4.1 Generation of datasets

The dataset generation process involved conducting dynamic analyses using the vehicle-structure interaction method across a wide range of operating conditions. Train speeds ranging from 120 to 420 km/h were simulated to capture the effects of varying velocities on the dynamic response. Additionally, multiple track irregularity profiles were generated and analysed for low, medium, and high degrees of irregularity using the German spectrum, ensuring a representative range of track conditions. Finally, different vehicle masses and suspension properties were also included the dataset generation process. From these simulations, key response parameters were extracted to form the dataset. After preliminary analyses of the influence of each of these parameters in the contact force, the displacement and acceleration responses of the vehicle mass, the displacement of the contact point, the irregularity profile under the wheel were determined to be the most influential parameters to the contact force calculation and were chosen as the input parameters in the machine learning algorithms. These parameters were selected based on their ability to comprehensively describe the wheel-rail interaction dynamics and their influence on the system's behaviour. The resulting dataset provided a robust foundation for training the neural networks, enabling them to learn the relationships between input features and output responses.

4.2 Training and tuning of the networks

The neural networks were trained using the generated dataset, with the input features consisting of the displacement and acceleration responses of the vehicle mass, the displacement of the contact point, the irregularity profile under the wheel, as well as the contact force of the previous step, while the predicted output was the contact force. To evaluate the performance of the models, several error metrics were employed, including mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), mean absolute percentage error (MAPE), and relative root mean squared error (RRMSE). These metrics provided a comprehensive assessment of the networks' accuracy and generalization capabilities. The dataset was split into training, validation, and testing subsets, with the validation set used to monitor overfitting and guide hyperparameter tuning and test set used to evaluate the final accuracy of the trained network. The division followed a 50-30-20% split for the training, validation and test sets respectively.

For the fully connected neural network (FNN), hyperparameter tuning focused on optimizing the network architecture and training process. The number of layers and neurons per layer were systematically varied to balance model complexity and performance. Activation functions, including Linear, ReLU and Leaky ELU, were evaluated to determine the most effective nonlinearity. The learning rate was adjusted to ensure stable convergence, and regularization techniques such as L2 regularization and dropout were applied to prevent overfitting. Similarly, for the hybrid convolutional-recurrent neural network (CRNN), hyperparameters such as the number of units in the convolutional, LSTM, and dense layers were tuned to optimize feature extraction and temporal modeling. The kernel size in the convolutional layer was adjusted to capture spatial patterns effectively, while the learning rate and batch size were optimized to ensure efficient training. Regularization methods, including dropout and L2 regularization, were also applied and tuned to enhance generalization. Through iterative tuning, both networks achieved a balance between accuracy and computational efficiency, enabling reliable predictions of wheel-rail contact dynamics.

4.3 Implementation of the hybrid algorithm

The conventional vehicle-structure interaction algorithm is based on the solution of nonlinear wheel-rail contact problem and integrate these results into the solution of the dynamic interaction algorithm. With the hybrid network, the conventional contact algorithm is replaced by a suitably trained machine learning model that predicts the contact forces given inputs from the dynamic responses of the systems.

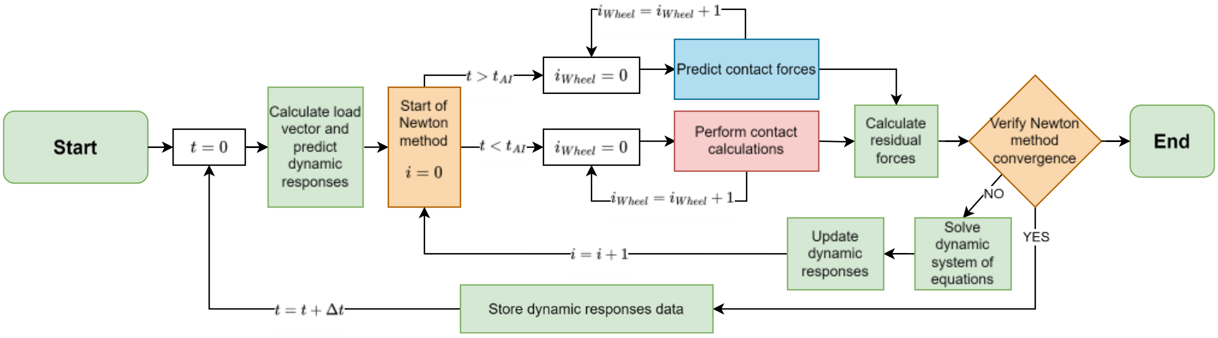

Figure 4: simplified flowchart of the hybrid algorithm

In Figure 4, a simplified view of the dynamic interaction solution flowchart is described, with focus on the non-linear solution of the contact problem. It can be observed that the machine learning algorithm, in blue, is integrated within the Newton method solution for the non-linear problem. Since the first steps of any dynamic solution tend to present some form of numerical disturbance, especially in high-frequency responses, and since the machine learning algorithm uses responses from previous steps to predict the contact forces, a number t_{AI} of time steps is still calculated using the conventional algorithm.

5 RESULTS

The results obtained for the proposed networks and hybrid algorithm are described in the following sections.

5.1 Neural networks

As described, two types of neural networks were investigated in this study, namely a feed-forward neural network (FNN) and a hybrid convolutional-recurrent neural network (CRNN), which were described in Section 3 and Figures 2 and 3. After building and tuning of the networks, the architecture and optimal hyperparameters found are given in Tables 1 and 2.

First and second layers – fully connected dense layers	
Number of units	128
Regularization	L2 – 0.001
Activation function	ReLU
Third and fourth layers – fully connected dense layers	
Number of units	64
Regularization	L2 – 0.001
Activation function	ReLU

Table 1: architecture and parameters of the FNN

The learning rate and batch size were also investigated, reaching values of 16 and 0.005 for the FNN and 8 and 0.0008 for the CRNN. A maximum number of epochs was implemented, with the adoption of early stopping criteria based on the value of the loss function over multiple iterations.

First layer – convolutional layer	
Number of filters	192
Number of kernels	15
Activation function	ReLU
Second layer – Bidirectional LSTM layer	
Number of units	96
Dropout	0.25
Regularization	L2 – 0.001
Third and fourth layers – fully connected dense layers	
Number of units	48 and 240
Regularization	L2 – 0.001
Activation function	ReLU

Table 2: architecture and parameters of the CRNN

After training using the complete dataset, the error metrics obtained from the test and validation sets are given in Table 3. It is noteworthy to mention that the metric used in the training process for optimization of the weights was the MSE, and the other metrics were calculated after the training process.

Metrics	FNN		CRNN	
	Test	Validation	Test	Validation
RRMSE [%]	0.0928	0.0921	0.0821	0.0723
RMSE [N]	153.81	152.727	136.058	119.78
MAE [N]	93.994	93.845	77.586	76.724

Table 3: error metrics for both the trained networks

From the results presented in Table 3, it is clear that both studied neural networks are able to predict the contact forces exceptionally well, with relative errors of less than 0.1% for each individual evaluation of the contact forces, and the mean average error of less than 100 N. It is important to note that these values refer to the evaluation of the error of the network using the whole database, including different degrees of irregularity, vehicle properties and other parameters described previously.

5.2 Dynamic analysis

After implementing the proposed networks into the vehicle-structure analysis framework according to Figure 4, the results obtained from the hybrid algorithm are compared to the same scenario calculated using the conventional nonlinear solver. The time histories of the results were compared using the coefficient of determination and root mean square error. The acceleration results for the vehicle and bridge and the contact forces for a single analysis considering high degrees of irregularities and vehicle speed of 300 km/h are given in in this section. In Figure 5, it can be observed that both curves for the acceleration responses are virtually identical, demonstrating that the hybrid algorithm correctly evaluates the dynamic responses of both systems.

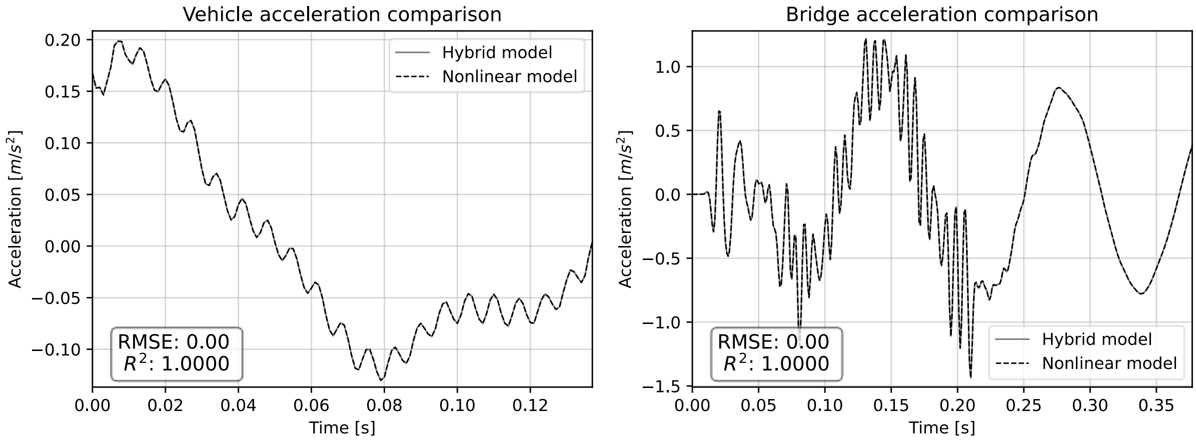

Figure 5: comparison between bridge and vehicle acceleration for both algorithms

The contact forces are also compared in **Erro! Fonte de referência não encontrada.**, where small differences are observed between the nonlinear and hybrid models. However, the error and coefficient of determination values show that these are extremely minor and the contact forces for both algorithms are nearly identical. Furthermore, the spectral analysis of both contact force results indicated that both possess the same frequency contents up to frequencies of 200 Hz, demonstrating extraordinary agreement between both results.

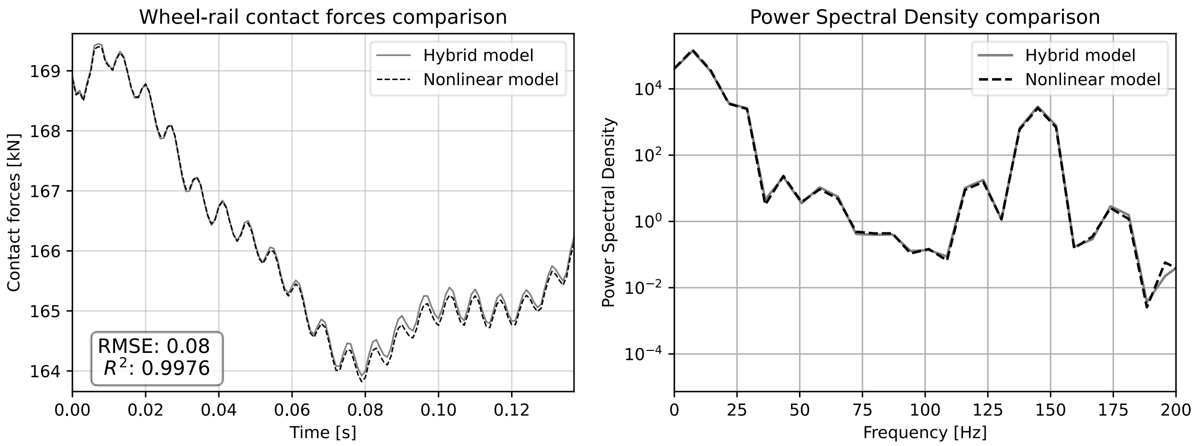

Figure 6: comparison of the contact force time history and spectral analysis

5.3 Systematic analysis

The hybrid algorithm results were also evaluated for all speeds described in the training data, from 120 to 420 km/h, with a focus on the contact force results. Both networks were implemented within the vehicle-structure algorithm framework and their results are presented separately. Here, both the RMSE and R^2 metrics for the contact forces curves (as presented in Figure 6) were calculated for all scenarios, as well as the difference between the maximum and minimum values observed in the contact forces during those analyses. The values for each speed are presented in Figures 7 and 8 for the FNN and CRNN hybrid algorithm, respectively.

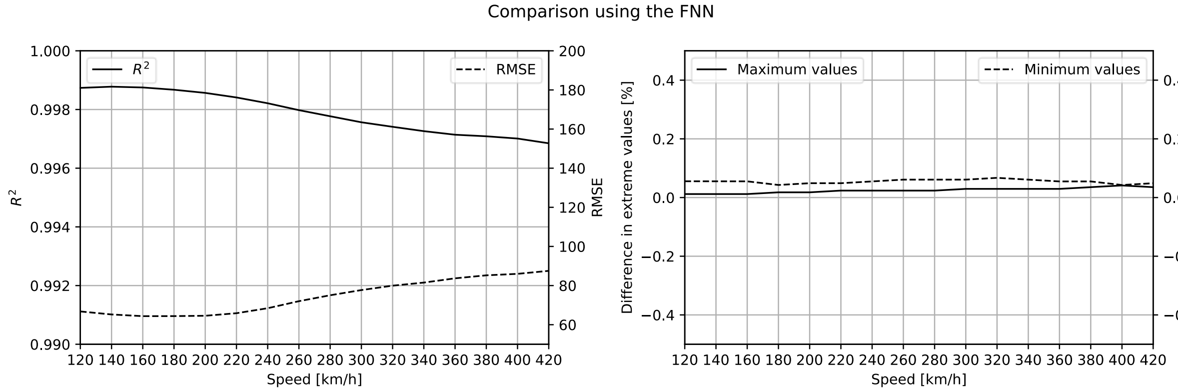

Figure 7: results for all speeds using the FNN hybrid network

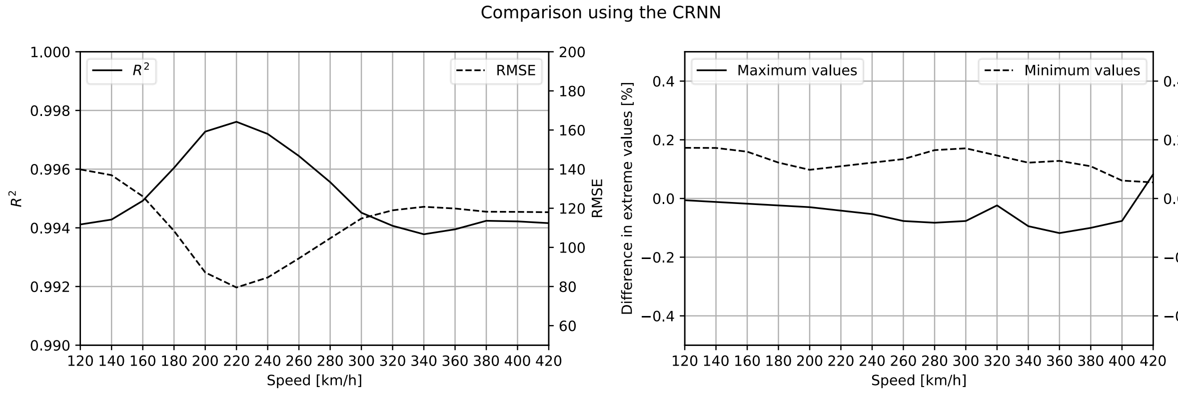

Figure 8: results for all speeds using the CRNN hybrid network

From these results, it can be observed that both networks can accurately predict contact forces, with slightly better results for the FNN. All metrics in all scenarios studied are satisfactory and indicate very similar behaviour, validating the methodology. Furthermore, analysis of the difference in maximum and minimum observed values for the contact forces, which are used in running safety analyses, indicate errors of less than 0.2% in all cases, demonstrating that these networks are suitable even for extreme cases when properly trained and implemented.

6 CONCLUSIONS

This paper presented a hybrid vehicle-structure algorithm that integrates AI methods to replace conventional wheel-rail contact algorithms. A comprehensive database of dynamic analysis results was generated using the conventional two-dimensional vehicle-structure algorithm considering different vehicle properties and track conditions. This data was used to train two different types of neural networks to evaluate their accuracy, finding that both the feedforward neural network and convolutional-recurrent neural network could accurately predict contact forces with negligible error. The hybrid vehicle-structure algorithm was also implemented, and results indicate high fidelity between the conventional and proposed algorithms, with nearly identical results for dynamic responses of the bridge and vehicle. For the contact forces curve comparison, the coefficient of determination values observed were of over 0.99 in all scenarios studied and the error in extreme values was less than 0.2%, indicating that the hybrid algorithm can reliably and accurately reproduce the contact behaviour within the dynamic analyses.

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