



APPLICATION OF PHYSICS AI IN RAILWAY VEHICLE DESIGN – A REVIEW

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Abstract – Modern railway vehicle design must satisfy numerous requirements related to safety, reliability, weight reduction, energy efficiency, and performance. Numerical methods such as FEM and multibody system models provide reliable results, but their application to complex problems and numerous operating conditions can require significant computational time and resources. Physics AI combines artificial intelligence with physical knowledge and offers a promising way to overcome these limitations. This paper reviews its applications in railway engineering, including collisions and braking, vehicle dynamics and control, structural analysis and fatigue, wheel–rail and vehicle–track interaction, aerodynamics, pantograph–catenary systems, and maglev systems. The reviewed studies show that incorporating physical knowledge into AI models can improve accuracy, robustness, physical consistency, and generalization while reducing data requirements and computational cost. These results highlight the significant potential of Physics AI for future railway system design, analysis, monitoring, and control.

Keywords – Physics AI, Railways, Physics-Informed Machine Learning, Railway Vehicle Design, Physics-Informed Neural Networks.

1. INTRODUCTION

When designing modern railway vehicles, it is necessary to meet multiple engineering requirements, including structural weight reduction, energy efficiency, passenger safety, and environmental sustainability [1]. Particularly in passenger railway vehicles, one of the most important issues is passenger safety, which is achieved through adequate vehicle crashworthiness [2]. In addition, increasingly complex requirements related to multi-system capabilities, vehicle crash behavior, and passenger comfort can lead to an increase in structural mass [3]. The fatigue life of bogie frames is also directly related to the reliability and safety of railway vehicles. At the same time, in high-speed and heavy-haul railway vehicles, there is a need to reduce the mass of components in order to decrease energy consumption and increase

speed and payload, while these same components are subjected to severe vibration loads that can increase the risk of fatigue [4]. All of the aforementioned requirements, which must be fulfilled and are often mutually conflicting, make the design process of railway vehicles highly complex. In recent years, computer simulation of railway vehicle behavior in motion has become an almost standard task in the design process within the railway industry [5]. Such tools enable static analyses of railway vehicle components, as well as dynamic analyses of multibody systems. For static analyses, the finite element method is most commonly applied, while multibody system models are used to analyze the dynamic behavior of railway vehicles [6]. Although detailed numerical simulations can provide highly accurate results, they may require considerable computational time and substantial computational

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resources. This issue becomes particularly pronounced when detailed models are used or when vehicle behavior needs to be analyzed under a large number of different load cases, operating conditions, or design variants [7]. As an example of such computational demand, a 1000 ms collision simulation of two trains, each consisting of four vehicles, may require more than 100 hours of computation on a typical high-performance workstation [8]. For this reason, there is a need for approaches that reduce computational time while maintaining the required accuracy in predicting railway vehicle behavior. One such approach is the application of Physics AI methods. Artificial intelligence offers a solution to this problem through the application of fast data-driven surrogate models [9]. In particular, combining machine learning with prior physical knowledge has proven effective for addressing limited training data, improving generalization, and ensuring the physical consistency of results [10]. For these reasons, the combination of artificial intelligence and physical knowledge has great potential in railway engineering.

This paper aims to present the potential applications of Physics AI methods in railway engineering through the analysis of existing approaches and published research.

2. PHYSICS AI APPLICATIONS IN RAILWAY ENGINEERING

The literature review shows that Physics AI methods are applied in various areas of railway engineering. Based on the conducted review, existing studies can be classified into applications related to collisions, crashworthiness, braking, and safety; railway vehicle dynamics and control; structural analysis, fatigue, and reliability; wheel–rail and vehicle–track interactions; and aerodynamics. Other significant applications include pantograph–catenary and maglev systems.

2.1. Crashworthiness, Braking and Safety

The high costs of acquiring data from full-scale train collision experiments limit the application of purely data-driven machine learning methods in train collision simulations. Therefore, Tang et al. [11] applied a Parallel Physics-Informed Neural Network (PPINN) to solve the multibody dynamics equations of train collisions. In the PPINN approach, the governing physical equations of the system are incorporated into the training process, while the considered computational time domain is divided into several subdomains that are solved in parallel, thereby reducing the computational cost. A full-scale numerical train collision model was developed and four collision scenarios were analyzed, considering dynamic responses, collision forces, absorbed energy,

and vertical wheel rise. The obtained results showed good agreement with FEM and conventional numerical methods, indicating the potential of the PPINN approach for accelerating complex dynamic simulations of railway vehicles. In contrast, He et al. [12] proposed a variable-fidelity surrogate model (VFSM) for optimizing the parameters of energy-absorbing elements in train collisions. The approach combines a large number of fast 1D simulations with a smaller number of more accurate 3D simulations connected through transfer learning. From the perspective of Physics AI, the use of an LSTM network with Motion Constraints (LSTM-MC) is particularly important, as it incorporates physical knowledge of system motion into the prediction process. This enables highly accurate predictions of displacement, velocity, and acceleration with significantly lower computational cost than using 3D models alone. The model was then applied to optimize the parameters of energy-absorbing elements with the aim of reducing train acceleration during a collision. One of the most important parameters, particularly from a safety perspective, is the stopping distance of a train. Sepahvand et al. [13] proposed a physics-informed Bayesian framework for its virtual prediction. The idea is to first estimate the stopping distance using physical equations that describe the train braking process and then further adjust this estimate based on experimental data using a Gaussian Process model and a Bayesian approach, which estimates and corrects model discrepancies based on the available data. In this way, physical knowledge is directly incorporated into the prediction process. Such a model enables not only the prediction of stopping distance but also the estimation of the uncertainty associated with that prediction, which can reduce the need for a large number of costly experiments and enable more reliable virtual testing of braking system performance.

The presented studies demonstrate the potential of Physics AI for train collision and braking analysis, while reducing computational time, resource demands, and the need for costly experiments.

2.2. Railway Vehicle Dynamics and Control

Although artificial intelligence represents a promising technology for solving dynamic response problems in real time, it has limitations in terms of generalization capability and prediction reliability. Han et al. [14] proposed a physics-informed neural network framework for railway dynamics problems. To improve prediction reliability and generalization, the dynamic equations of the vehicle–track system were incorporated into the network loss function as physical constraints. The authors also introduced a self-adaptive method for weighting these constraints and a SAT architecture, forming the SATPINN

model. Using both data and physical constraints, the model predicts dynamic responses such as displacement and velocity, achieving higher accuracy and better generalization than the baseline models. In addition to predicting dynamic responses, Physics AI can also be applied in the field of railway vehicle control. One of the important problems in this area is trajectory-following control for virtual rail trains (VRTs). Traditional model-based control methods have difficulties dealing with nonlinear dynamics and require highly accurate system models, while deep learning methods based solely on data lack sufficient physical interpretability and robustness. Ji et al. [15] proposed a physics-informed deep learning approach in which the Lagrangian equations of dynamics are incorporated into a neural network, forming a Deep Lagrangian Neural Network (DLNN). In this way, the network can learn the complex dynamics of the vehicle from data while simultaneously preserving the fundamental physical laws of the system. The developed model is used to determine the control inputs required for following a predefined trajectory and has demonstrated higher accuracy, better generalization, and greater robustness compared with conventional data-driven models. A similar approach has also been applied to the control of virtually coupled trains, where, in addition to trajectory tracking, differences in the dynamics of individual trains need to be taken into account. Liu et al. [16] developed a physics-informed neural network model for train dynamics (PINN-TDM), which incorporates the Davis formula to determine the parameters of basic train resistance. The model was then integrated into a Model Predictive Control (MPC) system for virtually coupled trains, improving trajectory tracking accuracy and train-set stability under different wheel-rail contact conditions.

The presented studies demonstrate the potential of Physics AI in railway vehicle dynamics and control, particularly for rapid dynamic response prediction, trajectory tracking, and advanced control.

2.3. Structural Analysis, Bogie Frames, Fatigue and Reliability

Accurate and efficient prediction of the fatigue state of bogie frames is important for structural optimization and rapid iterative design of railway vehicles. Yang et al. [17] developed an approach for rapid fatigue assessment of welded bogie frame joints based on full-field stress tensor reconstruction. Instead of directly predicting the maximum principal stresses, the approach uses physically defined stress tensor components and a multivariate Gaussian Process to approximately reconstruct the stress field while accounting for the physical coupling between its components. In this way, physical knowledge of the structural stress state is incorporated into the

prediction process. The reconstructed stress field is then used for fatigue assessment, achieving high accuracy while reducing the computation time from approximately 30 minutes to 0.1 s. In addition to bogie frames, fatigue behavior is also of great importance for other load-bearing components of railway vehicles, such as axles. Induction-hardened S38C steel axles used in high-speed trains are characterized by high static strength, but fatigue failure still represents a significant safety concern. The gradient in microstructure and mechanical properties resulting from induction hardening, with the properties changing from the surface toward the core, further complicates accurate prediction of their fatigue life. To address this problem, Deng et al. [18] proposed a machine learning model incorporating physical information related to the gradient. Since a conventional neural network only searches for mathematical relationships in the data, the authors first evaluated the importance of gradient-related physical quantities and then developed an explicit formula for fatigue life prediction using symbolic regression and dimensional analysis, whose predictions were incorporated into the loss function. Based on this, a Layered Input Deep Learning (LIDL) model was developed, which takes into account the interactions between adjacent layers. The developed model demonstrated high prediction accuracy and good generalization capability in predicting axle fatigue life. In addition to fatigue life prediction, Physics AI approaches can also be applied to the condition assessment and maintenance of railway vehicle wheelsets. The maintenance of high-speed train wheelsets in China is mainly carried out according to a planned schedule based on service mileage or operating time. Such an approach is often overly conservative and may lead to excessively frequent repairs, while wheel tread damage occurring between maintenance intervals may remain undetected and compromise operational safety. Although FEM enables detailed analysis of damage evolution in wheel-rail contact, its high computational cost and limited ability to cover a wide range of operating conditions make its application for rapid prediction difficult. Xiao et al. [19] developed a novel hybrid physics-data framework for rapid and intelligent risk prediction. Within this approach, the results of high-fidelity FEM simulations of rolling contact and crack propagation are used to generate the database. The simulations are coupled with an automated algorithm for tracking the growth of three-dimensional surface cracks under different operating conditions. A Gaussian Process Regression model was then trained on the generated data to rapidly predict the risk index, enabling efficient condition assessment of wheelsets with considerably lower computational cost.

Such approaches can significantly facilitate and accelerate the process of structural analysis, fatigue assessment, and reliability evaluation, while also improving the obtained results.

2.4. Wheel–Rail Interaction, Wear and Vehicle–Track Interaction

Among various safety concerns, derailment prevention represents one of the fundamental priorities in railway systems. Accurate estimation of wheel–rail forces (WRFs) is important for assessing vehicle stability and derailment risk. Direct measurement using instrumented wheelsets is expensive and requires structural modifications, making it unsuitable for vehicles in regular operation. Zhang et al. [20] proposed an approach that combines a physics-informed Force–Moment Equilibrium (FME) model with deep learning-based correction networks for the indirect estimation of wheel–rail forces. The FME model first provides initial estimates of the lateral and vertical forces, after which neural networks learn to correct errors in the physical model caused by complex and nonlinear effects under real operating conditions, since the behavior of a real vehicle cannot be fully represented by an idealized physical model. The corrected forces are then used to determine the derailment coefficient. The proposed approach demonstrated high accuracy under different track conditions and showed potential for real-time monitoring of wheel–rail forces. In addition, geometric deviations, i.e., track irregularities, increase the probability of derailment. At the same time, the growing safety requirements in railway transport have increased the need for efficient identification of track irregularities using data from trains in regular operation. However, physics-based models depend on accurately known system parameters, while data-driven approaches often have limited interpretability. Dai et al. [21] proposed a novel Physics-Informed Kolmogorov–Arnold Network (PIKAN) for identifying vertical track irregularities based on bogie acceleration signals during straight-track operation. The KAN is directly embedded into the vehicle inverse dynamics model, so that the model follows the physical laws of the system during prediction while simultaneously learning from data without requiring prior knowledge of vehicle parameters. Based on the measured bogie accelerations, PIKAN identifies track irregularities and demonstrated higher accuracy and robustness than conventional data-driven neural networks. Another problem that occurs is wheel polygonal wear, which causes pronounced periodic vibrations at the wheel–rail interface, thereby compromising ride safety and increasing maintenance costs. Diagnostic solutions based solely on deep learning often have limited generalization capability under changing operating conditions and depend

heavily on large datasets, mainly because they neglect the frequency-dependent physical characteristics and the coupling between multiple wheels in wheel–rail dynamics. Xu et al. [22] applied the physics-guided neural network Co-FRF-NN, in which physical knowledge of wheel–rail dynamics is incorporated through a MIMO FRF-Net architecture. In this way, the model directly accounts for frequency-dependent vibration behavior and interactions among multiple wheels. The network was used to diagnose wheel polygonal wear based on vibration signals, achieving higher accuracy, better generalization across different speeds, and a reduced need for large amounts of data compared with conventional data-driven models.

Incorporating physical knowledge into AI models improves prediction accuracy, robustness, and reliability in complex vehicle–track interaction problems.

2.5. Aerodynamics

Physics-informed neural networks (PINNs) represent an increasingly important approach in flow simulation because they enable the simultaneous incorporation of physical laws and measured data when solving the Navier–Stokes equations and their variants. Zeng et al. [23] proposed a physics-informed data-driven strategy for reconstructing the time-averaged flow field around a train under crosswind conditions. Data and physics residuals are simultaneously incorporated into the PINN loss function, allowing physical knowledge to directly guide the reconstruction process. The authors also determined an optimal distribution of available data, while the reconstructed flow field showed good agreement with reference numerical simulations. Chen et al. [24] proposed a Neural Physics approach for high-fidelity train aerodynamic simulations, using CNNs whose weights are defined by classical numerical discretization schemes rather than learned through training. Applied to a freight train under calm and crosswind conditions, the method showed good agreement with numerical and experimental results.

Physics AI is highly relevant for railway vehicle aerodynamics, enabling accurate flow-field reconstruction with improved data efficiency and lower computational demands.

2.6. Other Significant Applications

From the perspective of pantograph–catenary interaction, Physics AI approaches have also been increasingly applied to the prediction, monitoring, and state assessment of these highly dynamic systems. Cheng et al. [25] developed a physics-informed surrogate model for the pantograph–catenary system that combines physical knowledge with deep neural networks. The physical equations are incorporated into the loss function, while a neural operator based

on Transformer and convolutional structures learns the complex relationships within the system. The model was successfully applied to response prediction and state identification using both simulation and real-world data. Chu et al. [26] proposed a model called FENet for this problem, which combines physical information with a data-driven approach. The model uses a Temporal Convolutional Network to extract short-term features and an attention-based LSTM to capture long-term dependencies, while constraints derived from the equations of motion are incorporated into the loss function so that physical principles can guide the learning process. In this way, fast and accurate prediction of the long-term dynamic response of the system under different external excitations is achieved with very low computational cost. Yan et al. [27] developed a machine-vision-driven physics-informed neural network (VIPINN) for state detection of the pantograph–catenary system. The model combines physics-guided feature extraction with analysis in both the time and frequency domains, while data loss and physics loss are simultaneously incorporated into the training process. VIPINN demonstrated higher detection accuracy and greater robustness to noise under complex operating conditions. Another approach was presented by Wang et al. [28]. They developed a surrogate model based on the Koopman Neural Operator approach for rapid prediction of the high-frequency dynamics of the pantograph–catenary system. The model was trained using data generated by a fully flexible FEM model, while physical consistency was incorporated into the loss function. FEM-level accuracy was achieved with a significant reduction in computational time.

Physics AI can also be applied to maglev systems. Ni et al. [29] applied Physics-Informed Neural Networks (PINNs) and Bayesian Physics-Informed Neural Networks (B-PINNs) to identify the parameters and states of a maglev levitation system from a small amount of noisy data. Incorporating physical laws enabled reliable problem solving even in the presence of measurement noise and external disturbances. In another study, Ni et al. [30] applied a residual-augmented PINN for probabilistic prediction of the response of a maglev levitation system under uncertain parameters. The model significantly improved accuracy and achieved approximately 440 times faster computation compared with the finite difference method. Another application of Physics AI was presented by Zhang et al. [31], who developed a multi-domain physics-informed digital twin for a hydrogen-powered maglev train. Physical constraints from the electrical, mechanical, magnetic, and energy domains were incorporated into the PINN model, enabling accurate real-time simulation of the complex system with low computational cost.

3. CONCLUSION

Based on the conducted literature review, it can be concluded that Physics AI has significant potential for application in various areas of railway engineering. The analyzed studies demonstrate different approaches and application possibilities, ranging from the prediction of dynamic and structural responses to condition monitoring, control, and system reliability assessment. Physical knowledge can be incorporated into artificial intelligence methods in different ways, thereby improving the accuracy, robustness, and physical consistency of the obtained results. In addition, such approaches can significantly reduce the time required for numerical calculations and simulations, as well as the overall computational demand. They are particularly important in problems where collecting large amounts of experimental data is expensive or difficult, since incorporating physical knowledge can reduce the dependence of models on data and improve their generalization capability. Based on the presented results, further development and wider application of Physics AI approaches can be expected in the design, analysis, monitoring, and control of modern railway systems.

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