CETRA2026 27-30 May 2026, Bol, Island Brač, Croatia
9th International Conference on Road and Rail Infrastructure

UTILIZATION OF AN FEM TURNOUT MODEL FOR SMART DIAGNOSTICS

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Abstract

Since 2020, DT, a Czech manufacturer of railway switches and crossings, has been developing smart turnout diagnostics in collaboration with Czech universities. This innovative system involves installing sensors within the turnout structure to capture its dynamic response during vehicle passage. Strain gauges and accelerometers are used to measure changes in the signals over time, and the resulting data are evaluated using machine-learning algorithms. The processed data are stored in a database, evaluated through machine learning and ultimately displayed in an application accessible to the railway infrastructure manager. This information can support more efficient maintenance planning for railway turnouts and reduce the need for operational staff to be present on the track. For the purposes of developing the diagnostic system, a finite element model of the turnout and vehicle was created in ANSYS and then transferred to LS-DYNA for further simulation. The first step is model validation, which is essential to ensure that the data obtained from the model can be considered reliable. This is achieved by comparing sensor data collected from a real track location with the results of finite element analysis. Once validated, the model can be used for further applications. In particular, it enables the simulation of extreme turnout operating conditions that cannot be measured under real track conditions, such as turnouts in an exceptionally good condition or, conversely, in a state that no longer allows safe operation. Another important application is the identification of the optimal sensor arrangement within the turnout for smart diagnostics. Finite element analysis makes it possible to identify suitable sensor locations, which can subsequently be used to assess turnout condition. In the future, the model is also expected to be used as a digital twin of a real turnout in operation. This paper describes the finite element model of the turnout and vehicle, the related validation activities, and its subsequent applications.

Keywords: turnout, FEM, finite element model, finite element analysis, smart diagnostics, predictive maintenance, model validation

1 Introduction

Turnouts are critical components of railway infrastructure, and their proper functioning is essential to safe and efficient railway operations. As some of the most highly stressed elements of the railway system, they require regular monitoring and maintenance. Traditional maintenance approaches are either preventive or reactive, but current trends are shifting towards autonomous and predictive systems [1, 2]. These advanced systems continuously monitor turnout conditions using sensors that detect vibrations generated by passing trains.

DOI: https://doi.org/10.5592/CO/CETRA.2026.1859

Intelligent software then analyses these signals to predict potential failures before they occur. This not only improves reliability and safety but also optimizes maintenance planning, reduces operational costs and minimizes the need for hazardous physical inspections, especially on high-speed lines [3]. Between 2020 and 2024, the national research project “Turnout 4.0” developed an intelligent diagnostic system for turnouts manufactured by the Czech switches and crossings producer DT. This work is being further refined in the ongoing “DiMoSC” project (Diagnostics of Movable Parts of Switches and Crossings) [4]. DT is the principal investigator in both projects, and the other consortium partners are Czech universities specializing in railway engineering: Brno University of Technology and the University of Pardubice. As part of this development, finite element models of turnouts and typical vehicles are used to simulate extreme operating conditions that cannot easily be observed in the field, such as significant vertical track defects, excessive wear of the crossing nose, or switch rail breakage. In the future, the model will be used as a digital twin of a specific turnout installed on the track. This article presents the finite element model used, and its intended future applications. Model validation is a critical step in confirming the model’s accuracy. This process involves comparing the signals measured by sensors on a real turnout with the dynamic response obtained from numerical simulation at corresponding points in the model. Initial validation was carried out on a section of track before the turnout, and plans are in place to extend it to the full turnout structure. From the perspective of developing the smart diagnostic system, the model can also be used to identify suitable sensor locations by focusing on sensitivity to dynamic responses. This approach enables the targeted selection of optimal positions for sensor placement, followed by the installation of sensors that can effectively capture data for autonomous diagnostics.

2 Finite element model of the turnout

2.1 Description of the turnout model

Dynamic simulations were performed using the Finite Element Method (FEM). The turnout model used for these calculations was developed in ANSYS. The model is three-dimensional and consists primarily of spatial finite elements, as shown in figure 1. This comprehensive model includes the turnout itself, together with sections of the track before and after the turnout. Beneath the track structure, the ballast bed is modelled and supported by a stabilization layer. The lower layers are represented by an elastic foundation using the Winkler type subgrade interaction model. The dynamic interaction between the vehicle and the turnout is modelled using a locomotive model that incorporates the key mechanical properties of the vehicle. The model takes into account the axles and wheelsets, including their suspension systems, as well as the articulated connection between the vehicle chassis and bogies, including suspension elements. It incorporates the correct mass distribution of the vehicle components together with spring and damping elements. Dummy motors, transmissions, and braking systems are also modelled. The vehicle model is based on production documentation, and the material models reflect the materials actually used. Geometric tolerances are also taken into account. The vehicle’s mass distribution, the stiffness of the supporting elements, and the suspension were calibrated to match the behavior of the real vehicle [5].

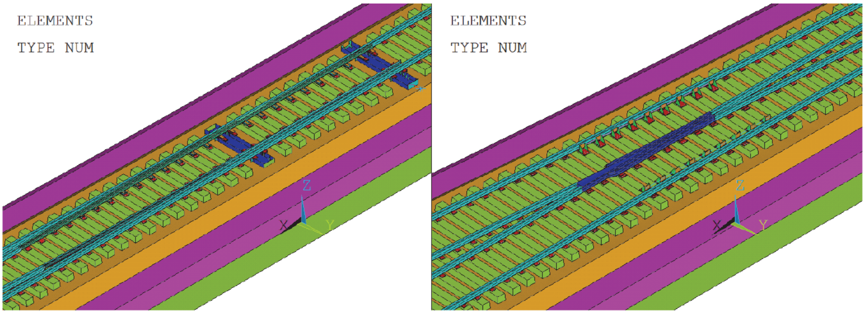

Figure 1 The turnout model is three-dimensional and consists primarily of spatial finite elements

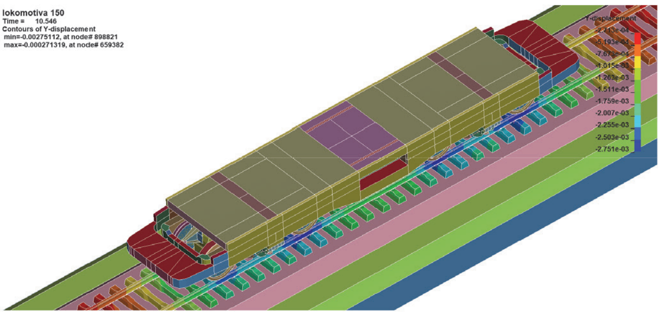

Figure 2 Example of a simulation result: vertical displacement of the turnout components under a moving vehicle load

To solve the dynamic response of a vehicle passing through the turnout, the turnout and vehicle models were transferred to the LS-DYNA. LS-DYNA is designed to solve high-speed dynamic phenomena using explicit numerical integration methods. A series of simulations were carried out for a vehicle travelling at different speeds. Structural defects in the turnout were then introduced to observe changes in the dynamic behavior of both the turnout and the vehicle. These simulations complement and extend the analysis of field-measurement results. Acceleration responses measured at the turnout crossing nose during train passage were analyzed to derive velocity and displacement data, which were then compared with the simulation results. The simulations provide additional insights into turnout behavior that cannot be captured by measurements alone. Figure 2 shows an example from the extensive result database, presenting the vertical displacement of the moving turnout components.

2.2 FEM turnout model validation

The aim of validating the computational model was to determine whether the signals generated by a real vehicle at a given turnout location corresponded to the signals obtained from the simulation. Relevant signals measured on the track for a known speed and locomotive type were selected for comparison. Figure 3 illustrates the selected signals used for comparison. On the left is the signal calculated in LS-DYNA, and on the right is the signal measured from a real vehicle. Piezoelectric materials generate an active voltage response under dynamic mechanical loading. The in-track voltage measurement was analyzed and converted to strain using a relationship published in [6], in which the strain rate is linked to the voltage generated by the piezoelectric element. The stress at the rail foot was then obtained by multiplying the strain by the modulus of elasticity.

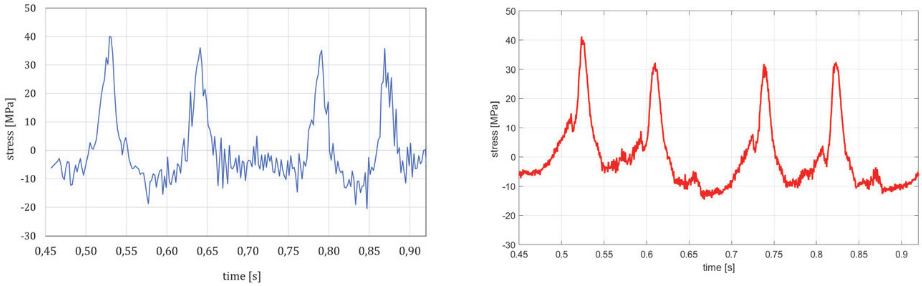

Figure 3 Comparison of rail stress from the numerical model (left) and from field measurement (right)

A comparison of the calculated and measured stress at the rail foot shows good agreement. The stress curves are similar in terms of periodicity, and their maximum and minimum occur at comparable moments. This confirms that the model captures the basic dynamic response of the turnout. Differences can be observed in the amplitudes with the measured data showing slightly higher values, while the model output is smoother. These deviations can be attributed to simplifications in the numerical model, as well as to factors related to operating conditions and the measurement environment. Nevertheless, the results are well correlated in their key characteristics, and the model reproduces the turnout's dynamic response with sufficient accuracy.

3 Applications of the model

3.1 Identification of optimal sensor locations

In the development of smart turnout diagnostics, a key area of research is not only the design of sensors capable of capturing the dynamic response of a vehicle passing through highly loaded areas (e.g. the fixed crossing nose), but also their arrangement within the turnout. Proper sensor placement ensures that the machine learning algorithms used to evaluate turnout condition on the basis of temporal changes in the measured signals can accurately detect all relevant faults [7, 8]. Based on long-term research, strain gauges (resistive sensors) and accelerometers were selected as the primary sensor types. Previous work at the Faculty of Mechanical Engineering, Brno University of Technology, also contributed to the development of piezoelectric sensors [9], which offer the additional advantage of energy harvesting and thus reduced power consumption [10]. The 3D finite element model of the turnout was then used to identify suitable sensor locations. This model can be used to analyze the dynamic response, specifically strain and acceleration during vehicle passage, across the entire monitored area of the turnout. The results provide a detailed profile of the monitored parameters, thereby guiding the selection of optimal sensor positions. Candidate locations identified from the theoretical analysis must subsequently be verified against the actual structural design of the turnout to confirm that sensors can be physically installed at the selected positions. Based on these analyses, an optimal sensor layout for the crossing nose area of the turnout was developed and subsequently protected as a utility model. A trial installation of the sensors in the proposed arrangement was also carried out on a real test turnout in the field. Figure 4 illustrates the sensor configuration for the crossing nose area.

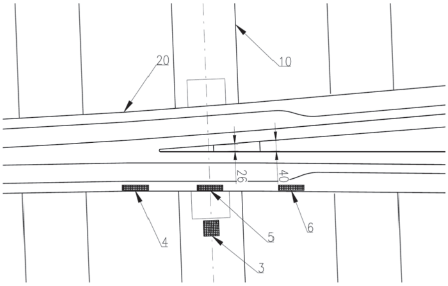

Figure 4 Section of the fixed crossing nose with the developed sensor layout for smart diagnostics; positions 4–6 are strain gauge sensors, while position 3 is an accelerometer

3.2 Simulation of turnout operational conditions

As part of smart turnout diagnostics, including condition prediction, machine-learning techniques (specifically neural networks) are used [11], and these require training on representative data. The typical training process is as follows. First, test turnouts are selected. This selection is based on the observed condition of the turnout (better or worse state), their operational load (higher loads are preferred because potential defects develop more quickly), the configuration of the turnout within the station, train passage speeds, and other factors. For the selected test turnouts, operational parameters are continuously monitored and converted into a global turnout condition index. These key parameters include track gauge, cant (superelevation), track alignment, wear of running rails and turnout components (e.g. the crossing nose and check rails), deviations from the ideal railhead profile, and settlement of the turnout area over time. Measurements are performed using both conventional methods (track gauges and railhead levelling) and more advanced techniques, such as specialized diagnostic measurement trains or 3D scanning of turnout running components. The scanned surfaces are then compared over time or under different traffic loads (figure 5).

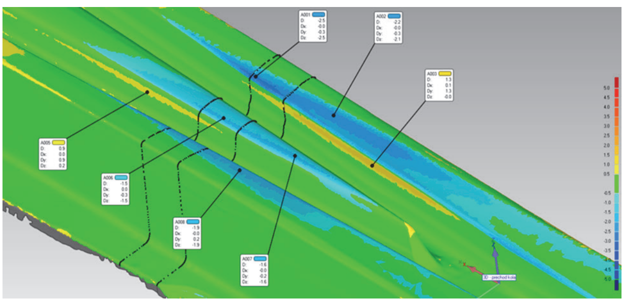

Figure 5 Example of wear on a fixed crossing nose measured with a 3D scanner

During research and development of the smart diagnostic system, a challenge arose in training the neural networks. Although the test turnouts were deliberately selected to represent both better and worse conditions, most of them were in a relatively similar, moderately good operational state. This reflects regulatory and normative requirements that keep operational parameters within defined limits so that safe train speeds can be maintained. For neural network training, however it is essential to include examples of both ideal conditions (theoretically perfect turnouts) and critical defects (such as rail breaks, crossing nose fractures, severe wear, or major geometric faults). Such defects cannot be artificially induced for testing purposes on in-service railway turnouts during normal passenger operations. To address this limitation, the finite element model of the turnout was used to simulate such conditions.

The model provides insight into the dynamic response under critical failure scenarios and generates data that can be used to train neural networks. This ensures that the system can detect not only minor deviations but also major defects that could compromise operational safety.

4 Conclusion

In the development of intelligent autonomous diagnostics, it is essential to use advanced tools that reflect the current state of technology in railway engineering. One key approach is computational modelling based on FEM. As three-dimensional modelling is routinely applied in turnout design, these existing 3D geometric models can be effectively used for subsequent static and dynamic analyses without additional geometric reconstruction. The performed basic validation carried out so far is less suitable in the fixed crossing area, because the dynamic response there is highly sensitive to the condition of the running surfaces, such as the nose and wing rails, ands well as to the quality of the transition zone. Further research will therefore focus on areas that are more dynamically stable, such as sections of plain track before or after the turnout or within the turnout closure panel. The turnout model is intended to be used as a digital twin in future applications. For a turnout model to be considered a digital twin, it must meet several key requirements that enable effective real-time monitoring and condition prediction. A digital twin is a virtual representation of a real turnout that provides detailed simulations and analyses of operational conditions based on current field measurements. A crucial factor is the realistic geometry of the turnout, which must accurately reflect its construction. In addition, the model must incorporate sensors that continuously monitor dynamic parameters during vehicle passage. These data must be synchronized with the digital model so that it provides up-to-date and accurate information on the turnout's condition. Another important aspect is the model's ability to perform dynamic simulations. These simulations include not only normal operation but also extreme scenarios, such as turnout wear, crossing defects, or the effects of weather on turnout functionality. This allows the model to predict the future condition of the turnout and optimize maintenance scheduling. For the effective implementation of a digital twin, emphasis is also placed on real-time updates based on field data, which allow potential failures to be identified before they occur. Furthermore, the model should support visualizations, which will be integrated into the web application. This is also planned as one of the outcomes of the DiMoSC project.
As part of ongoing research projects focused on the development of autonomous turnout diagnostics, including condition assessment and predictive maintenance strategies, a detailed 3D numerical model of the turnout type most widely used in the Czech Republic was developed. This was accompanied by a representative model of a commonly operated Czech locomotive. Following a comprehensive validation process, the model was used to optimize sensor placement within the turnout structure and to simulate operational loading states that cannot be directly measured under standard in-track conditions. In the next phase, the validated model will serve as a digital twin of a real turnout in service, enabling advanced monitoring, condition prediction, and decision support for infrastructure maintenance management. Similar procedures are being then prepared for the switch panel and for the crossing panel equipped by a swing nose crossing to extend the smart diagnostic coverage to other critical areas of the turnout.

Acknowledgements

The authors gratefully acknowledge the financial support provided by the Technology Agency of the Czech Republic under the Project No. CL02000125, Advanced Diagnostics of Railway Turnout Movable Parts (DiMoSC).

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