



## DIGITIZATION OF CONDITION MONITORING FOR CRITICAL PARTS OF THE TRACK SUPERSTRUCTURE

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### Abstract

The digitization of railway infrastructure is a major focus of current research and development across universities, research institutes, industry, and railway administrations. The primary aim is to improve the efficiency of monitoring and diagnostics by limiting manual inspections, enabling continuous or near-continuous data acquisition, and providing reliable assessments of technical condition to prevent failures and anticipate maintenance needs. Achieving this requires advanced sensing technologies capable of long-term operation under harsh track-side conditions. Equally important is the correct placement of sensors to obtain diagnostically meaningful data. The resulting large data volumes must be systematically stored, managed, and analyzed to extract information relevant to infrastructure condition. Modern digital approaches are applied, including IoT architectures, Digital Twin concepts with numerical models, and AI/ML techniques. However, machine learning alone is not sufficient. Effective diagnostics and prediction must be grounded in a mechanical understanding of track behavior, degradation mechanisms, and load–response relationships. Data-driven models must therefore be integrated with physics-based models and risk-informed frameworks that account for uncertainty, failure consequences, and operational criticality. Since track condition degrades over time due to traffic and environmental effects, predictive maintenance requires probabilistic and statistical tools combined with engineering judgement. An essential aspect is the integration of diagnostic outputs with maintenance and asset management systems, ensuring that results are clearly visualized and actionable for decision-makers. Research teams at Brno University of Technology, together with industrial partners, focus particularly on railway superstructure components, especially turnouts, where failures are costly and operationally disruptive. Current activities address the digitization of diagnostics for turnouts, crossings, switch blades (including tongue breaks), and bonded insulated joints. Infrastructure managers show increasing interest, and practical deployment of these systems is expected in the near future.

*Keywords: railway infrastructure, condition monitoring, digital diagnostics, machine learning, sensing, IoT, predictive maintenance*

### 1 Introduction

Safety and reliability are fundamental requirements in the design, operation, and modernization of railway infrastructure. A wide range of faults and defects of varying severity must be considered in relation to operational safety at both infrastructure and rolling stock levels. If insufficiently monitored, such defects may lead to critical failures, including derailments.

Early detection, diagnosis, and prediction are therefore essential not only for optimizing maintenance strategies and reducing lifecycle costs through timely interventions, but also for limiting infrastructure degradation and preventing major safety incidents [1, 2]. Among railway track components, switches and crossings are exposed to the highest dynamic loading. The most severe dynamic effects typically occur at fixed common crossings, where rail continuity is interrupted, and longitudinal stiffness variations are present. Mitigation of impact forces in these areas has been widely studied in European research initiatives, which have also highlighted the need for continuous autonomous monitoring as a technological basis for predictive maintenance. With increasing traffic intensity and operating speeds, manual inspection becomes progressively less feasible, while time windows for maintenance interventions become significantly constrained [3].

Corrective and preventive maintenance remain the dominant approaches for railway superstructure components, but they are associated with high operational costs and inefficient material utilization due to the frequency of scheduled interventions. Predictive maintenance offers an alternative by enabling the identification of early-stage deterioration and preventing structural failures. When based on systematic measurements of selected structural parameters, it can reduce both maintenance complexity and service disruptions [4, 5]. A particularly promising approach is model-based condition monitoring, which compares measured structural behavior with expected responses derived from physical or mathematical models. However, artificial intelligence and machine learning techniques applied within such systems must be informed by a mechanical understanding of structural behavior and embedded within risk-based assessment frameworks. Data-driven methods alone are insufficient unless they account for degradation mechanisms, load–response relationships, uncertainty, and the operational consequences of failure [6, 7].

The most common defects requiring repair or replacement of switches and crossings are non-uniform support of bearers in the ballast bed and wear of the crossing. Both mechanisms alter the wheel transition trajectory between the wing rail and crossing nose, significantly increasing dynamic impact forces. Experimental studies have demonstrated that acceleration and strain signals measured directly on turnout structures contain valuable diagnostic information on such defects, enabling their identification beyond the capabilities of conventional inspection methods [8, 9]. Recent research has therefore focused on the development of intelligent, autonomous diagnostic systems for railway turnouts, particularly in the crossing area. These systems integrate acceleration and strain measurements obtained directly from the structure with dynamic responses recorded on passing vehicles. AI and ML techniques are employed within the evaluation algorithms, but their outputs are cross-validated using physics-based models and interpreted within a mechanics- and risk-informed decision framework to support reliable maintenance planning. An overview of the system developed within the framework of the Turnout 4.0 project [10] is presented in figure 1.

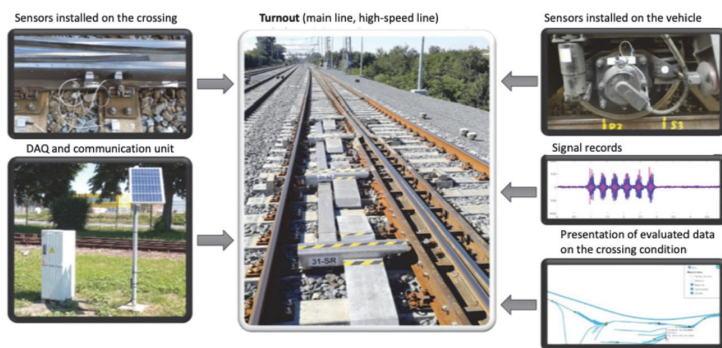


Figure 1 Overview of the diagnostic system turnout 4.0 [3]

At present, several commercially available systems employing digital technologies are used for the condition monitoring of switches and crossings. Commercial diagnostic platforms include Zentrak (formerly Roadmaster, VAE) [11], KONUX (Konux) [12], TrackSwitch360 (Rail-Monitor), POSS (Strukton), Survaig (Vossloh), Intelligent Infrastructure (Siemens), Continuous Track Control (FTS), ESAH (DB), and DSRT (DSRailTech).

According to publicly available information, the German company KONUX deploys its diagnostic solutions on railway switches and crossings. Its website ([www.konux.com](http://www.konux.com)) presents case studies documenting the use of its system by infrastructure managers such as Network Rail, Infrabel, and Deutsche Bahn. Among more recent systems is the DSRT platform by DSRailTech, which focuses primarily on monitoring dynamic responses. The diagnostics are oriented toward the detection and analysis of vibration signals generated during train passage over the common crossing. For movable components, these systems typically monitor only the electrical parameters of point machines and verify the attainment of the final (end) position. Furthermore, some of the above-mentioned systems are integrated with diagnostic solutions for plain line track, for example, for detecting rail breaks, obstacles, and other anomalous conditions. None of these diagnostic systems is currently installed or undergoing testing in the Czech Republic.

## 2 Digital diagnostic and monitoring system technology

Each autonomous, digitally implemented, model-based condition monitoring system consists of key components enabling operation and provision of diagnostic information:

- sensing technology, including sensors and DAQ systems, and means for transmitting, storing, and providing signal data
- an evaluation subsystem deriving diagnostically relevant information from measurements
- a mathematical, usually numerical, model of the structure or its element, implemented as a digital twin (DT)
- algorithms processing diagnostic data to forecast technical condition
- and mechanisms for communicating outcomes to infrastructure managers, from operational personnel (e.g., track supervisors) to middle management (e.g., track administrators).

Current technologies include acoustic emission monitoring, vibration measurement via accelerometers, and mechanical stress sensors using strain gauges or optical fibres. Long-term goals focus on wireless sensor nodes with active sensing elements, such as piezocomposite sensors [13], which operate with low power via energy harvesting or alternative sources. These nodes can complement or replace conventional systems and integrate into IoT infrastructures [14], installed either on rail vehicles [15] or within fixed infrastructure [16]. When a vehicle passes, rail deformation and vibration generate signals processed locally and transmitted to cloud storage.

### 2.1 Piezoelectric-based sensing techniques for railway infrastructure diagnostics

Predictive maintenance of the railway superstructure requires sensing technologies that provide physically interpretable quantities directly linked to structural degradation. While accelerometer-based systems are common, strain-based piezoelectric sensing integrated into rail components offers a more direct measure of mechanical demand. Macro Fiber Composite (MFC) piezoelectric sensors are a robust, experimentally validated option for railway monitoring [17]. Piezoelectric sensing allows direct estimation of rail deformation from measured voltage using established electromechanical relationships, requiring only a single numerical integration [17]. Unlike accelerometer-based systems, which need double integration and are prone to low-frequency drift, piezoelectric measurements are suitable for frequency-do-

main vibration analysis. Field experiments under realistic operating conditions confirm long-term stability and robustness against dynamic impacts [17]. Strain is a key variable directly associated with fatigue damage, local stiffness loss, wear, impact amplification, and wheel–rail dynamics. Reviews of smart railway technologies highlight the growing importance of embedded, component-level sensing for predictive maintenance [18]. IoT-enabled frameworks stress the need for scalable sensor networks capable of continuous, long-term operation [19]. Analyzing piezoelectric signals allows integration with physics-based degradation models and digital twins, improving condition assessment and prognosis.

## 2.2 Representation of sensor-derived data and edge-oriented computational architectures

The added value of piezoelectric sensing resides not only in its high measurement sensitivity but also in its capacity to transform raw measurements into diagnostically informative representations. Realizing this potential, however, necessitates appropriately structured data representations for downstream signal processing. At the sensing node, piezoelectric signals can be mapped to feature vectors comprising, for example, peak strain amplitudes, strain envelopes, load-cycle histograms, and frequency-band energy distributions. These derived features provide compact yet information-dense representations that are well-suited for subsequent machine learning–based inference.

Distributed machine learning paradigms tailored for Internet of Things (IoT) environments have been extensively surveyed in [20], establishing the viability of hierarchical architectures in which lightweight inference models are deployed at the edge, while model training and long-term adaptation are performed in the cloud. Within the proposed framework, pre-trained models, such as anomaly detection classifiers or degradation-state estimators, can be embedded directly on the microcontroller of the communication module. This configuration facilitates real-time classification of structural conditions, identification of abnormal impact signatures, and computation of condition indices prior to data transmission.

## 2.3 IoT communication

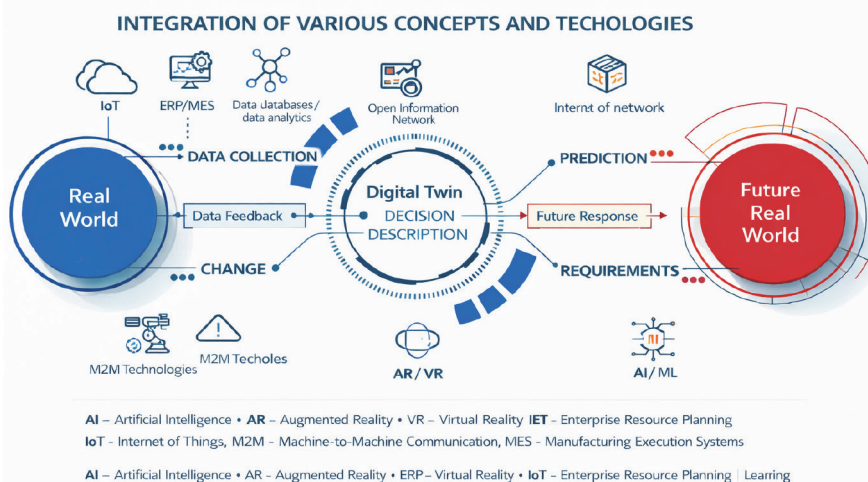
Within this framework, Internet of Things (IoT) communication technologies do not constitute the primary locus of innovation; rather, they function as an enabling infrastructure that interconnects distributed sensing nodes with the digital-twin environment. Cellular IoT standards such as NB-IoT and LTE-M have demonstrated their suitability for machine-type communications, providing extended coverage and standardized integration into existing cellular networks [21]. In parallel, emerging non-cellular, 5G-oriented technologies such as DECT-2020 NR offer scalable communication paradigms that support high-density IoT deployments [22, 23], while mesh-based energy consumption analyses substantiate their appropriateness for low-power, distributed systems [24]. Heterogeneous multi-RAT (Radio Access Technology) communication architectures further enhance communication reliability by supporting adaptive interface selection mechanisms that take into account prevailing radio channel conditions as well as application- and service-specific data priorities. This tight integration of sensing, edge-level inference, and communication functionalities is consistent with emerging paradigms of intelligent integrated sensing and communications (ISAC) envisioned for next-generation network architectures [25].

Crucially, the microprocessor embedded within the communication module is no longer restricted to protocol management but operates as an active computational node capable of executing machine learning inference workloads. This functional convergence of communication and data-driven analytics effectively transforms the IoT node into an autonomous diagnostic agent within the overarching distributed digital-twin ecosystem.

## 2.4 Digital twin technologies

The digital twin functions as an integration layer that connects sensing data, physics-based models, and data-driven predictors. Rather than being treated as a purely geometric representation or visualization tool, it is conceptualized here as a hybrid modelling environment that combines reduced-order structural models with data-driven updating mechanisms. Signal-derived condition indices are computed at the IoT edge and provided as inputs to the digital twin, which assimilates them with vehicle-track interaction models and historical maintenance records to infer asset degradation and estimate the remaining useful life. This hybrid methodology alleviates the extrapolation constraints inherent to purely data-driven frameworks while maintaining favorable computational scalability. Consequently, the digital twin undergoes continuous, state-dependent evolution driven by real-time strain measurements, rather than being updated only at discrete inspection intervals.

For infrastructure managers to make well-founded decisions, it is necessary to establish a continuous process of innovation and organizational learning and to systematically exploit emerging technologies such as data science and predictive simulation. Central to this development is the integration of digital twin technology into the infrastructure management workflow (figure 2). Artificial intelligence (AI) systems and machine learning (ML) methods are employed to detect and classify individual defects, while analytical insights derived from large-scale data (big data) provide critical information to enhance the efficiency of operational processes and maintenance activities. The analysis of acquired signals relies on both established and newly developed approaches, incorporating advanced evaluation methods that enable diagnostic applications for condition assessment and predictive maintenance of railway infrastructure and rolling stock. Furthermore, numerical modelling is utilized to identify and characterize typical dynamic signatures associated with specific defect types [26].



**Figure 2** Overview of a model-based condition monitoring system (based on Boom P. Demystifying the digital twin for railways, Bilbao: RailTech, 2021.)

The fundamental prerequisite for constructing a digital twin is rigorous preparatory work comprising three principal stages: (i) formulation of an appropriate mathematical model that captures the behavior of the railway structure or its constituent components, (ii) deployment of suitably selected sensors at critical locations on the structure, and (iii) establishment of a bidirectional interconnection between the model and the physical asset. Hybrid digital twin frameworks typically integrate model-based and data-driven methodologies, relying on necessary

model simplifications together with the acquisition, processing, and interpretation of measurement data by means of artificial intelligence (AI) and machine learning (ML) techniques [27]. A mathematical model constitutes the fundamental component of a digital twin. Its construction can follow two principal approaches: (i) derivation from simulations, most commonly through numerical solutions of differential equations, or (ii) identification from real operational data. Digital twins based on numerical simulation, typically implemented via the finite element method (FEM), are directly associated with the solution of systems of differential equations that characterize the physical behavior of the analyzed structure under various operating conditions [28]. These models are generally highly detailed, employing fine spatial and temporal discretization, and are therefore suitable for investigating both static and dynamic responses. Computational modelling further enables the identification of characteristic dynamic signatures associated with specific fault states within the model, which can subsequently be tracked in practice by analyzing measured signals (figure 3).

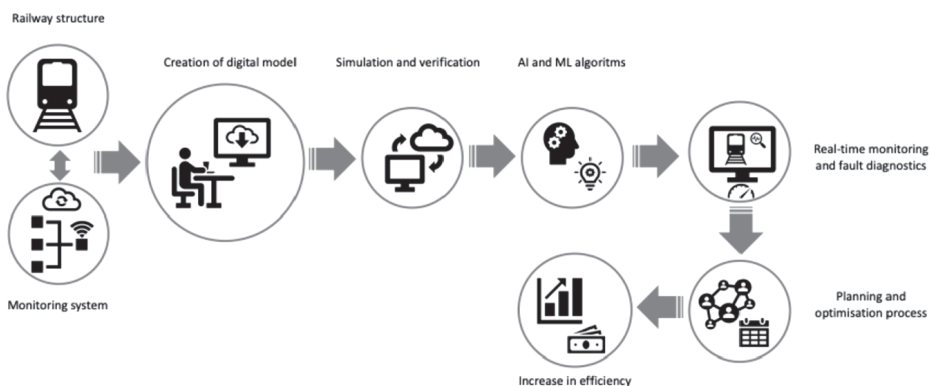


Figure 3 The process of digital twin development and implementation

## 2.5 Scientific challenges and strategic direction

The principal scientific contribution of the proposed approach resides in the systematic integration of piezoelectric sensing, edge-based machine learning, and digital twin modelling into a unified, coherent predictive maintenance framework for the railway superstructure. First, piezoelectric sensing furnishes a physically interpretable degradation metric that is inherently compatible with fatigue- and stiffness-based prognostic and structural response models. Second, the deployment of lightweight machine learning inference algorithms within embedded communication modules enables real-time classification of structural states without the need for continuous, high-bandwidth data transmission. Third, the digital twin functions as a dynamic data–model integration framework in which strain-derived condition indicators continuously update hybrid physics–data models, thereby facilitating the estimation of degradation trajectories instead of limiting the assessment to isolated anomaly detection.

By reconceptualizing Internet of Things (IoT) communication as a data transport backbone that underpins distributed digital twin architectures, the proposed framework transcends conventional structural health monitoring implementations and advances toward autonomous, scalable, and predictive infrastructure management systems. The integration of physically interpretable sensing modalities, embedded computational intelligence, and hybrid modelling approaches (combining physics-based and data-driven models), constitutes a technologically mature and implementable pathway for the digitalization of railway infrastructure and the optimization of its long-term lifecycle performance.

### 3 Examples of projects currently being implemented

#### 3.1 Advanced diagnostics of moving parts of railway switches and crossings – DiMoSC

The successor to Turnout 4.0 is the DiMoSC project (Advanced Diagnostics of Moving Parts of Railway Switches and Crossings, 2025–2027), funded by the Technology Agency of the Czech Republic (TAČR) under the Transport 2030 programme. The principal beneficiary is DT – Výhybkárna a strojírna a.s., with Brno University of Technology and the University of Pardubice as collaborators. Railway crossings with movable parts are increasingly deployed, offering higher travel speeds, improved guidance in curves, and reduced lifecycle costs by limiting frequent replacement of dynamically loaded components and bearer tamping. For high-speed lines, movable crossings are essential, as conventional fixed crossings are limited to 200 km/h (TSI Infrastructure). Minimizing line access for maintenance is critical. The project aims to develop an autonomous device for comprehensive condition monitoring of turnouts installed at the movable crossing nose. It will assess the state of critical moving elements and adjacent structures using application-specific dynamic response sensors. A dedicated database, autonomous data acquisition and communication system, and machine learning software for data processing have been developed, along with a user interface and visualization tools for interpreting diagnostic outputs.

Mathematical modelling generates computational representations of turnouts and vehicles. Detailed models cover conventional and high-speed turnouts with various structural configurations. The track bed is represented by ballast on a stabilizing layer, with the subgrade modelled as a Winkler foundation. Modular turnout segments, plain track, front/middle/rear sections, switch, and crossing zones, allow assembly of alternative configurations. Vehicle–turnout dynamic interaction applies inertial effects directly, rather than prescribed wheel–rail forces. A representative locomotive model includes axles, wheelsets, bogie connections, suspensions, drive units, gearboxes, braking systems, and appropriate elastic/damping elements. Constitutive material models match actual vehicle materials, and assembly clearances are included. The vehicle model is calibrated for mass distribution, stiffness, and suspension behavior. Turnout–vehicle dynamic response is analyzed within the LS-DYNA finite element environment.

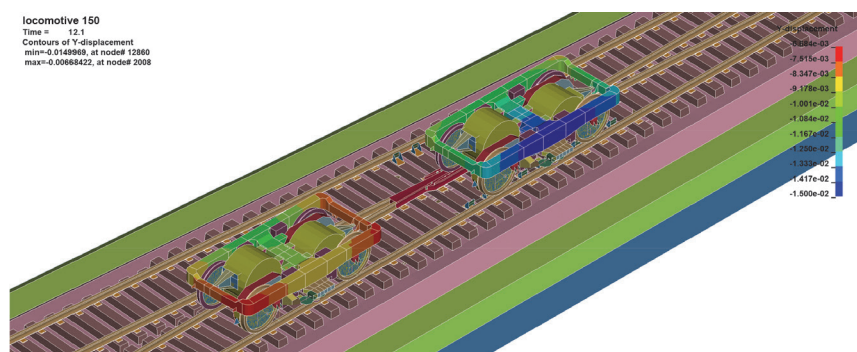


Figure 4 Numerical model of a railway turnout as a foundational component of a digital twin, incorporating detailed models of locomotive bogies

The project entails the development of a prototype diagnostic system for railway turnouts, which will be installed on the track for operational testing by the infrastructure manager, in accordance with mandatory procedures applicable to any new product or innovation.

Prior to trackside installation, it will be necessary to demonstrate the safety of the device, particularly with respect to electromagnetic compatibility and other safety requirements arising from the functional and operational characteristics of this type of equipment. Before deployment, the resulting prototype must undergo laboratory testing as prescribed by the aforementioned standards and related normative documents, as well as additional tests required by the internal regulations of the Czech railway infrastructure manager.

### 3.2 SMART rail glued insulated joint – SMARTLIS

The experience gained by research teams in the application of digital technologies for monitoring the condition of railway superstructure components has prompted the extension of these methods to the diagnostic assessment of glued insulated rail joints (LIS). In this context, the SMARTLIS research project (SMART rail glued insulated joint, 2024–2026) is being carried out with the support of the TAČR TREND programme. The principal beneficiary of this support is Form–Thermit, spol. s r.o., with Brno University of Technology and Drážní revize s.r.o. acting as co-beneficiaries.

The system developed for LIS will provide predictive recommendations for tamping activities and, in severe cases, for the replacement of glued insulated rail joints. This will prevent short-circuiting of track circuits and consequent disruptions to rail operations. In addition, the early detection of infrastructure damage resulting from technical defects will help to reduce dynamic loads on both the track and rolling stock, thereby lowering the associated maintenance expenditure and mitigating degradation processes. This, in turn, will extend the service life of infrastructure and vehicles and contribute to additional savings in material consumption and energy use.

Impact forces can be quantified using conventional sensors for physical quantities, such as accelerometers and strain gauges. Current research activities are concentrated on the application of piezoelectric materials for the detection of mechanical variables in railway superstructure components, an approach originally developed for aircraft structures. In 2022, initial experimental tests were conducted involving the installation of piezoelectric elements on glued insulated joints that are already in regular operation. The response of these elements is currently being measured and analysed for the development and validation of the SMARTLIS system. The response of commercial MFC piezoelectric structures to the passage of trains was experimentally investigated, with the MFC elements adhesively bonded to the exterior surface of the existing LIS (figure 5).

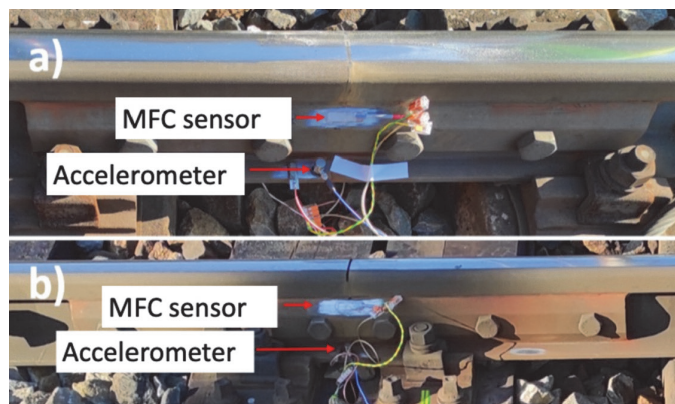
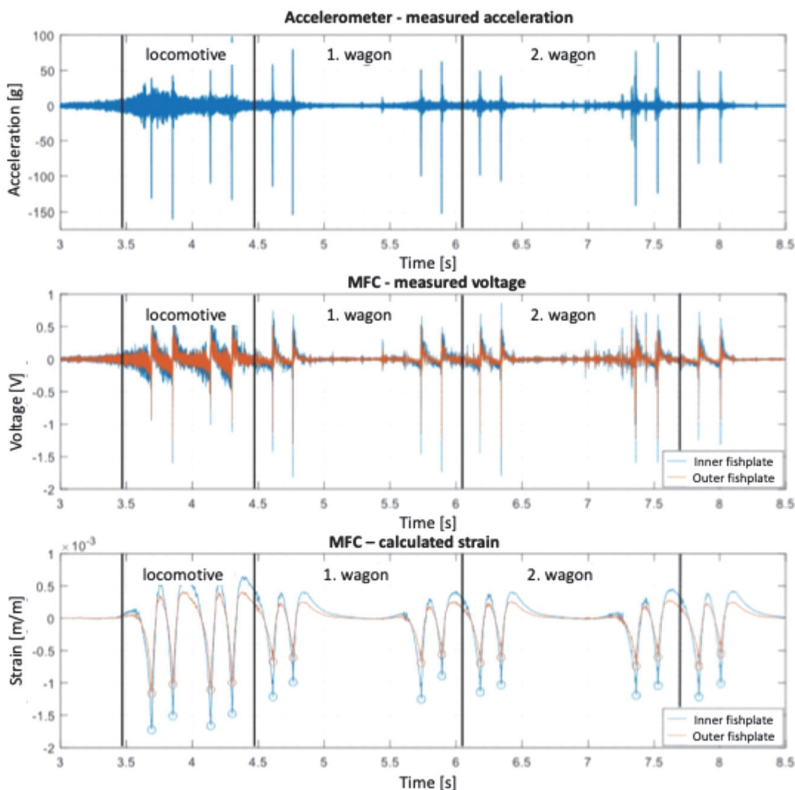


Figure 5 Test measurements with laboratory measuring equipment on two types of LIS: a) short LIS, b) long LIS

The measured response was compared with conventional acceleration measurements, in which accelerometers were mounted on both the LIS and the sleeper to characterize the mechanical behavior during train passage. A comparison between the acceleration signal and the voltage generated by the active MFC is presented in figure 6.

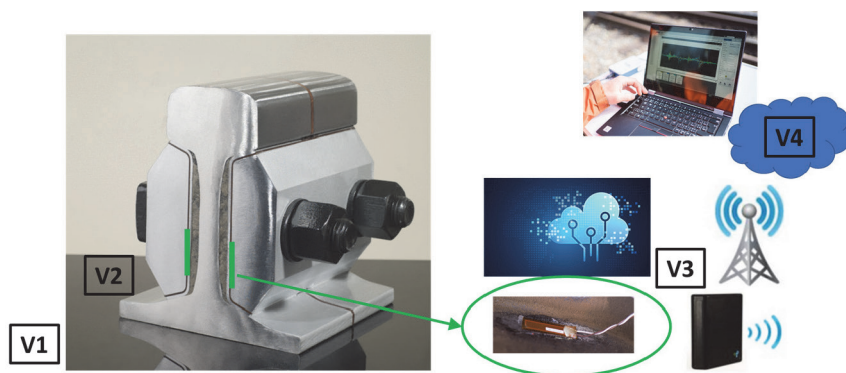
A principal advantage of this approach is that the voltage generated by the piezoelectric element is proportional to the mechanical stress and to its rate of change. In contrast to conventional resistive strain gauges, piezoelectric elements do not require an external power supply, which substantially increases the operational lifetime of battery-powered monitoring systems. Moreover, piezoelectric materials exhibit a significantly higher sensitivity to dynamic phenomena, and, based on appropriate mathematical models developed for a given element, the deformation of the piezoelectric layer – and therefore of the underlying structural component – can be readily determined. Consequently, the deformation of the LIS under load can be evaluated; see the lower plot in figure 6.

Based on the measurements obtained to date using laboratory-grade instrumentation during the measurement campaign, it can be inferred that the processed electrical response signal of the piezoelectric structure exhibits a direct correlation with the mechanical stress acting on the component. These findings indicate that the proposed measurement and data-processing methodology is suitable for in situ deployment using edge-computing architectures. In comparison with commonly employed accelerometers, the proposed solution demonstrates substantially greater practicality, not only with respect to hardware integration and installation, but also for the evaluation of mechanical quantities, as it yields significantly more relevant and accurate information.



**Figure 6** Acceleration and electrical voltage signals recorded during the test measurement, evaluation of the strain of the electrical voltage signal

As part of the project, an innovative modification of the existing mechanical design of the glued insulated joint was proposed, enabling the effective integration of a piezoelectric sensor system (figure 7). The sensor system is based on commercially available piezoelectric composite structures which, owing to their optimized placement on the SMARTLIS mechanical structure, generate an electrical signal during the passage of rail vehicles. The proposed solution additionally incorporates Edge Computing and wireless M2M (Machine-to-Machine) communication. The data processed and evaluated within the edge unit will be representative of the operational condition of SMARTLIS and its mechanical loading state. The communication architecture will employ mobile network technologies and will support the direct storage of processed data in a cloud environment. Based on these data, it will be possible to determine the technical condition and assess the long-term behavior of the glued insulated joint. These results will be visualized in a dedicated software application and will serve as a basis for predictive maintenance.



**Figure 7** Illustration of the SMARTLIS system concept: (V1) and (V2) cross-section with sensors, (V3) edge computing and IoT devices, (V4) personalized display of stored data

The data are transmitted via a secure communication channel to a cloud storage environment, where they are made available for subsequent processing, predominantly employing machine learning (ML) methods. The acquired data are interpreted on the basis of computational models implemented within a software application, which provides end users with information on the operational status of individual SMARTLIS devices, their geographic position, and battery charge level, and further generates alerts regarding required maintenance activities or the necessary replacement of the bonded insulated contact. Individual customers can continuously monitor the status and condition of specific SMARTLIS units installed along the track via the application interface.

### 3.3 Diagnostics and monitoring of switch rail cracks in railway switches

Another initiative concentrating on the application of digital technologies in inspection processes is the DIAGJAZ project (Diagnostics and Monitoring of Rail Switch Rails, 2025–2027). This project is being implemented with the support of the Technology Agency of the Czech Republic (TAČR) within the framework of the Transport 2030 programme. The primary beneficiaries and implementing institutions are ZAT, a.s., and Brno University of Technology. The project aims to prevent railway accidents and minimize risks to human health and assets by developing a tool for continuous monitoring and diagnostics of switch rails. Current ultrasonic inspection methods reduce fracture risk but have limitations: temporal gaps may allow fatigue cracks to propagate, and early-stage cracks may be inaccessible or weakly detectable.

A central emphasis of the project is therefore the systematic acquisition, processing, and visualization of monitoring data, as well as the derivation and communication of diagnostic recommendations. These functionalities are intended to be realized within the ZAT platform environment through the integration of Internet of Things (IoT) technologies, which are already routinely deployed by the company in applications for its customers, including but not limited to rail transport.

The project focuses on systematic acquisition, processing, and visualization of monitoring data, integrated within the ZAT IoT platform. Research targets continuous monitoring of operational loads, especially fatigue stresses in critical regions. Sensor systems with communication modules are developed, and analytical outputs will provide predictive maintenance recommendations. When fatigue life is exhausted, preventive rail replacement is advised. Crack formation from extreme load events is addressed via an acoustic monitoring system installed on the rail tongue, analyzing sensing-element interactions. Anomalous signals trigger operator alerts with visualized diagnostics and replacement recommendations. Once the optimal diagnostic principle is identified, a fully integrated device will be developed, including evaluation, data transmission, and visualization modules. The device will be validated in realistic conditions, designed for practical applicability, long service life, and cost-effectiveness while accounting for rapid changes in the electronics market.

## 4 Conclusion

The digitization of condition monitoring for critical components of the railway superstructure constitutes a fundamental milestone in the development of modern, safe, and sustainable railway infrastructure. The digital transformation of diagnostics and monitoring processes within the railway superstructure provides a systemic instrument for managing the safety, reliability, and economic efficiency of railway infrastructure operation. The integration of sensor technologies, mobile diagnostic systems, and advanced data analytics facilitates a shift from traditional interval-based maintenance strategies to intelligent, data-driven lifecycle management of superstructure assets. The technological convergence of sensors, data platforms, and analytical methodologies enables effective lifecycle management of critical superstructure elements and establishes the foundation for the future evolution of smart railway systems.

In the long term, this development represents not only a technological innovation but also a paradigmatic transformation in the governance and operational management of railway infrastructure.

## Acknowledgement

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