

DIGITAL TWIN VISION FOR RAIL HEALTH MONITORING FOR FREIGHT RAILROADS

SILVIA GALVÁN-NÚÑEZ^{†*}, ANISH POUDEL^{†*}, ANANYO BANERJEE[†], AND CHRIS JOHNSON[†]

ABSTRACT

This paper presents a vision and case study for a framework to implement the digital twin (DT) concept to support rail health monitoring and management in North American freight railroads. The DT system includes a DT of physical rail, rail maintenance and inspection data, digitalization processes for recording pertinent information, and software and analytics tools. The case study uses the 2.8 mi (4.5 km) Facility for Accelerated Service Testing (FAST[®]) track to assess the DT's ability to meet rail owners' requirements and provide necessary contextual information. At FAST, data streams generated by operations, maintenance, wayside and onboard detector technologies, and individual testing are employed to better understand the effects of heavy axle loads on track components at various stages of wear. The case study also demonstrates that actively managing rail health requires a methodological approach to collecting and managing data for predictive, preventive, and corrective maintenance strategies informed by rail metallurgy, operational factors, environmental factors, and rigorous maintenance techniques. Although the case study considers only FAST rail infrastructure, the DT system's scalability indicates its potential for larger implementations both within and beyond FAST.

KEYWORDS: rail, digital twin (DT), artificial intelligence (AI), Internet of Things (IoT), Facility for Accelerated Service Testing (FAST), FAST Internal Records for Statistics and Testing (FIRST), wayside inspection

Introduction

The railway industry is undergoing a significant transformation driven by the need for greater safety, operational efficiency, and sustainability. Among emerging technologies, the digital twin (DT) concept has gained relevance in recent years as a framework for creating virtual representations of physical assets or processes, enabling real-time monitoring, predictive analytics, and lifecycle management. Originally conceptualized in aerospace and manufacturing (Grieves and Vickers 2017; Shao and Helu 2020), DT technology is increasingly being adopted in railway systems to address challenges such as infrastructure degradation, maintenance costs, and the complexity of asset interactions.

Recent literature reviews and bibliometric analyses indicate increased effort in DT research within the railway sector. One study highlights a taxonomy of DT components—including data acquisition, modeling, integration, and lifecycle—and notes that most DT applications focus on maintenance and condition monitoring (34%), system performance optimization (29.4%), and inspection/defect detection (19.32%) (Ghaboura et al. 2023). Another recent article found that, while DTs have optimized maintenance strategies, barriers such as data integration challenges, high implementation costs, and cybersecurity risks, as well as the need to identify research clusters and gaps, persist in DT adoption for railways (Thompson et al. 2025; Zhang et al. 2025).

In terms of implementation maturity, the most recent developments target infrastructure maintenance, with static assets like tracks and facilities modeled frequently, while dynamic components such as signaling and traffic management remain under-represented (Krmac and Djordjevic 2024). Other case studies show practical DT applications for lifecycle management and resilience, including building information modeling (BIM)-based twins for metro systems and DT architectures for railway infrastructure (Kaewunruen et al. 2021; Doubell et al. 2023).

Rail inspection, a critical component of railway safety, presents a unique challenge to DT integration. Inspection methods can be labor-intensive and are often constrained by data scarcity, particularly for defects. Recent research addresses these limitations by combining physics-based simulations with data-driven approaches (Chen Shen et al. 2025; Ramatlo et al. 2020, 2023) and by generating synthetic data using artificial intelligence (AI) and procedural modeling (Ahmad et al. 2024). Similarly, researchers have proposed a DT-based nondestructive testing (NDT) method for bridge monitoring using multi-fidelity surrogate models, and the integration of the Internet of Things (IoT) and edge-cloud computing for

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continuous structural health monitoring of railway bridges (Lai et al. 2024; Armijo and Zamora-Sánchez 2024).

The reviewed literature indicates that while DTs offer significant potential for railway inspection and maintenance, data scarcity remains a critical barrier to broader implementation. The problem of data scarcity is not limited to new routes but also affects older routes, where the track structure is constantly evolving through rail, tie, and fastener replacements. To mitigate this, researchers increasingly rely on synthetic data generation and hybrid modeling techniques to simulate defect signatures that are rarely captured in operational data. However, current field implementations are largely siloed, focusing on individual components such as a single bridge or rail section rather than on collaborative, networked systems, suggesting that DT implementation and adoption in railroad systems are in the early stages. Additionally, there is a lack of standardized frameworks for integrating heterogeneous data sources, and the industry faces barriers related to high deployment costs and cybersecurity vulnerabilities. Future research directions identified in the literature include the development of collaborative or federated DTs that integrate multiple asset twins, the use of generative AI to further bridge data gaps, and the creation of standardized protocols to ensure interoperability.

The remainder of the paper presents (1) a brief overview of the Facility for Accelerated Service Testing (FAST), which serves as a research, development, and testing ground; (2) the DT vision and concept for rail health monitoring in freight railways; (3) a case study for DT design and implementation for rail health monitoring at FAST; and (4) discussions and conclusions.

FAST Overview

MxV Rail, a subsidiary of the Association of American Railroads (AAR), operates FAST under the AAR Strategic Research Initiatives (SRI) program. Since its creation in 1976, FAST has emerged as an industry-leading facility that tests and evaluates infrastructure and mechanical components and systems under heavy axle loads in a controlled environment. In 2023, MxV Rail built a new FAST test loop—an improved version of the previous loop—consisting of 2.8 mi (4.5 km) of mainline track designed to enhance the testing capabilities of track/mechanical components and inspection technologies (Johnson 2024). The FAST loop contains multiple tests, including, but not limited to, rails and welds, ties and fastening systems, ballast, rail neutral temperature monitoring, one-way low speed (OWLS) crossings, insulated joints, electromagnetic acoustic transducers (EMAT), in-motion wheel inspection systems, and broken rail inspection systems.

The design and construction of the new FAST loop offered the opportunity to reimagine data collection, storage, and analytics by drawing on lessons from the past four decades and looking ahead to enhance research, safety, and innovation. The data collection addresses not only the problem of data scarcity in revenue service railroad networks but also provides a holistic view of the train operating system in the freight environment across different track and mechanical components.

FAST Data Management

This vision of reimagining the processes and goal to leverage data at FAST led to the creation of a framework that incorporates the concept of digital engineering, which uses digital information management systems for designing, engineering, building, and maintaining complex projects. The foundational step in realizing this vision included the development of an in-house data collection, storage, and reporting system for FAST. This system, named the FAST Internal Records for Statistics and Testing (FIRST), was designed to enhance inspection and maintenance of FAST track and mechanical systems, train operations, and tests and measurements, enabling robust research, testing reports, and analytics for the North American railroad industry (Galván-Núñez 2025). Figure 1 shows an example of an operations graph from the FIRST dashboard.

FIRST involves multiple data streams, including hot bearing detectors (HBD), hot wheel detectors (HWD), dragging equipment detectors (DED), truck performance detectors (TPD), automatic equipment identification (AEI) readers, train operations, test and measurement scheduling, rail temperature, and nondestructive evaluation (NDE) of rails, welds, wheels, and axles. FIRST is designed to (1) replace paper documentation for FAST data with digital user interfaces, (2) centralize data storage previously hosted in independent locations, (3) increase visibility of infrastructure and mechanical components, tests, and operations throughout their lifecycle, and (4) produce analytics to support FAST operations and the railroad industry. Over two years of continuous development and deployment, FIRST has enhanced data-driven decisions for train operations and reduced data silos by providing real-time access to inspection and maintenance data for mechanical and infrastructure components. Centralized, continuously transmitted data creates a wide range of opportunities for leveraging FAST data—opportunities in which the DT framework will play an important role in addressing current and future industry challenges.

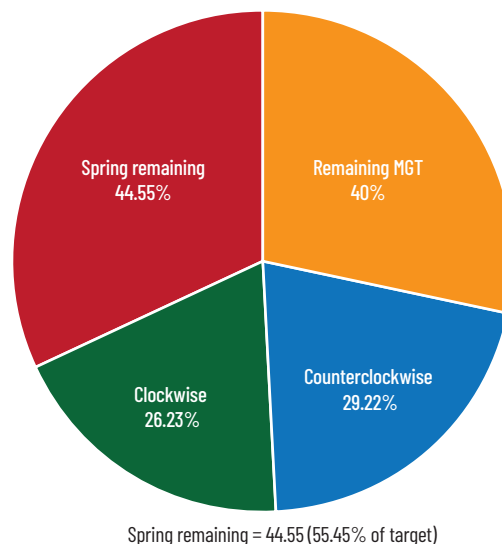


Figure 1. Example of million gross tons (MGT) progress in the FIRST (FAST Internal Records for Statistics and Testing) dashboard.

DT Vision for Rail Health Monitoring at FAST

There is increasing railroad industry interest in leveraging the data collected from continuous monitoring and data streaming of railroad track conditions to improve safety, efficiency, and reliability. At FAST, a general vision for building and realizing a DT framework was defined to help advance the learning required to achieve this goal. Because railroads are complex systems, it is important to begin with meaningful applications for specific components while keeping the interconnection of multiple DTs in mind to achieve a holistic, system-level representation of track infrastructure. The vision for DTs in rail health monitoring for freight railroads, as shown in Figure 2, consists of four implementation levels: mirroring, monitoring, modeling and simulation, and federation.

Level 1: Mirroring

This level establishes the physical-digital link, consisting of the physical object and the data acquisition systems used to collect data, which can result in a static or semi-static digital representation. For rail inspection purposes, rail segments on the track are the primary physical objects, and inspection

technologies may include automated track geometry measurement, ultrasonic/electromagnetic systems, alternative broken rail detection, and visual inspection, among others.

Level 2: Monitoring

This level consists of processing, storing, fusing, and visualizing available data streams to characterize the condition of the physical objects captured in the mirroring level. Rail inspection data can be complex and siloed, making it challenging to establish direct relationships that facilitate the extraction of valuable information about rails and welds. Despite this complexity, the step is crucial for ensuring that data is available for further analysis and can be communicated to various stakeholders.

Level 3: Modeling and Simulation

This level involves the design, development, and deployment of models that support an enhanced understanding of the physical asset—rails in this case—and thereby advance the research and safety of railroad systems. Models are selected based on the questions to be answered and may include statistical analysis, operations research, mechanistic models, and machine learning and AI approaches.

Level 4: Federation

Because railroads are complex systems, a single DT is insufficient to characterize, represent, and monitor the entire infrastructure; multiple DTs are therefore needed, with knowledge transfer to components where data is not available. Data privacy and security protocols are crucial throughout the DT lifecycle and must be considered at all levels of design, development, and deployment.

Case Study

Railroads actively manage rail life (health) through predictive, preventive, and corrective maintenance strategies to maximize asset longevity, safety, and performance. These strategies depend on several factors, including rail strength, operational factors (loading, tonnage, curvature, train speed), environmental factors, and maintenance techniques. This research explores the proposed DT concept to monitor rail health and implement the concept in the FAST environment. In 2023, contractors built the new FAST track using uniform materials based on current North American heavy-haul mainline railroad standards to maximize testing opportunities (Johnson 2024). The track design for the main 2.8 mi (4.5 km) operating loop included 136RE rail, a mix of concrete and timber ties with 16 in. (40.6 cm) tie plates with cut spikes, and 12 in. (30.5 cm) of ballast under the ties. Spiking patterns were based on a combination of railroad practice and previous FAST experience. Materials in test zones also included composite ties, various elastic fasteners in wood ties, intermediate- and high-strength rails from multiple suppliers, and a bridge deck testing facility. All these details were imported and recorded in the FIRST system for future monitoring, testing, and analysis as tonnage accumulates under heavy axle loads.

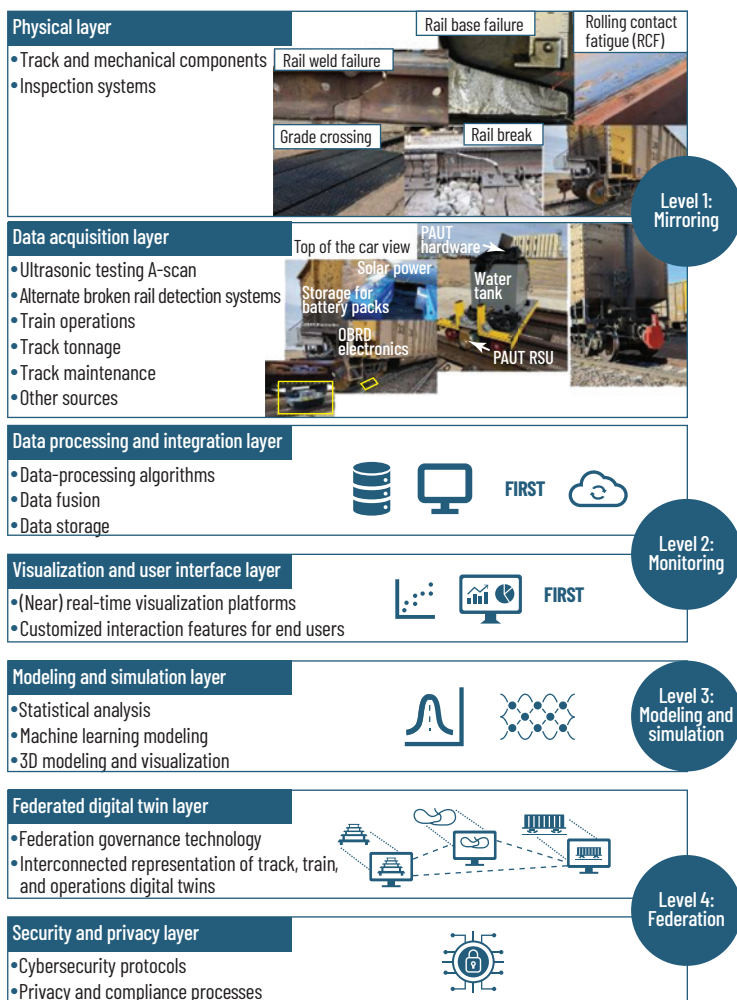


Figure 2. Digital-twin vision implementation levels and layers for rail health monitoring.

FAST

Track

Mechanical

Operations

Tests & Measurements

Reports

Maps

Dx Reports

Admin

Consist Run Log

Max Records To Load

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of 23

Run Number	Start Date	Stop Date	Total Vehicles	Laps	Direction	Miles	MGT
1229	5/6/2026	5/7/2026	118	86	CW	240.8	1.59
1228	5/5/2026	5/6/2026	118	35	CC	98	0.65
1227	5/4/2026	5/5/2026	118	112	CC	313.6	2.07

Figure 3. FAST (Facility for Accelerated Service Testing) train operation logs and accumulated tonnage (MGT).

At FAST, measurements are conducted at different tonnage intervals, measured in million gross tons (MGT), depending on specific test requirements. Often used to gauge traffic density, predict rail wear, and plan track maintenance, MGT is a crucial metric that represents the total weight of all trains (locomotives, cars, and cargo) passing over a specific section of track in a year. With higher numbers indicating heavier usage and faster track component deterioration, especially on curves, MGT is a key indicator of a track’s structural demand. Figure 3 shows an example of FIRST operations logs for the FAST train, including calculated MGT for all tests conducted at FAST.

Rail and Weld Installation

Rails installed in the FAST loop are predominantly 136 lb/yd (67.46 kg/m) (136RE) and consist of a combination of standard-, intermediate-, and high-strength rails from several suppliers, selected for superior hardness and wear resistance. For example, the high-strength rail wear test being conducted in FAST Section 5 uses both high and low rails from different manufacturers installed in a 1200 ft (365.76 m), 6° curve (Banerjee and Shrestha 2025). This curve has 5 in. (12.7 cm) of superelevation and is kept unlubricated to achieve accelerated wear. Traffic is bidirectional, operating ~50% of the time in each direction. In addition to the new rails, five unused rail types from previous tests were also installed for side-by-side comparison.

Individual rail lengths in FAST were joined into strings primarily through in-track welding—the process of joining rails directly in their installed location (the track) using the electric flash butt (EFB) welding process, rather than in a plant. Aluminothermic welding is also used for replacement welds at FAST. Continuous welded rail (CWR) provides smoother, safer, and more durable track with fewer joints. All installed welds are assigned an identification number, and details on weld installation location within FAST (track, section, subsection, tie, and side) are recorded. Figure 4 shows an example of a rail weld entry in the FIRST system.

FAST

DashboardTrackMechanicalOperationsTests & MeasurementsReportsMapsDx ReportsAdminUsersDx Report Designer

Electric Flash Butt Weld Install

This form is locked and cannot be edited. For any assistance, please reach out to FAST Program Manager.

Task Information

Task ID1972

Task Date01/17/2024 00:00:00

Work TypeMobile EFB Weld Install

SideOutside Rail

Section1

Subsection8

Tie71

Created ByDoug Stoltz

Work Order

ReasonMaintenance

TrackMain Loop

Additional Information

Weld Number4144

Air Temperature

Pre-Weld Crown

Pre-Weld Horizontal Offset, Gauge

Pull Stroke

Rail Consumed

Finish Grind Head

Finish Grind Taper Length

ManufacturerMxV Rail In-Track Weld

Rail Temperature

Pre-Weld Vertical Offset, Head

Pre-Weld Vertical Offset, Base

Pull Force

Rail Size(s)136

Finish Grind Gauge

Welder Setting

Figure 4. FIRST entry for a rail weld.

Rail Profile Measurement

Cross-sectional railhead profiles are measured using a portable, handheld profilometer that attaches magnetically to the railhead. Rail wear analysis is conducted by comparing measured rail profiles with template profiles and previous measurements. This analysis allows users to (1) calculate the gradual loss of rail material from wheel contact, which is critical for operational safety and maintenance planning, and (2) understand wear behavior (vertical and lateral) as influenced by speed, curve radius, track cant, lubrication, and material properties. This understanding enables the operational team to plan for rail grinding and replacement. Figure 5a shows the handheld profilometer used at FAST, and Figure 5b shows the profilometer’s

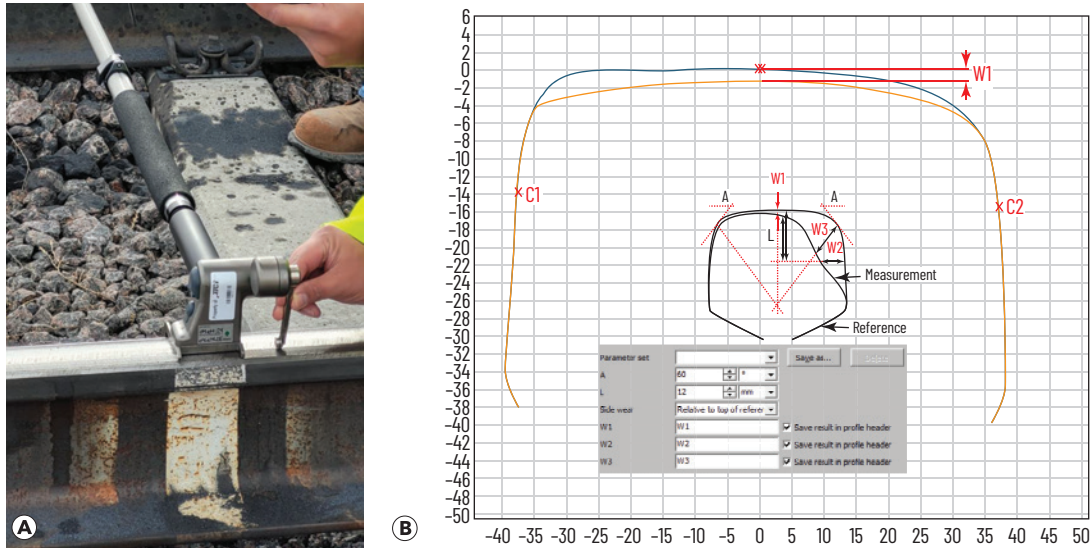


Figure 5. Profilometer rail profile measurement: (a) instrument; (b) overlaid profiles (blue line = pre-grind, orange line = post-grind) using the analysis software tool. W1, W2, and W3 are the rail wear measurements.

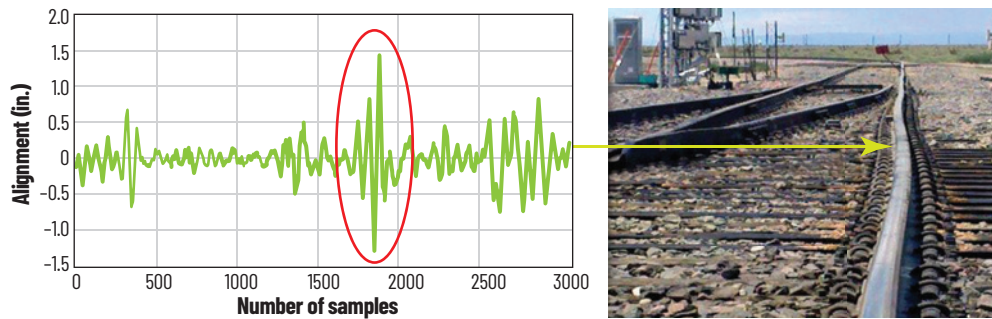
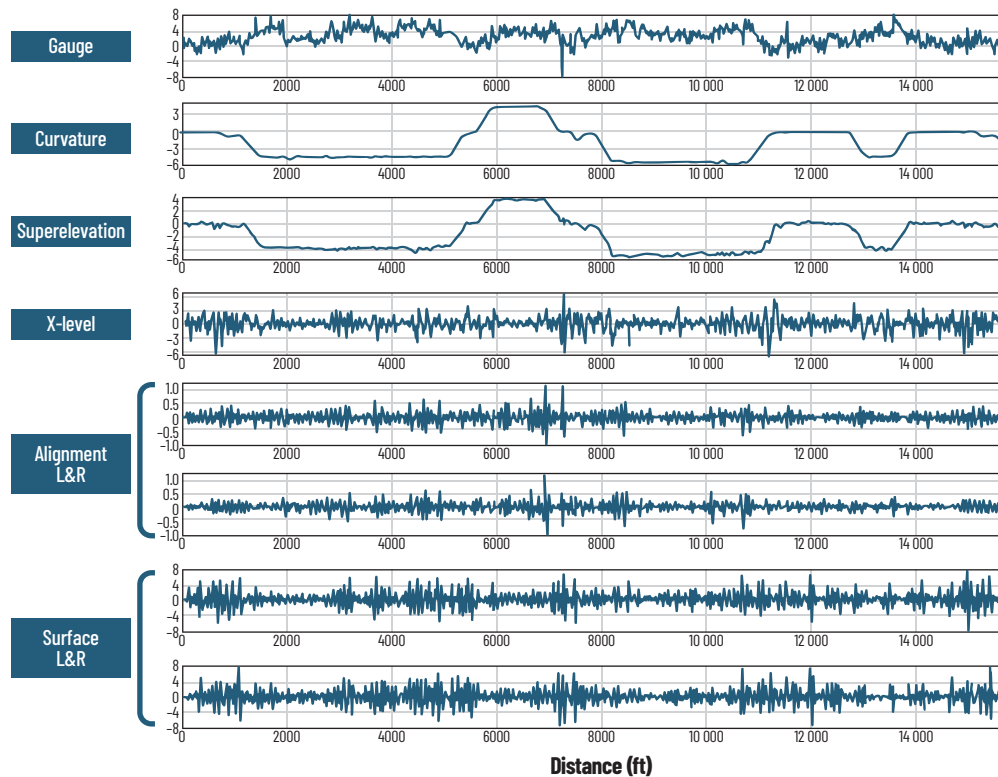


Figure 6. Example of ATGMS (automated track geometry measurement system) readings and outputs.



analysis software tool. Two profiles are overlaid, with the blue line representing the pre-grind profile and the orange line representing the post-grind profile.

Automated Track Inspections

Since the 1940s, North American freight railroads have used a variety of track inspection technologies to enhance rail safety and operational efficiency. These technologies have evolved to incorporate a range of NDE methods—including ultrasonics, electromagnetics, X-rays, lidar, ground penetrating radar (GPR), lasers, accelerometers, and optical-based systems—to monitor tracks at speed across the nearly 140 000 mi (225 308 km) network (Witte and Poudel 2019).

AUTOMATED TRACK GEOMETRY MEASUREMENT SYSTEMS (ATGMS)

ATGMS enable railroads to measure how the track structure performs under train load. These systems, often installed on locomotives or dedicated inspection trains, use lasers, accelerometers, and cameras mounted onto locomotives or rail cars to inspect the track as the train travels across the network (Poudel et al. 2023). Each foot of track is tested under the force of a loaded train, generating data on gauge, curvature, superelevation, cross-level, alignment, surface, twist, and rail cant at mainline speeds. Inspection data is transmitted to a centralized location where employees verify results and schedule maintenance as needed.

Figure 6 shows an example of the data output from such systems. When used in conjunction with traditional or crewed systems, ATGMS have proven effective—providing autonomous, frequent inspections, large volumes of data, and early detection of track geometry degradation, often without requiring additional track time beyond that of regular train operations. The deployment of ATGMS has increased safety and effectiveness in railway operations.

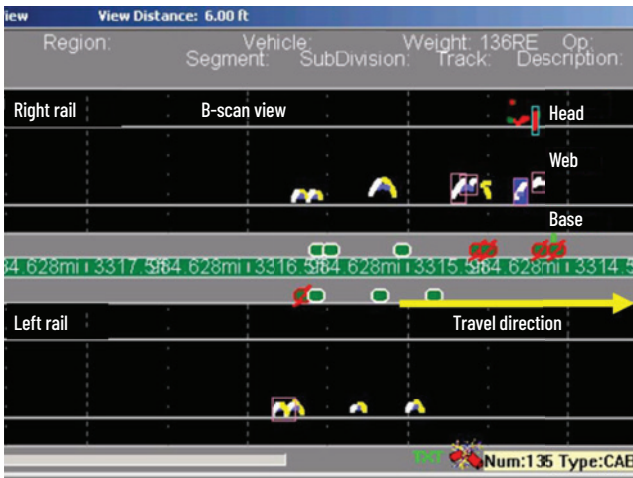


Figure 7. Ultrasonic B-scan results for rail at FAST.

RAIL INSPECTION

Ultrasonic NDE methods for rail defect detection are the primary techniques employed by railroads and rail service providers to monitor, detect, and characterize rail defects and ensure the structural safety, integrity, efficiency, and reliability of the rail network. Rail detector cars use fixed-angle piezo-electric transducers housed in liquid-filled membrane wheels called roller search units (RSUs) to generate and emit ultrasonic waves in the rail. Transducers are arranged in various configurations to provide different inspection capabilities for detecting different types of internal defects (Poudel et al. 2019a). Each RSU houses approximately six transducers with as many as twelve transducers per rail. Figure 7 shows ultrasonic B-scan results for rails at FAST. Both rail defect inspection and visual inspection are conducted biweekly at FAST to monitor rail surface conditions and internal anomalies. Detected anomalies are logged and monitored continuously—during and

FAST

Dashboard
Track
Mechanical
Operations
Tests & Measurements
Reports
On Reports

Rail & Weld Defect Inspection Summary

Create New Load Removed Defect(s)

Max Records To Load 500 Load View Map

Export

1 2

Track Defect ID	Defect Location (Section, Subsection, Tie)	Side	Date Defect Found	Direction of Inspection	Defect Type	Current Length (in)	Current Width (in)	Current Height/Depth (in)	Current Transverse Fracture (TF) %	Weld Number	Weld Manufacturer	Previous Length (in)	Previous Width (in)	Previous Height/D (in)
155	14-05-058	Outside Rail	10/12/2025	CC	Web Defect	0.35	0.6			Weld Number Not Found				
154	01-02-039	Outside Rail	10/17/2025	CW	Transverse Fracture (TD) - TF		0.2	0.2	0.7	3243	M/V Rail in-Track Weld			
153	14-14-064	Outside Rail	10/15/2025	CW	Shelly Spots	4.2	0.7	0.25						
152	14-13-002	Outside Rail	10/3/2025	CW	Transverse Fracture (TD) - TF		0.4	0.3	0.2	PH2	Pandrol			
149	14-12-103	Outside Rail	9/25/2025	CC	Transverse Fracture (TD) - TF		0.5	0.9	7.3	PH01	Pandrol		0.5	0.6
148	14-04-005	Outside Rail	9/24/2025	CC	Shelly Spots	3	0.4	0.4				2.5	0.4	0.4
147	09-05-100	Inside Rail	9/19/2025	CC	Spalling									
143	14-17-089	Outside Rail	5/30/2025	CC	Web Defect	0.2	0.2					0.2	0.2	
141	16-01-051	Outside Rail	5/16/2025	CW	Web Defect	0.4	0.4			4097	M/V Rail in-Track Weld	0.2	0.2	
136	14-05-089	Outside Rail	4/18/2025	CW	Web Defect	0.2	0.2			4117	M/V Rail in-Track Weld			

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Figure 8. FAST rail defect log from ultrasonic testing.

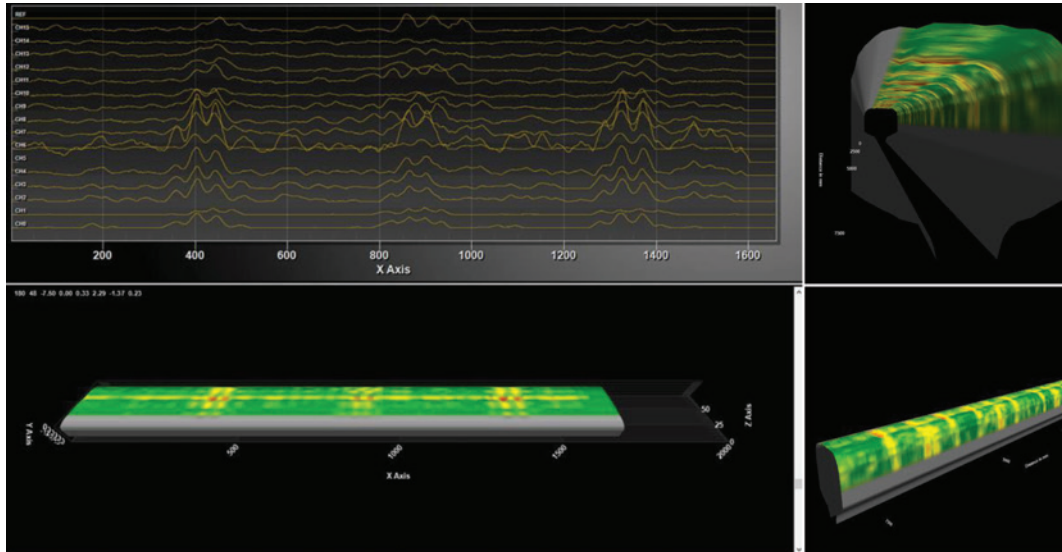


Figure 9. Electromagnetic field imaging (EMFI) C-scan results for rails with rolling contact fatigue (RCF).

after FAST operations—and are protected or removed before they pose a risk of service failure. Figure 8 shows rail and weld defect logging in FIRST.

In addition to ultrasonics, electromagnetic field imaging (EMFI) is used to monitor rolling contact fatigue (RCF) at FAST, with information collected and analyzed before and after rail grinding. EMFI is a noncontact NDE method that uses an exciter core and coil to generate a focused electromagnetic field (EMF) in a conducting material (Poudel et al. 2019c; Poudel 2023). A series of antennas—field deviation sensor elements—precisely placed around the periphery of the excitation field creates a full three-dimensional map of EMF shape changes, while a total energy sensor measures the exact field strength emitted by this exciter assembly. Figure 9 shows EMFI C-scan results for rails with RCF. Information generated from EMFI aids in planning rail maintenance and rail grinding.

BROKEN RAIL DETECTION SYSTEMS

Both broken rail and occupancy detection are traditionally provided by track circuits, which are essential components of railway safety and signaling systems in North America. Track circuit operation is based on the principles of electric current flow and circuit continuity through the rail. Although designed to be fail-safe, track circuits have some limitations for detecting rail breaks and for integration into moving block communications-based train control (CBTC) systems for real-time monitoring. An alternative broken rail detector (ABRD) system that improves on track circuits in territories where moving block positive train control (PTC) will be deployed presents several opportunities for railroads to monitor their networks (Shrestha and Poudel 2025).

Both internally developed rail break detection systems and ABRD technologies are implemented at FAST to monitor broken rails during train operations. Figure 10 shows examples

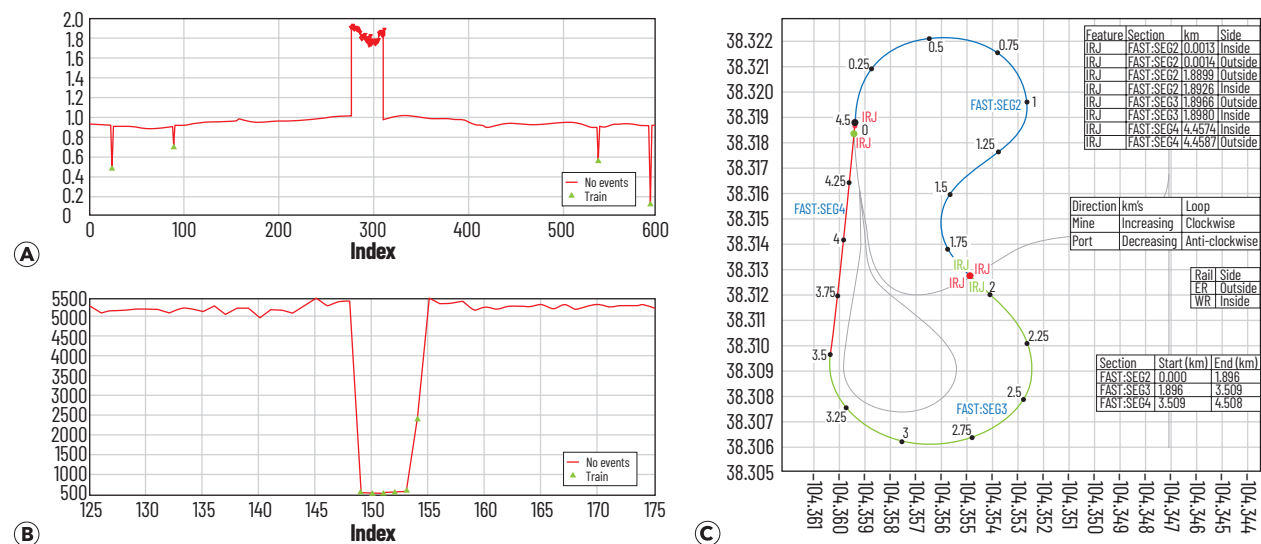


Figure 10. Alternative broken rail detector (ABRD) system alert examples: (a) broken rail signature, on-track system; (b) train presence signature, on-track system; (c) FAST track map features, onboard system.

of broken rail detection alerts generated by ABRD technologies under investigation at FAST.

WHEEL IMPACT READINGS

Deficiencies in rolling stock component performance increase vertical and lateral loads on the track, accelerating the deterioration of alignment, profile, and gauge geometry. Elevated vertical wheel loads can promote the growth of internal rail defects, resulting in faster fatigue and premature failure of suspension and truck components. North American railroads use several wayside detection systems to continuously monitor the health of rolling stock components. One such system is the wheel impact load detector (WILD) system, installed along the network to identify bad-actor wheels—wheels with polygonization issues (Poudel et al. 2023), meaning out-of-roundness (OOR) defects where the wheel tread develops a noncircular, multi-lobed shape due to uneven periodic wear. This defect leads to severe vibrations, increased noise, and structural damage to both the wheelset and track.

North American railroads often use WILDs to identify high-impact wheels, with primary removal criteria set at 90 000 lbs (90 kips) or higher, and wheels are often classified under AAR Rule 41 for out-of-round wheels (AAR 2025). At FAST, truck performance detectors (TPDs) are installed. Both TPDs and WILDs are wayside safety systems that use instrumented rail sections to monitor wheel lateral and vertical forces. TPD data provides near-real-time information about vertical (V) and lateral (L) wheel/rail contact forces and the L/V ratio, offering insight into the condition of wheelsets and trucks so maintenance can be prioritized. Figure 11a shows a FIRST TPD data visualization for a night of train operations, including minimum, maximum, and mean values for the TPD location on tangent track at FAST (Galván-Núñez et al. 2025). Regarding the vertical forces on the low rail for lead axles, the horizontal axis shows the train axle sequence, and the vertical axis shows forces in kips (pounds $\times$ 1000). Figure 11b presents histograms showing the tails of the L/V ratio distribution at one of the TPD locations. This visualization identified a single wheel with an L/V ratio greater than 0.6 on the tangent section, prompting engineers and operations staff to conduct a closer inspection of the corresponding vehicle for maintenance intervention.

Rail Modeling and Simulation

Several scientific approaches have been considered for predicting rail performance as a function of wear, fatigue, or both over the past three decades. These include (1) finite element analysis (FEA) using strength of materials (SOM) (Banerjee and Shrestha 2025), (2) fracture mechanics-based crack-growth models (Banerjee and Morrison 2019; Banerjee et al. 2017), and (3) statistical modeling methods such as Random Forest (Banerjee and Liu 2019). Figure 12 shows a three-dimensional FEA analysis conducted on a wheel/rail contact patch (Fry et al. 2015). Figure 12a shows stress analysis results for the elements in the region (nodes) expected to make contact.

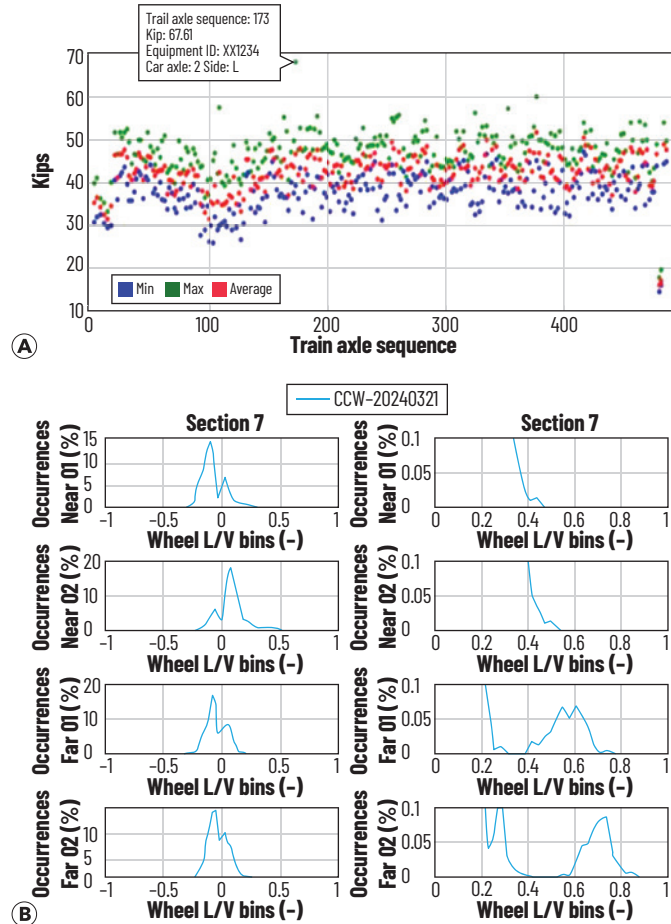


Figure 11. FAST truck performance detector (TPD) data: (a) at the wheel level; (b) at the car level (Galván-Núñez et al. 2025).

Figures 12b and 12c show the von Mises stress distribution in the contact patch region for wheels and rails, respectively. Figure 13 shows results from a fracture mechanics model for rail defect life prediction, comparing 1980s rails using this approach (Figure 13a) with MGT to failure for modern high-, intermediate-, and standard-strength rails (Figure 13b) (Banerjee and Morrison 2019). The 1980s rails show a longer rail life before fracture than modern rails. The model assumes crack growth starting from the same defect size; however, crack growth also depends on factors beyond the fatigue crack growth rate (FCGR) properties shown in Figure 13a and may be shorter for any rail of any age. In reality, modern rails have a reduced likelihood of defect formation compared to older rails, a difference mainly attributed to reduced voids and inclusions (stress risers) resulting from cleaner steel manufacturing processes such as continuous casting and degassing. A fracture mechanics approach cannot, however, address questions about what factors cause defect formation, since it does not account for metallurgical differences such as grain size, presence or absence of inclusions, or variation in interlamellar spacing in the steel. Figure 13b is included to illustrate the risks of relying on modeling data alone: because assumptions in a scientific approach can significantly affect results, this figure

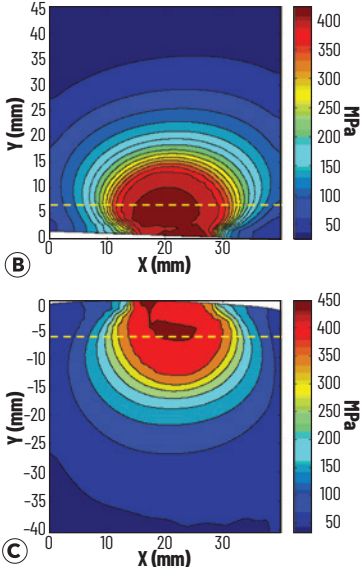
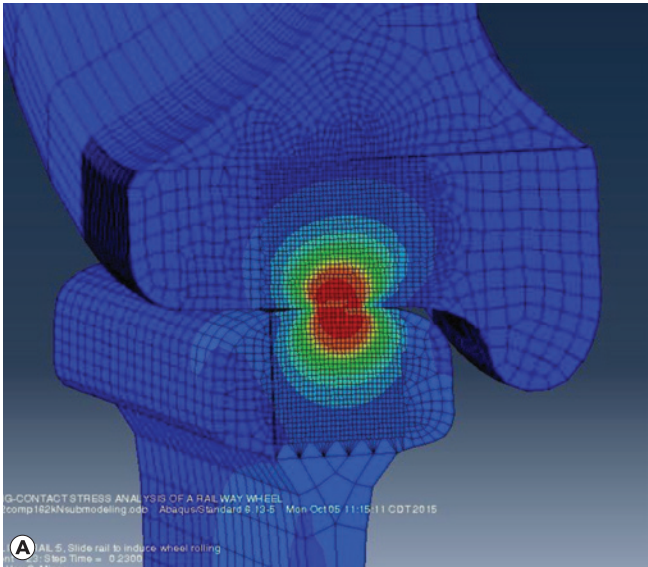


Figure 12. Finite element analysis (FEA) on a wheel/rail contact patch: (a) stress analysis results for the elements in the region (nodes) expected to make contact; von Mises stress distribution in the contact patch region for the (b) wheels and (c) rails (from Kiani and Fry 2018).

demonstrates the limitations of simulation approaches, such as fracture mechanics, when applied to real-rail-life prediction models. Comparing modeling results with real test data is therefore essential for evaluating model validity.

Statistical approaches can also be used to predict rail defects using historical rail service failure data and operating and maintenance data. Work by MxV Rail researchers has demonstrated that machine learning algorithms can automate rail defect prediction based on model inputs

(Banerjee and Liu 2019). Table 1 shows the parameter ranges and default values for the model. For example, the model output indicates that a quarter-mile (402 m) rail section has an estimated fatigue-defect probability of 0.13 over one year.

TABLE 1
Input for rail defect prediction tool (Banerjee and Liu 2019)

Input	Input range	Default value
Rail age (years)	0-80	24
Segment length (mi)	0-10	0.25
Annual traffic density (MGT)	0-100	20
Annual number of car passes (in thousands)	0-700	250
Max allowed speed (mph)	0-60	35
Curve (degrees)	0-20	0 for tangent; 3 for curved track
Grade (%)	0-4	0.4
Rail position	Tangent rail, high rail, low rail	Tangent rail
Rail size (lb/yd)	0-155	132
Number of turnouts/mi	0-2	0.5
Rail quality index	New rail, relaid rail	New rail
Ballast cleanings/year	0-2	0
Grinding passes/year	0-4	1
Prior defects (all types) per mi/year	0-10	0.3
Prior vehicle track interaction (VTI) exceptions per mi/year	0-15	0.5
Prior track geometry defects per mi/year	0-10	2

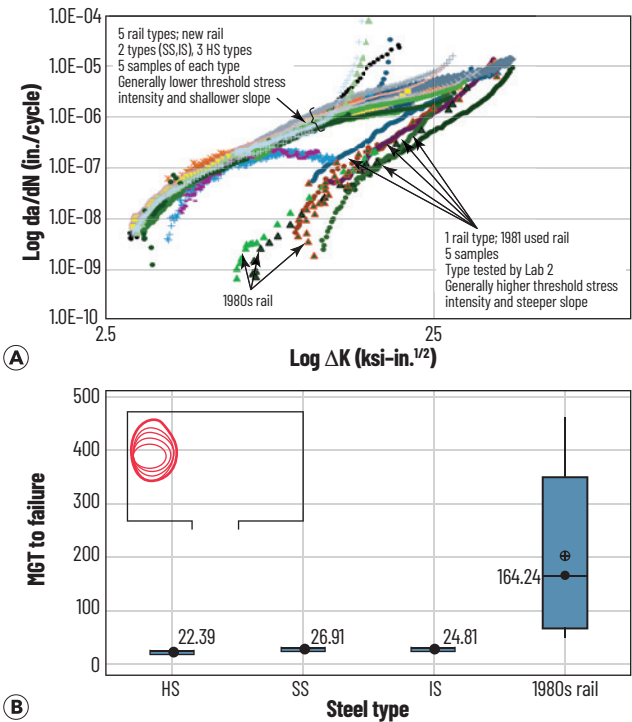


Figure 13. Fracture mechanics modeling for rails: (a) comparison of fatigue crack growth rate (FCGR) curves; (b) comparison of MGT to failure for different rail types (Banerjee and Morrison 2019).

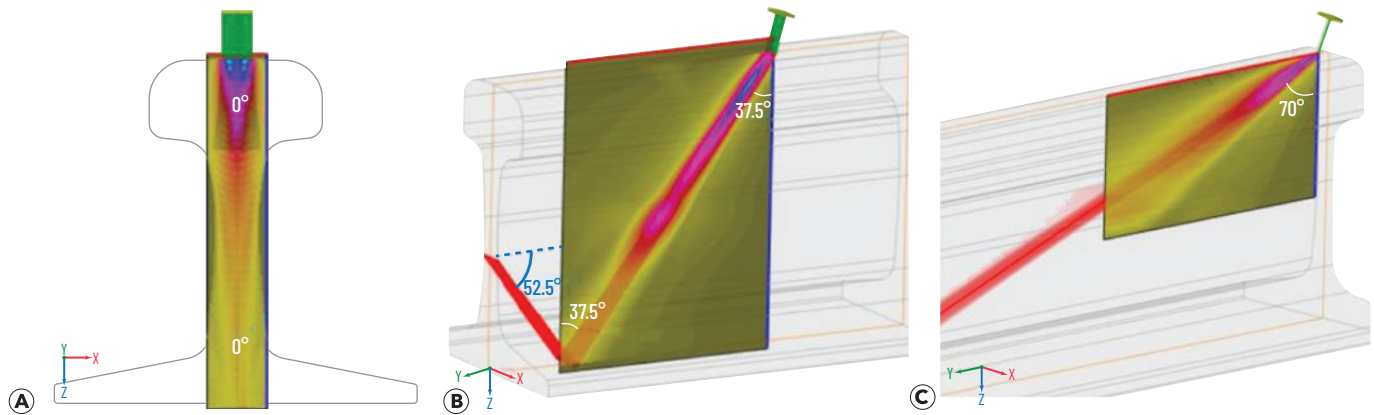


Figure 14. Roller search unit (RSU) ultrasonic beam field computation (transmission) in 136RE rail: (a) 0°, (b) 37.5°, and (c) 70° transducers.

If the rail age increases to 80 years, the probability is expected to rise to 0.20. If annual traffic density increases from 20 to 60 MGT, the rail fatigue defect probability increases to 0.26, all other factors being equal. Because the machine learning model accounts simultaneously for multiple inputs in a complex way, the marginal effect of each variable depends on the values of the others.

Ultrasonic beam field modeling and inspection simulation for rails with and without defects can also be performed using CIVA simulation and analysis software, a multi-technique NDE

platform whose algorithms are validated against international benchmarks. Figure 14 shows ray tracing and ultrasonic beam field computation results for individual transducers in the RSU without rail defects (Poudel et al. 2019b). These simulation tools allow for the modeling of internal rail defects, the analysis of ultrasonic beam response, and the simulation of inspection scenarios for different cases of rail geometry (wear), surface conditions, and environmental conditions.

Rail Maintenance

Rail maintenance is complex, mainly due to the involvement of multiple interrelated components. The primary objective is to maintain the railhead profile, which improves wheel-rail interaction, reduces contact stress, and prevents the initiation and growth of cracks and surface defects. Ineffective rail maintenance can lead to defects, premature failure, and reduced rail life. Effective predictive maintenance requires reliable tools and remains an evolving practice. Traditionally, rail maintenance is either corrective—addressing failures after they occur—or preventive, performed on a routine schedule based on MGT and routes.

Rail gauge face (GF) lubrication and top-of-rail (TOR) friction modifier (FM) application are important maintenance strategies used for preventing premature rail and wheel wear and maintaining good locomotive traction. Friction control is achieved by applying friction products to either the wheel or the rail, with the primary goals of extending rail and wheel life and reducing fuel consumption. GF and TOR friction levels influence rail/wheel wear, vehicle system dynamics, and train rolling resistance. Lubrication is applied to the GF to lower friction, while TOR FM materials are applied to the top running surface to control friction to a target level. An improved understanding of wheel/rail friction aids in future improvements to lubrication systems, materials, and performance guidelines (Reiff et al. 2005). Research has led to the development of GF and TOR implementation guidelines and recommended best practices that have been incorporated into the American Railway Engineering and Maintenance-of-Way

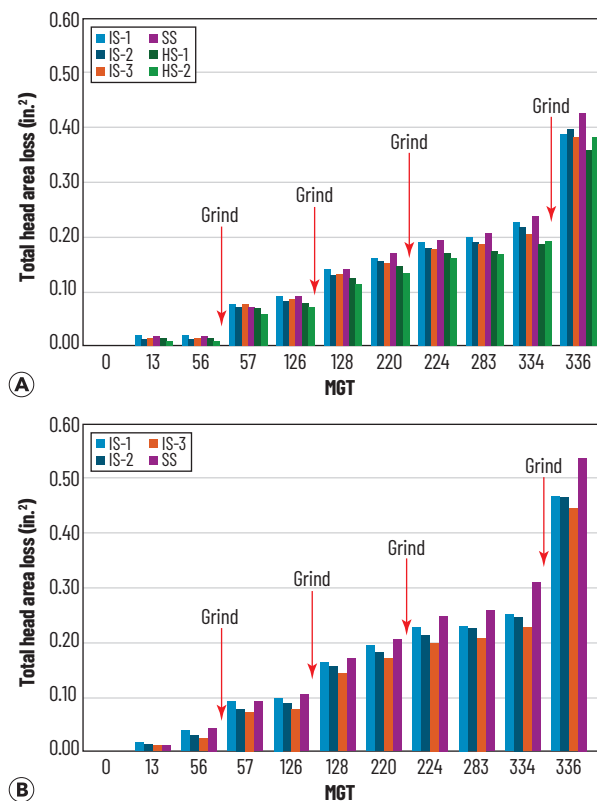


Figure 15. Example of FAST rail wear analysis showing median head area loss for (a) high rail and (b) low rail.

Association (AREMA) *Manual for Railway Engineering* (AREMA 2025) for industry-wide use. FAST currently uses both TOR and GF lubrication techniques with two GF lubricators and one TOR system located around the loop. Depending on testing needs, GF or TOR lubrication can be turned on or off individually or simultaneously.

Rail grinding and rail milling are maintenance processes used to remove surface or subsurface defects caused by RCF and to restore the rail profile, improving operational efficiency, extending rail life, and avoiding premature rail replacement. At FAST, rail grinding is usually performed at defined MGT intervals. RCF details and rail profiles before and after grinding are documented, allowing the calculation of rail wear and providing insight into rail life as a function of MGT. Figure 15 shows an example of rail wear analysis for the ongoing FAST intermediate-strength rail test (Morrison et al. 2024). Rail wear information is critical for understanding rail deterioration, predicting useful life, and selecting appropriate maintenance practices. For the current rail test, similar measurements are being conducted and recorded in the FIRST system. Preventative rail grinding remains the preferred approach because it (1) removes just enough metal to stop uncontrolled RCF growth, (2) maintains optimal rail profiles matched to operating conditions, and (3) controls rail corrugation and weld dipping (AREMA 2025). Rail milling, by contrast, is a corrective rather than preventive strategy, intended for cases where deep surface cracks require removal of a substantial amount of metal—a more time-consuming process than grinding that would not be cost-effective. Rail milling has not yet been explored at FAST. Details of rail grinding at FAST will be included in the FIRST database.

Federation

The federation of DTs is particularly valuable in complex systems such as railroads, where multiple twins are often needed to represent different infrastructure components. Once individual DTs are created, they should be connected so they do not operate in isolation, enabling knowledge transfer to assets with limited or no data. For example, one DT may focus on rail health monitoring while another addresses the specific behavior of rail welds; together, multiple twins can capture the effects of high-impact loads and share results across the system to improve the collective understanding of overall behavior. At FAST, work in this area is still developing, and the approach offers significant research opportunities as implementation progresses.

Current State of DT Implementation

The current state of DT implementation at FAST encompasses Levels 1–3, with Level 3 currently under development to integrate data sources—including ultrasonic testing (UT), broken rail data, track maintenance records, and wayside detector data—that will support the development and integration of models for rail track health monitoring. Ongoing work also

includes addressing the synchronization of heterogeneous datasets within the DT framework, cybersecurity considerations, and the identification of meaningful models to support rail track health monitoring.

Conclusions

This paper presents an overview of a DT system focused on monitoring rail health and supporting data-led decision-making. The concept has been developed at and is being evaluated at FAST to support maintenance decisions, with broader application anticipated in the future. While challenges remain in making DTs fully capable of predicting rail health, the work presented for Levels 1–3 provides a strong foundation for future progress. Continued development to improve DT accuracy and utility will be important for supporting more advanced applications—such as predicting when repairs are needed—and for strengthening and improving the efficiency of railroad operations. Realizing these benefits at scale will require industry agreement on the value and role of DTs, as well as solutions to implementation challenges related to system security and interoperability with existing infrastructure.

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