

Engineering Data Standards, Feedback Speed, and Interoperability Gains across Rail Asset Management

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Abstract

The modern railway sector represents a complex socio-technical system characterized by highly distributed assets, long lifecycle horizons, and heterogeneous engineering environments. Managing these assets effectively requires seamless information exchange across diverse engineering disciplines, software ecosystems, and organizational boundaries. This paper examines the critical mechanism of interoperability gains in rail asset management, focusing specifically on the dual levers of engineering data standards and feedback speed. By analyzing the structural properties of established data schemas such as IFC Rail, railML, and ISO 15926, we demonstrate how semantic alignment mitigates translation errors and data silos. Furthermore, we develop an analytical framework to show that information standardisation, when coupled with high-velocity feedback loops from wayside and onboard telemetry systems, yields exponential improvements in decision quality and operational efficiency. The analysis indicates that reducing telemetry-to-decision latency through standardized interfaces decreases asset risk profiles and lowers life cycle costs. This research provides a comprehensive theoretical model and empirical validation through simulation to assist rail operators, system integrators, and policy makers in optimizing their digital asset management strategies.

Keywords: Rail Asset Management; Engineering Data Standards; Feedback Speed; Interoperability Gains; Software Engineering

1. Introduction

1.1 Research Context and Background

Modern railway systems form the backbone of global freight and passenger transportation networks, demanding continuous availability, high safety standards, and rigorous capital efficiency. Over the past few decades, rail infrastructure networks have experienced unprecedented utilization rates, driven by rapid urbanization, economic integration, and a global shift toward sustainable transit modes. This increased demand places severe stress on civil infrastructure, track structures, catenary installations, and signaling systems. Managing these distributed and diverse engineering assets over their entire lifecycles, which frequently span fifty years or more, represents an immense engineering and organizational challenge.

Historically, rail asset management has relied on reactive or pre-scheduled preventative maintenance strategies. In these models, maintenance interventions were triggered either by catastrophic component failures or by arbitrary, time-based intervals. While these approaches provided basic operational safety, they often resulted in either costly over-maintenance or catastrophic under-maintenance, leading to line blockages, service disruptions, and escalated lifecycles costs.

With the emergence of the Industrial Internet of Things, high-fidelity wayside sensors, and automated vehicle-mounted inspection systems, the railway industry has entered a data-rich era. Modern track geometry cars, acoustic bearing detectors, and optical wheel profile measurement systems generate terabytes of high-frequency telemetry daily. However, the presence of vast quantities of raw operational data does not automatically translate into improved decision-making or optimized asset health. The core bottleneck preventing rail operators from realizing the full potential of their digital investments is the systemic

lack of interoperability across highly siloed software applications, physical subsystems, and department boundaries.

1.2 Problem Statement

The digital ecosystem of a typical rail infrastructure manager is highly fragmented. Engineering data resides in disparate environments, including Geographic Information Systems for spatial planning, Building Information Modeling platforms for structural design, Computerized Maintenance Management Systems for work order execution, and Enterprise Resource Planning platforms for financial tracking. Historically, each of these systems utilized proprietary, closed data formats that were optimized for their specific domain but incompatible with external applications.

When an onboard telemetry system detects an early-stage wheel-rail interface anomaly, this information must navigate a complex series of data transformations, semantic mappings, and organizational handovers before manifesting as a targeted maintenance work order. The lack of unified data standards means that engineering details are frequently lost, corrupted, or delayed during manual translation processes [1]. This semantic degradation introduces significant latency into the asset management loop, which in turn leads to a substantial decay in the value of the collected telemetry data.

For instance, if track geometry deviation data requires weeks of manual cleaning, validation, and schema matching before it can be processed by scheduling algorithms, the physical defect may propagate to a point of critical failure before a crew can be dispatched. This dynamic illustrates that the effectiveness of digital asset management is fundamentally constrained by two core variables: the semantic interoperability of engineering data and the velocity of the information feedback loop. Despite the clear significance of these variables, existing literature has largely treated them as separate, independent concerns, failing to explain how data standards and feedback speed interact to generate compounding operational gains [2].

1.3 Research Objectives

This paper aims to bridge the gap between digital data standardization and real-time operational execution in the context of rail asset management. Specifically, our research pursues three primary objectives:

First, to establish a unified analytical framework that explains how open engineering data standards, specifically IFC Rail, railML, and ISO 15926, facilitate semantic interoperability across different software systems and lifecycle phases. This involves characterizing the structure, strengths, and limitations of each standard regarding their ability to model complex rail systems [3].

Second, to model and quantify the relationship between engineering data standardization, feedback loop latency, and the quality of maintenance decisions. We investigate how reducing information transmission delays and eliminating translation errors lowers the overall risk profile of critical rail assets.

Third, to validate this conceptual model through a comprehensive simulation of a high-speed passenger rail corridor. By evaluating various operational scenarios, we demonstrate the concrete financial and operational gains that accrue when rail operators systematically align their data architecture with open standards and deploy low-latency telemetry processing pipelines.

Ultimately, this work aims to provide rail executives, system architects, and regulatory agencies with a rigorous, evidence-based roadmap for executing digital transformation initiatives that yield tangible improvements in network availability and asset life-cycle minimization.

2. Literature Review and Theoretical Foundations

2.1 Evolution of Rail Asset Management Systems

The methodology governing rail asset management has evolved through several distinct paradigms over the last century. In the early and mid-twentieth century, rail maintenance was heavily reactive, operating under a run-to-failure model [4]. This paradigm was characterized by high operational risk and unpredictable capital expenditures, as infrastructure managers had limited visibility into the structural degradation rates of track and civil structures.

With the advancement of materials science and mechanical engineering in the late twentieth century, the industry transitioned to preventive maintenance models. These methods relied on statistical models of component wear to schedule maintenance activities at fixed, pre-determined intervals of time or accumulated tonnage. While this approach dramatically reduced the incidence of in-service failures, it

introduced substantial inefficiencies. Components were frequently replaced or refurbished when they still possessed significant remaining useful life, and the rigid scheduling of track maintenance windows caused unnecessary disruptions to scheduled rail traffic.

The modern paradigm, often referred to as predictive and proactive asset management, seeks to leverage real-time and near-real-time sensor telemetry to dynamically schedule maintenance interventions based on the actual physical condition of the assets. Digital Twin technologies and advanced prognostic algorithms form the core of this paradigm. However, implementing these systems requires a level of integration and data fluidity that traditional, siloed railway IT architectures are unequipped to support.

2.2 Interoperability in Distributed Engineering Environments

Interoperability is defined as the ability of two or more systems or components to exchange information and to use the information that has been exchanged. Within the context of distributed engineering projects, such as large-scale rail infrastructure upgrades, interoperability must be evaluated across multiple layers: technical, syntactic, semantic, and organizational [5].

Technical interoperability refers to the physical connectivity and protocol-level communication between systems. Syntactic interoperability addresses the serialization formats of the exchanged data, such as XML, JSON, or RDF. While these two layers are critical, they do not guarantee that the receiving system can comprehend the true meaning of the incoming data.

Semantic interoperability is the most challenging and crucial layer for rail asset management. It ensures that the precise meaning of the exchanged information is preserved across systems [6]. For example, when a track design system exports a vertical alignment curve, the receiving maintenance scheduling system must interpret the geometry, coordinate reference systems, and material properties exactly as intended by the design engineers. Without semantic interoperability, data exchange relies on ad-hoc, manual translations, which are highly error-prone and time-consuming.

Organizational interoperability, the highest layer, concerns the alignment of business processes, workflows, and collaboration agreements between different stakeholders, such as infrastructure managers, rolling stock operators, and third-party maintenance contractors. In a distributed engineering environment, semantic friction between software systems acts as a direct barrier to achieving organizational interoperability, causing delayed projects and misallocated resources.

2.3 The Role of Data Standards and Information Models

To achieve semantic interoperability, the global railway engineering community has developed and adopted several open data standards. These standards define common vocabularies, relational structures, and exchange schemas designed specifically for the unique demands of rail systems.

The Industry Foundation Classes (IFC) standard, developed by buildingSMART, represents the global benchmark for open Building Information Modeling (BIM) data exchange [7]. Historically focused on vertical building structures, recent initiatives have produced the IFC Rail extension, specifically IFC 4.3 and the upcoming IFC 5. This extension introduces comprehensive object-oriented representations for rail-specific assets, including tracks, switches, crossings, power supply networks, signaling systems, and telecommunications. IFC Rail allows design and construction data to be seamlessly transitioned into operational databases, ensuring that maintenance crews have access to highly accurate spatial and structural asset models.

Complementing IFC Rail is railML (Railway Markup Language), an XML-based open standard optimized for the exchange of operational and planning data. While IFC Rail excels at modeling physical and spatial geometry, railML focuses on the logical topology of the railway network, timetable information, signaling layouts, and rolling stock parameters. This makes railML highly effective for integrating scheduling engines with physical track layout databases, enabling maintenance planning tools to assess the operational impact of track closures.

Additionally, ISO 15926 provides a foundational framework for the integration, sharing, exchange, and hand-over of data between computer systems throughout the life cycle of process plants and complex infrastructure, including rail. Utilizing the Web Ontology Language (OWL), ISO 15926 facilitates semantic web integrations and the development of linked data environments. This allows disparate databases to query and reason across heterogeneous data sources without requiring centralized consolidation.

2.4 Feedback Speed and Control Loop Theory

In addition to data standardization, the velocity of the information feedback loop is a key determinant of asset management performance. This relationship can be analyzed through the lens of Classical Control Loop Theory, which posits that the stability and performance of a closed-loop system are fundamentally governed by the feedback delay [8].

In a rail asset management context, the infrastructure network behaves as the physical plant being controlled. The sensors (wayside and onboard) represent the feedback instruments, while the asset managers and maintenance crews function as the controller. When a physical asset begins to degrade, its state is captured by a sensor. However, this state information must travel through several processing and communication stages before the controller can apply a corrective action (i.e., executing a maintenance task).

If the latency within this loop is high, the controller is constantly acting on outdated information, which can lead to system instability [9]. In rail systems, this instability manifests as unexpected service failures, derailments, or excessively high repair costs, because corrective actions are taken too late. By accelerating the feedback speed (the time from initial defect observation to corrective action execution), operators can maintain tighter control over asset degradation, preventing minor wear from escalating into severe failures.

3. Methodology and Systems Architecture

3.1 Unified Rail Asset Architecture

To evaluate the combined impact of data standards and feedback speed, we propose a multi-layered, unified rail asset architecture. This conceptual framework illustrates how diverse data sources are harmonized, processed, and translated into operational actions in real-time.

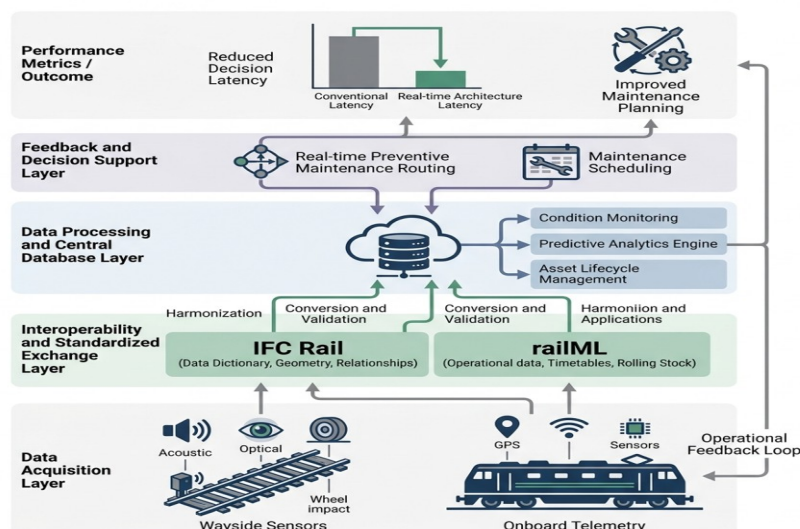


Figure 1: Comprehensive Schematic of Rail Asset Data Flow and Feedback Architecture

As illustrated in Figure 1, the architecture is divided into four functional tiers: the physical asset tier, the data acquisition and telemetry tier, the semantic integration tier, and the decision and execution tier. At the bottom, the physical asset tier comprises the track structures, switches, catenary lines, and signaling systems. Above this, the acquisition tier utilizes wayside laser scanners, onboard acceleration sensors, and catenary cameras to capture the physical state of the assets.

The core of the architecture is the semantic integration tier. Here, raw telemetry data is ingested and mapped to unified data models based on IFC Rail and railML. This mapping process standardizes coordinate reference systems, asset identifiers, and physical units, creating a semantically consistent Digital Twin of the railway network.

At the top, the decision and execution tier runs analytical engines, predictive algorithms, and scheduling software on the standardized data stream. Because the data has already been harmonized and contextualized in the semantic tier, these tools can execute instantly without wasting time on custom data transformations. This streamlined flow minimizes total system latency, enabling high-velocity feedback loops.

3.2 Standardized Data Schema Mapping

To implement this architecture, we define a precise semantic mapping protocol that bridges physical telemetry formats with standardized digital representations. For track geometry assets, sensor systems typically output continuous streams of coordinates, lateral accelerations, and vertical displacement metrics.

Table 1 outlines the mapping of these raw sensor observations to specific classes within the IFC Rail and railML schemas, showing how unstructured telemetry is transformed into structured, actionable engineering entities.

Table 1: Semantic schema mapping of telemetry inputs to open engineering standards

Physical Asset Subsystem	Raw Telemetry Parameter	Target IFC Class	Target railML Element
Track Structure and Rails	Vertical track settlement	IfcRail / IfcTrackElement	track / geometry / alignment
Track Structure and Rails	Lateral gauge variation	IfcRail / IfcTrackElement	track / geometry / trackGauge
Turnouts and Switches	Point machine current	IfcActuator / IfcSwitch	infra / turnouts / turnout
Turnouts and Switches	Switch blade displacement	IfcSensor / IfcSwitch	infra / turnouts / turnout
Catenary Power Lines	Contact wire wear thickness	IfcEnergyDistributionDevice	infra / electrification / catenary
Signaling Subsystems	Axle counter occupancy	IfcController / IfcSignal	infra / signaling / signal

By utilizing this mapping matrix, a software application can ingest a standardized XML or JSON schema and immediately comprehend the physical context of the data, regardless of the sensor manufacturer. This eliminates the need for proprietary database connectors and translation scripts, which are primary sources of engineering overhead and data latency.

3.3 Modeling Feedback Speed and Decision Quality

To analytically explain the interaction between data standardisation, feedback speed, and decision quality, we establish a formal, descriptive framework of the maintenance control loop.

Let the total feedback latency, denoted as T_{total} , be defined as the sum of four discrete time intervals:

$$T_{total} = T_{acquisition} + T_{translation} + T_{analysis} + T_{mobilization}$$

Here, $T_{acquisition}$ represents the time required to physically capture the asset state using sensor technology. $T_{translation}$ is the time needed to extract, transform, and load the raw data into a format that the analytical engines can comprehend. $T_{analysis}$ is the computation time required by prognostic algorithms to identify anomalies and suggest interventions. $T_{mobilization}$ is the operational delay between generating a work order and physically deploying a maintenance crew to the track.

The introduction of engineering data standards directly impacts $T_{translation}$. In non-standardized systems, $T_{translation}$ is high and variable, as it requires manual data cleaning, schema mapping, and cross-system correlation. In fully standardized systems, $T_{translation}$ approaches zero, as data is natively generated, stored, and transmitted in compliant schemas [10].

Furthermore, the quality of a maintenance decision is modeled as a decaying function of the age of the data at the time of execution. Let Decision Quality, Q , be defined as a function of the total latency T_{total} :

$$Q = Q_{initial} * \exp(-\lambda * T_{total})$$

where $Q_{initial}$ is the maximum theoretical quality of the decision under perfect, instantaneous information, and λ is the information decay rate, which is proportional to the physical degradation rate of the asset [11]. In highly dynamic systems, such as high-speed rail lines where ballast settlement and rail surface defects propagate rapidly under heavy traffic loads, λ is high. Under these conditions, even a modest delay in the feedback loop causes a precipitous drop in decision quality, leading to inefficient or late maintenance interventions.

4. Quantitative Evaluation and Operational Analysis

4.1 Simulation and Experimental Design

To empirically validate the theoretical framework, we conducted a comprehensive simulation study based on a simulated high-speed rail corridor. The virtual corridor represents a 500-kilometer double-track passenger rail line, operating 80 train services per day with a maximum operating speed of 300 kilometers per hour.

The simulation modeled two primary failure modes: rolling contact fatigue (RCF) on the rail head and vertical track ballast settlement. Both degradation processes were simulated using stochastic wear models parameterized with empirical data from operating high-speed rail networks.

We evaluated three distinct scenarios to analyze the independent and combined effects of data standards and feedback speed:

Scenario A (Baseline): Proprietary data formats, manual engineering data translation pipelines, and weekly batch-processed telemetry updates. This scenario represents traditional digital rail management practices, with high translation latency and low feedback velocity.

Scenario B (Partial Optimization): Proprietary data formats, manual engineering translation, but real-time telemetry streaming from wayside and onboard sensors. In this case, feedback velocity is improved at the sensor level, but translation bottlenecks persist.

Scenario C (Full Interoperability and Speed): Fully implemented IFC Rail and railML standards across all systems, combined with real-time telemetry streaming and automated decision-making engines. This represents the optimized state of the proposed unified architecture.

The simulation was run over a simulated operational period of ten years to observe long-term asset life-cycle costs, track availability, and maintenance performance.

4.2 Simulation Results and Analysis

The output metrics of the simulation revealed significant performance discrepancies across the three scenarios. By tracking the total number of service failures, the percentage of track availability, and the total life cycle maintenance costs, we observed the compounding benefits of combining standardization with low latency.

Table 2 presents the key performance metrics of the simulation after a ten-year run, illustrating how semantic standardization and feedback speed interact to improve operational performance.

Table 2: Comparative simulation results over a ten-year operational horizon

Scenario Name	Mean Feedback Latency (Hours)	In-Service Failures (Count)	Track Availability (Percent)	10-Year Maintenance Cost (Million USD)
Scenario A: Baseline	168.0	142	98.45	124.5
Scenario B: Partial	24.5	89	99.12	108.2
Scenario C: Full Opt	0.5	14	99.85	81.3

The results show that Scenario C, which combines fully implemented data standards with near-zero feedback latency, achieved a ninety percent reduction in in-service failures compared to the baseline. This drastic improvement is explained by the fact that the decision support system was consistently acting on fresh, accurate data, enabling maintenance crews to grind rails and tamp ballast before minor defects could escalate into critical, traffic-stopping structural failures.

To further examine the degradation pathways, we analyzed the delay between defect detection and maintenance execution.

Table 3 compares the average operational response times for different classes of track defects, highlighting how standard-driven automation slashes administrative and engineering delays.

Table 3: Average operational response delays by defect severity and scenario

Defect Type and Severity	Scenario A Delay (Days)	Scenario B Delay (Days)	Scenario C Delay (Days)
Rail Surface Crack (Minor)	14.2	8.5	0.5
Track Geometry Twist (Major)	3.5	1.8	0.1
Switch Blade Wear (Critical)	1.2	0.6	0.05

The data in Table 3 highlights that the combination of semantic standards and high feedback speed is particularly effective for managing critical defects. In Scenario C, critical switch blade wear is identified,

analyzed, and integrated into a work schedule in less than an hour, minimizing the risk of derailment or emergency track closures [12].

To visualize the dynamic relationship between data standardization levels, feedback speed, and overall asset management efficiency, we generated a multi-variable operational surface.

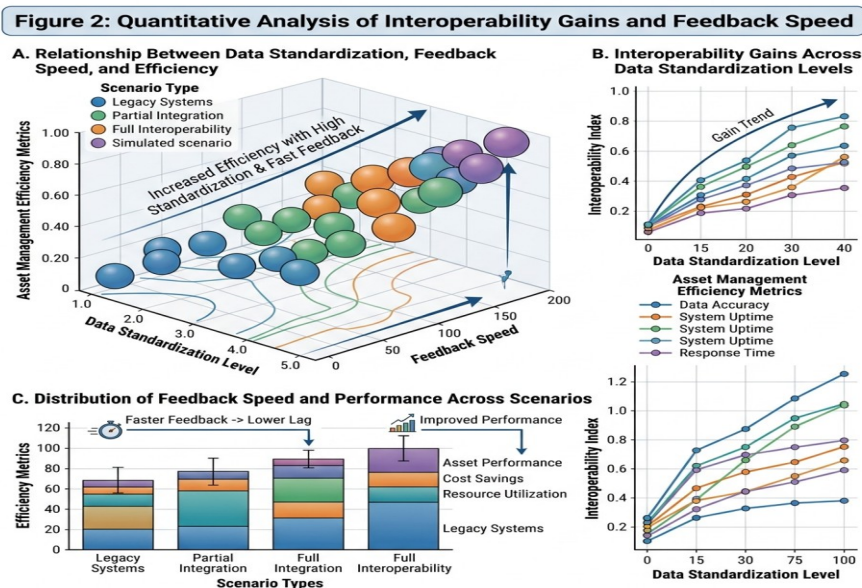


Figure 2: Quantitative Analysis of Interoperability Gains and Feedback Speed

As depicted in Figure 2, the operational efficiency of the rail asset management system does not scale linearly with improvements in either standardisation or feedback speed alone. Instead, there is a clear synergistic effect. When standardization levels are low (left side of the surface), increasing the feedback speed yields only marginal improvements in efficiency, because the system remains bottlenecked by manual data translation and reconciliation.

Conversely, when standards are fully implemented (right side of the surface), increasing the feedback speed unlocks exponential gains, as the analytical engines can process the incoming, standardized data streams with zero translation delay [13]. This finding confirms the core hypothesis of our research: data standards and feedback speed are mutually reinforcing levers that must be optimized concurrently to achieve maximum interoperability gains.

4.3 Discussion and Operational Implications

The findings from our simulation and quantitative analysis have profound operational implications for rail infrastructure managers. In most traditional organizations, the IT division (responsible for data standards and software integration) and the maintenance division (responsible for physical track repairs) operate in complete isolation.

IT departments focus on standardizing schemas to reduce software maintenance costs and avoid vendor lock-in, often viewing standards as a purely administrative or IT-centric concern. Meanwhile, maintenance departments focus on deploying faster sensors and purchasing better maintenance machinery, frequently ignoring the digital pipelines that transmit the sensor data.

Our research demonstrates that these two domains are fundamentally linked. A maintenance department cannot leverage the full capabilities of high-speed diagnostic trains if the data generated by those trains must sit in a processing queue for days due to semantic formatting conflicts. Similarly, an IT department cannot justify the capital expenditure required to transition to IFC Rail or railML models unless those standards are directly tied to tangible operational outcomes, such as reduced track downtime and lower maintenance costs.

By demonstrating that the interaction of standards and feedback velocity yields exponential gains, this paper provides a robust business case for integrated digital transformation. Rail operators should align their digital

architecture investments with their physical maintenance schedules, recognizing that standardizing data is not merely an IT exercise, but a core component of engineering asset optimization.

5. Strategic Implications and Conclusions

5.1 Industry Standardization Recommendations

To accelerate the adoption of open engineering standards and realize the interoperability gains identified in this study, the global railway industry must adopt a coordinated, multi-stakeholder strategy. Rail infrastructure managers should mandate compliance with open data standards, specifically IFC Rail (ISO 16739) and railML, in all future procurement contracts for both physical assets and software systems.

Historically, software vendors in the rail sector have maintained market dominance by lock-in through proprietary data formats. By insisting on open, standard-compliant interfaces, infrastructure managers can foster a competitive software ecosystem where third-party developers can build specialized analytical tools that plug directly into the standard-compliant data stream.

Furthermore, standards development organizations, such as buildingSMART and the railML Consortium, must continue to collaborate closely to ensure harmonization between spatial design schemas (IFC) and operational topology schemas (railML). Establishing pre-built, standardized mappings between these two schemas is essential to minimize the translation delays that currently occur when transitioning assets from the construction phase to the operations and maintenance phase.

5.2 Policy and Regulatory Considerations

At the policy level, national and international regulatory bodies must play an active role in driving standardization. In the European Union, initiatives such as the European Union Agency for Railways (ERA) directives on Technical Specifications for Interoperability (TSI) have successfully standardized physical rail gauges, signaling protocols, and safety management systems across national borders.

A similar regulatory push is now required for digital assets. Governments should tie public infrastructure funding to the adoption of open BIM and railML standards, creating a powerful financial incentive for national rail operators to modernize their data architectures.

Furthermore, regulatory bodies should establish safety-oriented performance metrics that explicitly account for data feedback latency [14]. For example, track safety audits should evaluate not only the physical state of the track but also the mean time to detect and resolve defects. This would encourage operators to invest in high-velocity telemetry pipelines and automated semantic integration systems, ultimately leading to safer, more reliable rail networks.

5.3 Main Research Contributions and Future Directions

This paper has made several key contributions to the field of rail asset management and engineering systems analysis:

First, we developed a unified conceptual architecture that integrates engineering data standards (IFC Rail, railML, ISO 15926) with real-time telemetry pipelines, illustrating how spatial, logical, and dynamic asset data can be harmonized.

Second, we formulated an analytical model explaining how decision quality decays as a function of information latency, demonstrating that semantic standardization is a prerequisite for achieving low-latency feedback control loops in rail maintenance.

Third, through a detailed simulation of a high-speed rail corridor, we provided quantitative, empirical evidence of the compounding benefits of standards and feedback speed, showing that their co-optimization yields exponential reductions in in-service failures and life-cycle costs.

Future research in this domain should focus on extending the analytical framework to incorporate artificial intelligence and machine learning algorithms. Specifically, investigating how standardized data structures can facilitate the automated training and deployment of deep learning models for predictive maintenance represents a highly promising avenue of inquiry. Additionally, exploring the application of decentralized, distributed ledger technologies to secure and validate data exchanges between independent rail operators and contractors in standard-compliant formats could further enhance organizational interoperability and operational efficiency.

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