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# ADVANCING RAIL INFRASTRUCTURE: INTEGRATING DIGITAL TWINS AND CYBER-PHYSICAL SYSTEMS FOR PREDICTIVE MAINTENANCE

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## Abstract

The railway sector struggles with infrastructure inefficiencies due to traditional maintenance methods, resulting in high costs and unplanned disruptions. This paper provides a conceptual framework that integrates Digital Twins (DT) and Cyber-Physical Systems (CPS) to enhance predictive maintenance (PdM). By establishing a technical architecture for real-time monitoring and fault detection, the framework will facilitate seamless data exchange for automated decision-making. The findings contribute to advancing intelligent railway maintenance, fostering sustainability, and enhancing resilience in railway operations. This research provides actionable insights for industry stakeholders, supporting the transition towards data-driven, adaptive maintenance strategies in modern rail networks.

## Background and Motivation

The railway industry is a crucial for global transportation, facilitating the mobility of goods and passengers supporting 2.3 million jobs and contributes €143 billion annually (European Commission, 2015). In 2023, railways transported over 429 billion passenger-kilometres, underscoring their critical role in passenger mobility (Eurostat, 2024). Efficient maintenance is essential for sustaining the operational performance of rail systems, as maintenance costs exceed £1 billion annually in the United Kingdom (UK), representing 18% of Network Rail's expenditure (UK Research and Innovation (UKRI), 2019). These costs are further exacerbated by disruptions caused by planned and unplanned maintenance.

Traditional maintenance practices, such as scheduled and corrective approaches, are inadequate. They result in inefficiencies, unexpected downtime, elevated costs, and safety risks. In the UK alone, unplanned maintenance costs exceed £169 million annually, with unscheduled failures and delays forming a significant portion of these expenses (Network Rail, 2024b). Predictive maintenance (PdM) presents a transformative alternative, leveraging technologies like the internet of things (IoT), big data analytics, and artificial intelligence (AI). PdM predicts failures before they occur, enabling condition-based repairs. This approach has yielded a 15% improvement in reliability, a 20% reduction in maintenance costs, and a 30% decrease in train breakdowns (International Union of Railways, 2024).

The complexity of rail systems stems from their interconnected assets and subsystems, each requiring unique maintenance strategies (Francesco, Gabriele and Stefano, 2016; Shang *et al.*, 2023). These assets must operate cohesively across vast networks. Disruptions in this complex system, ripple through networks, causing delays and inefficiencies (Lyu *et al.*, 2023; Network Rail, 2024a). As urban populations grow, reliable and sustainable rail systems are vital. However, aging infrastructure and regionally variable rail assets complicate maintenance efforts (United Nations Economic Commission for Europe (UNECE), 2018). Innovative PdM techniques are therefore essential to addressing these challenges, ensuring rail systems meet environmental goals while providing cost-effective, reliable, and safe transport solutions.

The integration of digital twin (DT) and cyber-physical systems (CPS) emerges as a groundbreaking solution to address challenges in PdM (Gbadamosi *et al.*, 2021; De Donato *et al.*, 2023; Yan *et al.*, 2023). A DT is a digital replica of a physical asset, continuously updated with real-time data from embedded sensors (Grieves and Vickers, 2017). Extensive research within the railways has explored DTs, focusing on creating interconnected ecosystems that enable near real-time data access to support both functional and operational aspects of rail infrastructure (Kaewunruen and Lian, 2019; Kampczyk and Dybeł, 2021; Aksenov *et al.*, 2022; Ariyachandra and Brilakis, 2023; Kaewunruen *et al.*, 2023; Reis and Melão, 2023; Krmac and Djordjevic, 2024). Conversely, CPS links physical infrastructure with computational models, facilitating seamless data exchange and real-time asset monitoring.

The integration of DT and CPS in railways presents substantial cost-saving opportunities by enhancing maintenance efficiency and operational reliability. The European Commission estimates that rail operators could save up to €3 billion annually by implementing PdM through integrated DT-CPS technologies (Groenendaal, Akkermans and Kempen, 2023). Furthermore, PdM with integrated DT and CPS technologies can improve safety by detecting faults before they escalate into hazardous situations. Additionally, integrated DT and CPS ecosystems can contribute to the sustainability of railways by reducing waste, minimising energy consumption, and extending infrastructure lifespan. For instance, the High-Speed Rail 2 (HS2) employs DT-powered CPS to monitor infrastructure, aiming to reduce carbon emissions by 3.2 million tons over the first 60 years of operations (Bentley Systems, 2020).

Nevertheless, while other industries successfully implemented the fusion of DT and CPS (Lee *et al.*, 2020; Park *et al.*, 2020), their application within rail remains in its infancy. One of the key challenges is the need for a robust technical architecture that can facilitate seamless data interoperability among disparate systems (Tao *et al.*, 2019; Qian *et al.*, 2022). This architecture must enable the integration of legacy systems, which often rely on outdated technologies and processes, thereby impeding the efficient flow of information. Moreover, it must ensure scalability and manage the high costs associated with sensor installation and software development. The integration of CPS with DT requires the fusion of diverse data streams from sensors, control systems, and AI algorithms (Monostori *et al.*, 2016; Zhong *et al.*, 2017), which must be processed in real-time to derive actionable insights. Without a well-defined technical architecture, addressing these integration challenges becomes difficult. Additionally, ensuring data accuracy, system reliability, and the security and privacy of operational data are critical concerns that a robust technical architecture can help mitigate. Therefore, developing a comprehensive technical architecture is essential for overcoming these barriers and realising the full potential of DT and CPS technologies in enhancing PdM and operational efficiency in the railway sector.

### Originality and Knowledge Contribution

Addressing the above challenge, this paper aims to advance the state of research by proposing a novel conceptual framework for the technical architecture of DT integrated CPS, specifically tailored for PdM in railways. The research objectives are as follows:

1. To establish precise definitions and interrelations of DT, CPS, and PdM procedures in the context of rail infrastructure.
2. To design a conceptual framework illustrating the technical integration of DT and CPS for PdM in railway infrastructure.
3. To identify and evaluate data streams between DTs and CPS to enhance PdM capabilities in rail infrastructure.

This research goes beyond a general discussion of DT and CPS concepts by proposing a conceptual technical architecture, advancing theoretical understanding, and fostering interdisciplinary dialogue on DT and CPS integration. The proposed framework will equip industry stakeholders with actionable insights into deploying an integrated DT-CPS for improved asset management, reduced downtime, and enhanced operational efficiency. Its scalability and adaptability will accelerate the adoption of advanced technologies within rail infrastructure, supporting innovation and operational resilience. From a societal perspective, this research aims to improve the reliability and efficiency of railways, reducing delays and enhancing passenger satisfaction. This conference paper focuses on developing the conceptual framework as the initial step, which will serve as the foundation for the subsequent detailed design of the prototype of the DT-CPS technical architecture.

## Origin, Development and Definitions for CPS and DT

### Origin, Development and Definition for CPS

CPS represent a paradigm shift in engineering and technology, integrating physical processes with computation and networking to create intelligent systems capable of autonomous operation and real-time decision-making (Akanmu, Anumba and Ogunseiju, 2021). The origins of CPS can be traced back to the early 2000s, when researchers recognised the potential of embedding computational elements into physical systems to enhance their performance and functionality (Yan and Sakairi, 2019). As industries embraced digital technologies, CPS evolved rapidly, with applications emerging in various sectors, including manufacturing, transportation, and healthcare. In the construction industry, CPS has gained traction in recent years, driven by the need for enhanced efficiency, safety, and sustainability (Alaloul, 2022). The integration of IoT and building information modelling (BIM), and advanced analytics has facilitated the development of CPS tailored to construction processes, enabling real-time monitoring, predictive analytics, and data-driven decision-making (Tang *et al.*, 2019). In this context, CPS can be defined as systems that seamlessly combine physical elements, computational algorithms, and communication networks to optimise operational performance and enhance safety in the built environment. For PdM in rail infrastructure, a specific definition of CPS would emphasize its role in continuously monitoring the health of rail assets through embedded sensors and data analytics, allowing for PdM interventions to minimise disruptions and enhance the reliability of rail services.

### Origin, Development and Definition for DT

The concept of DTs originated from the convergence of physical and digital worlds, gaining significant traction in the early 2000s as a result of advancements in the IoT and CPS. Initially conceptualised by Dr Michael Grieves in 2002, the DT was envisioned as a digital representation of a physical object or system, allowing for real-time monitoring and simulation (Grieves and Vickers, 2017). Over the years, the evolution of CPS has further propelled the development of DT, particularly within various industries, including manufacturing, aerospace, and, notably, construction. In the construction sector, the integration of DTs has been instrumental in optimising project management, enhancing design processes, and improving operational efficiencies (Moshood *et al.*, 2024). The proliferation of sensors, advanced analytics, and big data has facilitated the real-time data acquisition necessary for effective DT implementations. Consequently, the construction industry has witnessed a paradigm shift towards digitalisation, enabling stakeholders to harness PdM strategies for infrastructure. In the context of rail infrastructure, DT can be specifically defined as virtual replicas of railway system that leverage real-time data and advanced analytics to PdM needs, thereby enhancing safety, operational efficiency, and lifecycle management. This tailored definition underscores the potential of DT in transforming PdM practices within the rail industry, ultimately contributing to more resilient and efficient infrastructure.

**PdM Procedures for Rail Infrastructure**

The selection of PdM procedures outlined in the proposed technical architecture for rail infrastructure (Table 1) is grounded in empirical evidence, industry best practices, and a systematic multi-criteria decision-making (MCDM) approach. This rigorous selection process enables us to optimise the reliability and safety of over a thousand components and hundreds of systems by prioritising techniques based on their effectiveness in detecting potential failures, mitigating risks, and their applicability across various rail infrastructure components.

*Table 1: PdM procedures outlined in the proposed technical architecture for rail infrastructure*

| Components | PdM procedures |
|---|---|
| Track and Rail | |
| Rails | Ultrasonic Testing: Detect internal cracks, fatigue, and material flaws.<br>Eddy Current Testing: Identify surface defects, such as head checks and corrugation. |
| Sleepers | Load Monitoring: Use strain gauges to assess load distribution and detect cracking or deformation |
| Ballast | Ground Penetrating Radar (GPR): Assess ballast conditions, including contamination and voids. |
| Fastenings | Visual and Acoustic Analysis: Monitor fastener integrity to prevent loosening under dynamic loads. |
| Signalling Systems | |
| Interlockings | Logic Circuit Testing: Continuously evaluate interlocking functionality using automated tools. |
| Track Circuits | Current Flow Analysis: Detect electrical discontinuities or signalling dropouts. |
| Axle Counters | Pulse Signal Monitoring: Ensure accurate train position reporting by analysing counter signals. |
| Control Panels | Temperature and Voltage Monitoring: Identify overheating or power fluctuations in signalling relays. |
| Rolling Stock | |
| Wheels and Axles | Acoustic Emission Testing: Detect cracks or flat spots through wheel noise patterns. |
| | Laser Scanning: Measure wear and irregularities on wheel surfaces. |
| Brakes | Dynamic Brake Testing: Monitor braking force and heat dissipation during operations. |
| Doors | Motor Health Monitoring: Use vibration sensors to detect faults in door mechanisms. |
| HVAC Systems | Thermal Load Analysis: Evaluate efficiency and identify blockages in air circulation. |
| Overhead Line Equipment (OLE) | |
| Catenary Wires | Wear and Tension Monitoring: Use tension meters and visual inspections to predict wire degradation. |
| Masts and Gantries | Structural Fatigue Analysis: Use accelerometers to measure vibrations and stress points. |
| Insulators | Thermal Imaging: Detect hotspots caused by contamination or cracking. |
| Bridges and Tunnels | |
| Bridge Decks | Load Testing with Strain Gauges: Evaluate stress levels under dynamic and static loads. |
| Tunnels | Moisture and Leak Detection: Use humidity sensors and thermal imaging for water ingress monitoring. |
| Expansion Joints | Ultrasound and Visual Inspections: Detect wear, corrosion, and joint misalignments. |
| Stations and Platforms | |
| Escalators | Chain and Step Monitoring: Use IoT-enabled sensors to measure chain tension and detect abnormal vibrations. |
| Elevators | Motor Efficiency Testing: Analyse motor currents and lubrication status to identify potential faults. |
| Platform Surfaces | Slip Resistance Testing: Monitor wear and reduce slip hazards with surface coating analysis. |
| Drainage Systems | |
| Culverts | Blockage Detection with Sonar Sensors: Identify sediment accumulation and flow obstructions. |
| Pumping Stations | Pump Efficiency Monitoring: Analyse vibration and flow rate data to detect clogging or motor faults. |
| Open Drains | Camera Inspections: Use robotic cameras for real-time assessment of debris and erosion. |

The MCDM approach involved several key steps. First, the authors conducted an extensive literature review to identify existing PdM procedures utilised in rail infrastructure. Following the literature review, the authors completed data-driven assessments of existing maintenance practices within the railway sector. This involved analysing failure rate data, maintenance logs, and incident reports to quantify the performance of different PdM methods. This quantitative analysis enabled the authors to identify patterns in equipment failures and correlate them with specific PdM procedures. To synthesize these insights, the authors finally employed a scoring model that evaluated each PdM method against predetermined criteria, including effectiveness in failure detection, cost implications, ease of integration with existing systems, and historical performance data. Each criterion was weighted based on its significance to railway operations, allowing the MCDM approach to prioritise procedures that demonstrated the highest potential for improving safety and operational reliability.

## Technical Architecture of CPS-DT for PdM in Rail Infrastructure

The proposed framework, designed to address the unique challenges of PdM procedures, is structured around three interconnected domains (Figure 1):

1. The Physical Domain with the Physical Twin
2. The Communication Layer serving as the cyber-physical bridge
3. The Cyber Domain housing the Digital Twin.

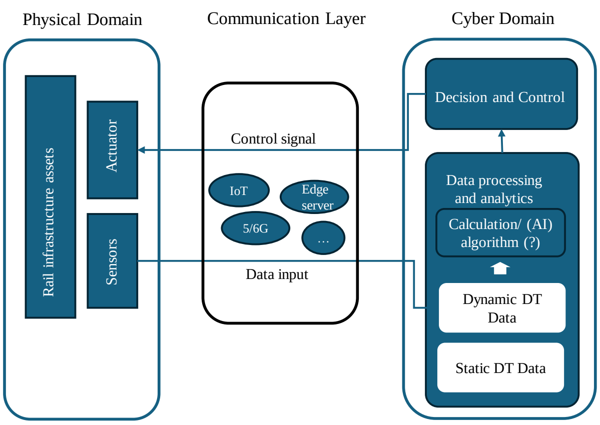


*Figure 1: Three domains in the technical architecture of CPS-DT for PdM in rail infrastructure*

### Physical Domain: The Physical Twin

The physical domain/twin serves as the foundational layer of the CPS-DT framework, encompassing two primary categories of physical elements that underpin rail operations. The first category includes the fundamental rail assets such as tracks, sleepers, rolling stock, signalling systems, and auxiliary structures like bridges, tunnels, and OLE systems. These elements constitute the core physical infrastructure that facilitates railway operations and ensures system functionality. The second category comprises advanced sensing and actuation technologies integrated into the rail assets. These include a diverse range of sensors such as load cells, ultrasonic sensors, strain gauges, deformation sensors, and GPR systems. Together, these components serve as critical nodes for capturing dynamic, high-fidelity data from the physical environment, forming the essential input layer for the proposed CPS-DT technical architecture.

The physical domain/twin ensures real-time interaction between the physical rail environment and the cyber systems by continuously supplying raw, high-resolution data streams. This data forms the backbone of the DT domain, enabling real-time monitoring, predictive analytics, and decision-making processes. For example, ultrasonic sensors detect internal rail cracks that may otherwise go unnoticed during routine inspections; strain gauges measure load distribution across sleepers to identify uneven stress; and GPR systems evaluate ballast conditions to detect contamination or structural weakening. Actuators complement these sensors by facilitating responsive actions within the rail system. For instance, actuators automatically adjust the tension in OLE wires to prevent sagging, which can disrupt train operations, or activate heating elements embedded within tracks to mitigate freezing hazards during extreme weather conditions. These dynamic responses enhance the resilience and reliability of rail infrastructure by preventing operational failures. Figure 2 presents the Physical Domain illustrating some of the physical assets and sensor placements in the proposed framework.

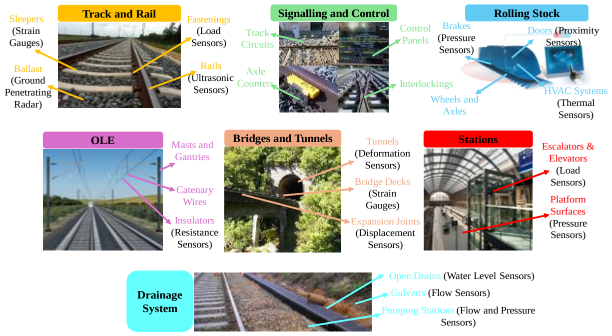


*Figure 2:Physical domain illustrating some of the physical assets and sensor placements in the proposed framework*

### Communication Layer: The Cyber-Physical Bridge

The communication layer serves as the cyber-physical bridge, facilitating seamless, high-fidelity data exchange between the physical and cyber domains. This bidirectional layer is essential for real-time PdM in rail infrastructure, ensuring the transmission of sensor data from the physical twin to the digital twin while enabling precise control and adaptive interventions. Given the complexity and safety-critical nature of rail operations, this layer is underpinned by an advanced integration of edge computing, 5G-enabled IoT networks, and AI-driven data processing frameworks to support ultra-reliable low-latency communication (URLLC).

The communication layer operates through a multi-tiered network architecture comprising sensor nodes, edge gateways, cloud platforms, and control systems. High-resolution data from ultrasonic sensors, eddy current probes, strain gauges, and thermal imaging cameras will be captured in real time and transmitted via IoT networks. For instance, ultrasonic testing of rails detects internal cracks, while eddy current sensors identify surface defects, such as head checks and corrugation. These high-frequency signals require rapid processing at the edge to enable immediate fault detection and mitigate risks of catastrophic failures.

The incorporation of 5G-enabled IoT enhances the responsiveness of this layer, particularly in time-sensitive applications like axle counter pulse signal monitoring. The ultra-low latency of 5G ensures that axle counter signals are processed instantaneously, preventing discrepancies in train positioning. Furthermore, GPR systems, deployed for ballast condition assessment, transmit terabyte-scale data to edge computing nodes for preprocessing, thereby reducing the bandwidth load on central cloud servers and accelerating anomaly detection. Edge computing nodes, integrated within railway substations and trackside units, perform real-time analytics on raw data before forwarding aggregated insights to centralised cloud platforms. These edge systems are equipped with AI-driven models trained on historical maintenance records, enabling predictive diagnostics of critical railway components. For example, acoustic emission analysis of rolling stock wheels can detect subsurface cracks before they propagate into structural failures. AI models process frequency-domain signals at the edge, correlating them with historical degradation patterns to predict the remaining useful life of wheels and axles. Similarly, dynamic brake testing relies on distributed temperature and force sensors, which stream real-time thermal dissipation data to edge nodes. By employing machine learning-based anomaly detection, brake malfunctions can be anticipated, reducing the likelihood of brake fade or failure during operations. In OLE, real-time tension meters and thermal imaging cameras continuously assess the wear of catenary wires, with AI models identifying patterns indicative of fatigue-induced failures.

Given the critical nature of railway operations, cybersecurity mechanisms are embedded within the communication layer to safeguard against cyber threats and data corruption. Blockchain-based distributed ledgers ensure the integrity of PdM data streams by providing tamper-proof logging of sensor transmissions. Moreover, AI-driven intrusion detection systems (IDS) continuously monitor network traffic patterns, identifying anomalies that could indicate cyberattacks on interlocking systems or signalling circuits. Redundant communication channels further enhance the resilience of the system. For example, in the event of a failure in the primary 5G network, sensor data from track circuits (which monitor electrical discontinuities) and control panel voltage monitors can be rerouted through fibre-optic networks or satellite-based connectivity to maintain uninterrupted operations. These fault-tolerant designs are crucial for ensuring operational continuity, particularly in remote or underground railway sections where network disruptions are more prevalent.

The bidirectional nature of this layer facilitates automated responses based on real-time diagnostics. For instance, upon detecting excessive vibration in bridge expansion joints using accelerometers, control systems can initiate automated inspections or alert maintenance crews before structural integrity is compromised. In drainage systems, sonar sensors embedded within culverts detect sediment accumulation, triggering automated flushing mechanisms or scheduling robotic camera inspections to assess blockages. Similarly, in stations and platforms, IoT-enabled escalator chain and step monitoring systems provide real-time feedback to maintenance teams. When abnormal vibrations are detected, predictive algorithms determine whether immediate intervention is necessary, thereby minimising unplanned outages and optimising maintenance schedules.

### Cyber Domain: The Digital Twin

The cyber domain is the computational core of the CPS-DT framework, housing the DT, which is continuously synchronised with real-time data. This domain bridges the physical infrastructure with advanced digital analytics, leveraging high-fidelity models and predictive capabilities to enhance PdM procedures. Through continuous data exchange with the Communication Layer, the DT ingests and processes sensor-derived information, enabling data-driven decision-making that influences interventions in the Physical Domain. The cyber domain operates across two critical functions: data processing and analytics; and decision and control. These functions rely on the Communication Layer to receive and transmit data from the Physical Domain.

#### *Data Processing and Analytics*

Raw sensor data (Table 2) undergoes transformation into actionable insights using technologies such as big data analytics, AI and ML. Advanced computational models identify failure patterns, predict asset degradation, and optimise railway operations. For instance:

- AI-driven analytics process vibration data from rolling stock to detect early signs of motor faults, enabling condition-based maintenance.
- ML models predict structural degradation in bridges and tunnels under dynamic loads, informing long-term maintenance planning.
- Graph-based AI integrates multi-source data to model complex interdependencies, such as rail-track interactions under varying train loads.

Computational tasks are distributed between edge computing (for real-time, latency-sensitive operations) and cloud platforms (for high-volume analytics). For instance:

- Edge AI detects immediate track defects using onboard sensor fusion techniques, triggering alerts for rapid intervention.
- Cloud-based processing aggregates and analyses data over time to develop system-wide predictive models for infrastructure resilience.

*Table 2: Key static and dynamic DT data in the proposed technical architecture*

| Key static DT data | Key dynamic DT data |
| --- | --- |
| Track and Rail | |
| • Track layout, material specifications<br>• Historical wear data<br>• Track maintenance history | • Stress, strain, and deformation data<br>• Vibration and temperature<br>• Train load and speed<br>• Real-time track geometry |
| Signalling and Control | |
| • Signal types, layout, and lifespan<br>• Circuit diagrams and hardware configurations | • Signal operation and response times<br>• Fault occurrences and system downtime |

| | |
|---|---|
| • Historical maintenance logs | • Voltage and power fluctuations<br>• Environmental impacts on signalling equipment |
| Rolling Stock | |
| • Fleet inventory<br>• Maintenance records (e.g., wheel wear, axle condition)<br>• Axle load and fatigue limits<br>• Design and performance specifications | • Wheel-rail interface forces<br>• Speed, acceleration, and braking performance<br>• GPS for train location<br>• Brake performance and temperature fluctuations<br>• Vibration and tilt sensors |
| Overhead Line Equipment (OLE) | |
| • Material specifications<br>• Support structure layouts and specifications<br>• Environmental impact thresholds | • Real-time wire tension and sag<br>• Voltage, current, and load variations<br>• Pantograph-wire interaction data<br>• Weather-related impacts |
| Bridges and Tunnels | |
| • Structural design models (e.g., CAD)<br>• Material specifications<br>• Inspection and repair history<br>• Load capacity and fatigue limits<br>• Construction and modification history | • Real-time strain and stress measurements<br>• Vibrations caused by train movement, crack growth, deformation<br>• Water infiltration and corrosion levels<br>• Weather conditions (e.g., humidity) |
| Drainage Systems | |
| • Layout and design models<br>• Soil and water flow characteristics<br>• Inspection records | • Footfall counters<br>• Real-time water level and infiltration monitoring<br>• Real-time blockages and silt accumulation<br>• Water flow rates during rainfall |
| Stations and Platforms | |
| • Layout (spatial relationship) of station assets<br>• Safety and emergency protocols<br>• Accessibility compliances<br>• Passenger flow<br>• Asset inventory and inspection records | • Passenger flow and crowd density (CCTV and security systems)<br>• Vibrations and structural stress measures<br>• Real-time condition of escalators, elevators, and systems<br>• Weather conditions (i.e temperature) |

***Decision and Control: The Feedback Loop***

The decision and control function converts analytical insights into operational actions, forming a self-adaptive CPS-DT system. This feedback mechanism allows automated responses, optimised maintenance scheduling, and real-time control decisions, such as:

- Predictive alerts: If GPR data detects ballast contamination, an automated maintenance work order is generated for cleaning or replacement.
- Dynamic load adjustment: If stress anomalies are detected in rails, automated control systems adjust axle loads dynamically to prevent further deterioration.
- Autonomous diagnostics: AI-driven decision engines cross-validate sensor data anomalies, minimising false alarms and enhancing fault detection accuracy.

By tightly integrating data analytics, communication networks, and physical assets, the cyber domain ensures railway infrastructure operates with maximum efficiency and minimal disruption. Figure 3 depict the proposed CPS-DT framework in a track maintenance scenario.

## Future Development Strategy

The proposed technical architecture establishes a conceptual framework for integrating DT technology with CPS to enhance predictive maintenance in railway infrastructure. The next phase involves transitioning from conceptual framework to a functional prototype to evaluate system performance under real-world conditions. This process encompasses several key steps.

1. DT model development will involve constructing high-fidelity virtual replica of the railway system. This step will include incorporating multi-source sensor data to simulate real-time asset conditions.
2. The edge and cloud computing infrastructure deployment will establish a hybrid computational architecture. Latency-sensitive tasks, such as vibration analysis for track defects, will be processed on edge devices, while cloud-based analytics will handle long-term trend analysis and decision support. Federated learning techniques will be leveraged to improve model training without extensive data transfer, ensuring data privacy and reducing bandwidth constraints.
3. The integration of IoT and 5G-enabled connectivity will involve deploying a robust sensor network with IoT-enabled condition-monitoring devices mounted on railway assets. 5G URLLC will facilitate real-time data transmission, enabling near-instantaneous feedback loops for dynamic maintenance scheduling. Middleware will be implemented for seamless data aggregation and standardisation across heterogeneous systems.
4. Testing and validation will be conducted through controlled pilot implementations on designated railway corridors to evaluate PdM accuracy, system responsiveness, and interoperability with legacy railway management systems. Key performance indicators (KPIs) will be established, including fault detection lead time, false positive rate in anomaly detection, and maintenance cost reductions.
5. The researchers will partner with industry to co-develop implementation guidelines. Workshops will be conducted with regulatory bodies to align DT-CPS deployment with existing railway safety and cybersecurity standards.

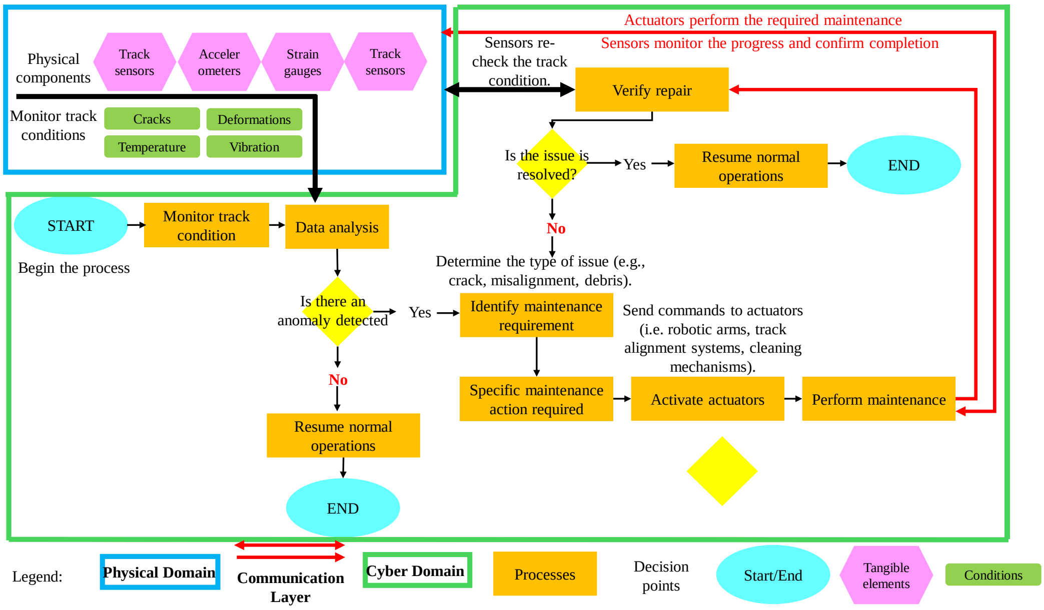


*Figure 3: Proposed CPS-DT framework in a track maintenance scenario*

## Limitations and Further Research

While the proposed DT-CPS framework presents significant advancements, several technical challenges require further research. Data integration and interoperability pose challenges due to legacy railway systems operating on fragmented data structures and proprietary software. Future research should focus on developing standardised semantic data models, such as Industry Foundation Classes (IFC) for rail, RailML, and openBIM standards, to enable seamless integration. Additionally, the reliance on IoT and cloud infrastructure exposes the system to potential cyber threats, necessitating the incorporation of advanced security protocols. Furthermore, real-time analytics demand high computational power, particularly for deep learning-based fault prediction models. Investigating lightweight machine learning models (e.g., TinyML) and neuromorphic computing approaches is essential for optimising performance on resource-constrained edge devices. Finally, while pilot-scale testing is a step forward, long-term validation in operational railway networks is required to assess real-world feasibility. Future studies should explore multi-year deployments across diverse railway systems, to refine model generalisability and adaptive learning capabilities.

## Conclusion

This research introduces a novel DT-CPS integration conceptual framework that advances PdM strategies in rail infrastructure. Key contributions include enhanced PdM through AI-driven fault diagnostics and real-time sensor fusion, a scalable and interoperable architecture that supports both legacy railway systems and next-generation digital rail initiatives, and real-time decision support using an adaptive decision-making framework leveraging reinforcement learning models. Furthermore, the framework promotes sustainability and asset longevity by implementing condition-based maintenance strategies that optimise material usage. By addressing the mentioned limitations through continued interdisciplinary research and industry collaborations, the proposed DT-CPS framework can serve as a transformative solution for PdM in rail infrastructure, fostering safer, more efficient, and cost-effective railway operations.

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