Leveraging Digital Twin Technology for Data-Driven Pavement Maintenance

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ABSTRACT: Integrating Digital Twin (DT) technology with data from automated pavement data collection resources, such as Autonomous Vehicles (AVs), offers a revolutionary approach to proactive pavement maintenance planning. This article proposes a comprehensive framework that utilizes diverse data sources, including AVs, sensors, automated data collection vehicles, and maintenance vehicles, to provide precise, real-time pavement condition data for better-informed maintenance decisions. Building Information Modeling (BIM) is used to create a digital representation of the pavement, facilitating visualization and simulation, leading to cognitive DT. Advanced AI analytics are utilized to detect pavement distress, optimize maintenance planning, and predict deterioration. The framework's strength is demonstrated through a case study on a Finnish motorway, highlighting potential improvements in maintenance efficiency, reduced reactive repair costs, and enhanced road safety. This research highlights the benefits of DT technology in pavement maintenance, including improved performance, longevity, and sustainability of road infrastructures, paving the way for wider adoption by road agencies.

1 INSTRUCTIONS

1.1 *Road DT Advancements*

Digital Twin (DT) technology creates dynamic digital replicas of physical systems, evolving to include IoT and machine learning (Tao et al., 2019). DTs are crucial in manufacturing and Industry 4.0, linking design and execution (Uhlemann et al., 2017), and in construction, often paired with Building Information Modeling (BIM) (Aengenvoort & Krämer, 2018; Borrmann et al., 2018; Arup, 2019).

DTs can significantly advance road infrastructure management by enhancing efficiency and effectiveness. Key benefits include:

Real-Time Monitoring: Using IoT for continuous asset monitoring (Tang et al., 2023).

Condition Assessment: AI-driven analysis for accurate evaluations (Wang et al., 2023).

Advanced Modeling: BIM integration for detailed virtual models (D'Amico et al., 2022).

Proactive Maintenance: Predictive analytics to anticipate issues (Callcut et al., 2021).

Simulation and Scenario Analysis: Virtual testing environments (Martínez et al., 2022).

Decision Support: Data-driven insights for strategic planning (Consilvio et al., 2023).

DTs offer transformative opportunities in road maintenance, reducing costs and improving conditions (Vieira et al., 2022; Talaghat et al., 2024).

1.2 *New methods of data collection in DT*

Data collection methods for pavement condition include sensors like radars, laser scanners, cameras, and UAVs (Coenen & Golroo, 2017). Smartphones are useful for crowdsourced data collection (Staniek, 2021). Techniques include image-based methods, point cloud imaging, and vibration-based methods (Sholevar et al., 2022). Automated data collection vehicles, such as Road Surface Profilers (RSP), use lasers and cameras to estimate the International Roughness Index (IRI) (Fahmani et al., 2024).

Autonomous Vehicles (AVs) offer a cost-effective approach to data collection, reducing operational costs and providing comprehensive coverage. AVs monitor pavement conditions in real-time, aiding in Maintenance and Rehabilitation (M&R) decisions. Equipped with sensors, AVs collect extensive real-time data, enhancing traffic flow, optimizing routing, and improving safety. AVs can also collect data from other infrastructures, helping prioritize M&R activities (Vieira et al., 2022; Martínez et al., 2022).

Challenges include user data privacy, real-time data transmission, and automotive industry regulations. Despite these, AVs can revolutionize transportation infrastructure management (Vieira et al., 2022; Martínez et al., 2022).

1.3 *AI in Road DT maintenance planning*

Despite advancements in road pavement DT teSchnology, there's a need to improve AI utilization for better decision-making. DT maturity levels include digital model, digital shadow, and digital twin, with the next level being cognitive DT, which integrates AI. AI applications in road pavement management include:

Pavement Distress Detection: AI algorithms detect and classify defects, improving inspection efficiency (Sierra et al., 2022).

Pavement Performance Development: AI develops predictive models for pavement deterioration (Yu et al., 2020).

Pavement Maintenance Planning: AI prioritizes maintenance tasks, optimizing routines and reducing costs (Consilvio et al., 2023).

Integrating AI into DT frameworks can revolutionize pavement management, creating more sustainable and resilient networks. This paper presents a framework for cognitive DT, focusing on AI-based data-driven maintenance planning, optimal data acquisition, and enhancing conventional DTs with AI.

To summarize, integrating AI into road pavement Digital Twin (DT) maintenance planning can revolutionize pavement management, creating more sustainable and resilient transportation networks. This paper presents a framework for cognitive DT, focusing on AI-based data-driven maintenance planning and optimal data acquisition systems. The main objectives are:

- Provide a conceptual design of cognitive road DT for maintenance planning.
- Explore AI applications in optimal road maintenance planning.
- Scrutinize automated data collection tools for pavement condition data.
- Enhance conventional DTs with AI for improved maintenance planning.

2 ROAD DT CONCEPTS AND FRAMEWORK

2.1 *Conceptual design of road pavement DT*

Figure 1 illustrates the conceptual design of the cognitive DT for road pavement. This system integrates sensors, vehicles, and cloud-based analytics to create a comprehensive digital representation of road pavements. Autonomous Vehicles (AVs) equipped with sensors like LiDAR, cameras, radar, GPS, and V2X communication gather real-time data on pavement conditions, traffic flow, and environmental factors. Embedded sensors within the pavement structure at critical points provide continuous, localized data on structural integrity and environmental influences.

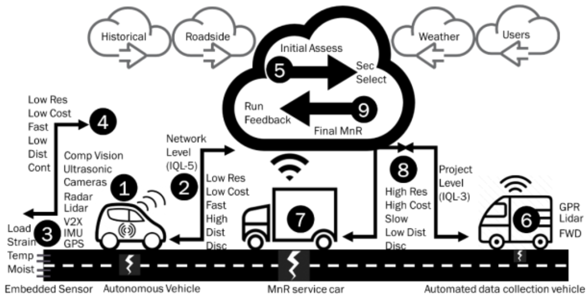

Figure 1. Concept of road pavement DT

Automated data collection vehicles using Ground Penetrating Radar (GPR), Falling Weight Deflectometer (FWD), and laser scanners offer high-resolution insights into pavement thickness and subsurface conditions. Maintenance and Repair (M&R) service vehicles ensure consistent monitoring and assessment during and after maintenance actions. This integrated approach ensures a detailed and dynamic understanding of road pavement conditions.

2.2 *Framework of cognitive DT for road pavement*

Figure 2 illustrates the cognitive DT framework for road pavement, consisting of four layers:

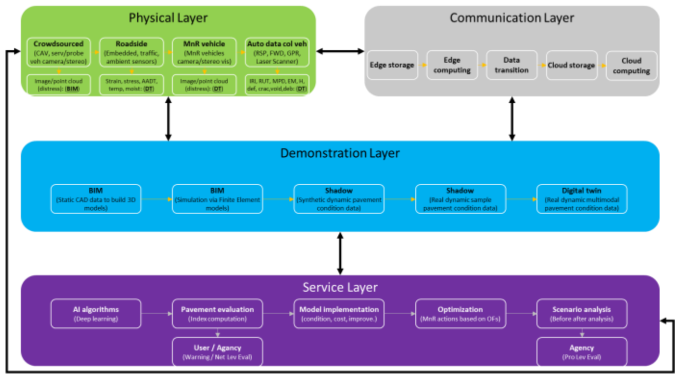

Figure 2. Framework of road pavement DT

1- Physical Layer: Continuously monitors pavement conditions using various instruments. Crowdsourced inputs from AVs, connected AVs, probe vehicles, and service cars collect pavement images or point clouds for distress detection and feed into BIM. Roadside sensors gather data on stress, strain, traffic volumes, temperature, and moisture. M&R vehicles acquire pavement images or point clouds for distress detection. Automated data collection vehicles equipped with RSP, FWD, GPR, and laser scanners collect data on IRI, rut depth, surface texture, and subsurface characteristics.

2- Communication Layer: Supports data transmission and storage, including edge storage and computing for rapid data processing, seamless data transition protocols for efficient transfer, and scalable cloud storage and computing for advanced analytics and long-term data management.

3- Demonstration Layer: Creates digital representations for visualization and simulation. BIM and digital models depict road geometry and material properties. Digital shadows mirror real-time pavement conditions using synthetic and sampled real dynamic data streams. Digital twins combine real-time data with predictive modeling to simulate future scenarios and assess potential outcomes.

4- Service Layer: Provides services to road users and agencies, leveraging collected data and digital representations to optimize road pavement management strategies. It includes AI algorithms for data analysis and prediction, pavement evaluations to assess current conditions and prioritize maintenance efforts, DT models to guide decision-making processes, optimized M&R practices through simulation and scenario analysis, and proactive maintenance planning for real-time feedback and enhanced road safety.

By integrating these layers, the cognitive DT framework offers a comprehensive approach to road infrastructure management, enabling informed decision-making, proactive maintenance strategies, and optimized resource allocation to improve road performance and safety.

3 CASE STUDY

The case study focuses on a 3-kilometer section of the Räyskälän kantatie motorway (KT54/3/300-KT54/3/3300) in Loppi, Finland, as shown in Figure 3. This road connects Hollola, Riihimäki, and Tammela, serving as an alternative route from Lahti to Turku. The selected section includes bridges and tunnels, with an average daily traffic of 15,000 vehicles, including many heavy goods vehicles. The region experiences cold winters and mild summers, making it an ideal testbed for the DT framework.

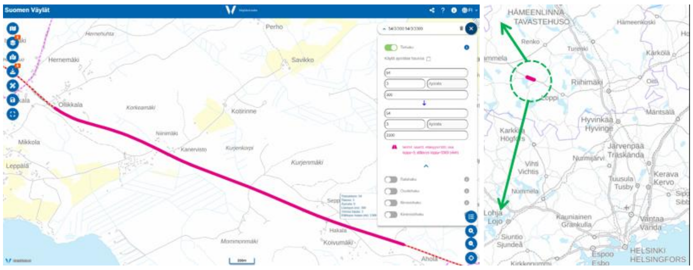

Figure 3. Selected section of Räyskälän motorway.

Data collection involves multiple methods. Crowdsourced georeferenced data from AVs and probe vehicles monitor road surface conditions, traffic flow, and identify potential congestion points. Roadside and embedded sensors measure temperature, moisture, strain, and load, providing continuous data on pavement integrity. Automated data collection vehicles, such as Road Surface Profilers, use technologies like GPR and FWD to assess pavement thickness and subsurface conditions. M&R vehicles, equipped with advanced sensors, collect high-resolution images, LiDAR data, and pavement profiles before and after maintenance actions. This comprehensive approach ensures detailed monitoring and assessment of road pavement conditions, enabling informed decision-making and optimized maintenance strategies.

To create a digital representation of the section, Autodesk InfraWorks software integrates various data sources, including crowdsourced data, sensor data, and imagery. This generates a detailed BIM model of the 3-kilometer motorway section, incorporating geometric details, material properties, and environmental factors, as shown in Figure 4. The BIM model serves as a DT of the physical motorway, providing a dynamic and constantly updated virtual counterpart. It enables engineers and maintenance teams to visualize the motorway's current state, simulate maintenance scenarios, and assess potential impacts on traffic flow and pavement performance.

Figure 4. BIM model of the selected section.

The dataset, comprising sensor and vehicle data along with BIM model information, is analyzed using advanced AI algorithms. These algorithms detect and classify pavement distress types, such as cracks and potholes, improving inspection efficiency and accuracy. Predictive analytics forecast pavement deterioration and optimize maintenance planning by analyzing historical and current data, along with environmental parameters. This proactive approach allows maintenance teams to schedule interventions before defects become critical, reducing reactive repairs and extending pavement lifespan. AI-driven analyses also prioritize maintenance tasks based on defect severity and impact, ensuring safety and smooth traffic flow.

Figure 5 presents a detailed visualization of the DT model for the selected section. This model provides a comprehensive overview of pavement conditions using the PCI and the IRI. The PCI, ranging from 100 (Excellent) to 0 (Failed), indicates the severity and density of pavement distress, while the IRI measures ride quality. Each pavement section is color-coded from green (Excellent) to red (Poor) for easy interpretation, allowing quick assessment of the overall condition. Warmer colors like yellow and orange highlight sections needing attention, with red indicating critical areas requiring immediate maintenance.

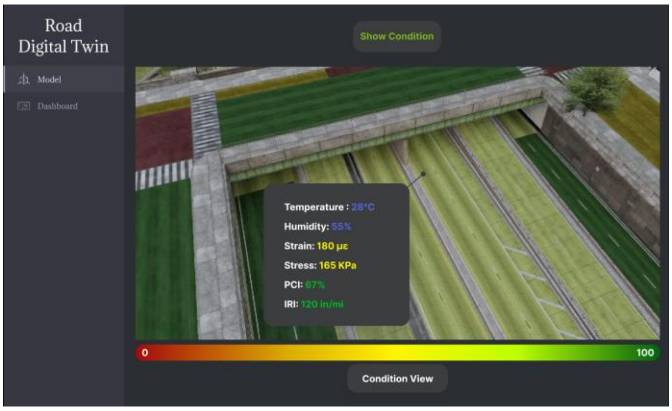

Figure 5. DT of the selected section.

The DT model also incorporates real-time data on temperature, humidity, strain, and stress, superimposed on the pavement model. Blue represents temperature and humidity data, which influence pavement performance and maintenance strategies. Yellow indicates strain and stress data from embedded sensors, showing structural integrity. Higher strain and stress values may signal potential weaknesses.

Users can interactively explore the pavement condition and associated parameters, with each section linked to detailed information, including historical data, maintenance records, and predicted deterioration rates. This interactive functionality aids informed decision-making, allowing maintenance teams to prioritize interventions and optimize repair strategies. By integrating real-time data and advanced analytics, the DT model enhances continuous monitoring, predictive maintenance, and overall pavement management, improving road safety and performance.

The DT framework enhances pavement maintenance by combining real-time data collection, BIM modeling, and AI-driven analyses. This approach improves maintenance efficiency, reduces reactive repairs, and extends pavement lifespan through predictive analytics. DT simulations optimize maintenance strategies and minimize traffic disruptions, while scenario analyses aid decision-making and improve road safety. The platform also facilitates stakeholder collaboration, enhancing overall management efficiency.

This case study offers several novel contributions to pavement maintenance and DT technology:

Enhanced Data Collection: Diverse sources improve accuracy and reduce costs.

Advanced Digital Representation: BIM models aid proactive planning.

AI-Driven Analysis: Improves distress detection and maintenance planning.

Predictive Maintenance: Optimizes scheduling and resource allocation.

Improved Collaboration: Centralizes information for better planning.

Extended Lifespan and Reduced Costs: Proactive maintenance promotes sustainability.

These contributions highlight the DT framework's potential to revolutionize pavement maintenance, improving efficiency, safety, and sustainability.

4 CHALLENGES AND FUTURE DIRECTIONS

Developing a cognitive road digital twin involves key challenges, including ensuring accurate and up-to-date data, integrating diverse sources like LiDAR and cameras, enabling real-time updates, safeguarding data privacy, and ensuring scalability to handle large datasets efficiently.

Future applications include proactive maintenance for early issue detection, real-time traffic management to enhance safety, environmental impact assessments for sustainable planning, performance modeling to prioritize resources, and resilience planning to mitigate the effects of extreme events.

5 CONCLUSIONS

This paper presents a cognitive road DT framework for pavement maintenance, integrating data from various sources to create a digital representation of road pavement. Advanced AI analytics detect distress, optimize planning, and predict future conditions. A Finnish motorway case study demonstrates its potential.

Automated data collection tools provide real-time, comprehensive data for informed decisions. BIM models facilitate visualization and analysis. AI-powered analytics improve distress detection and predictive maintenance, extending pavement lifespan.

The Finnish case study shows the DT's ability to enhance maintenance efficiency, reduce costs, and improve road safety. The framework promises to transform pavement maintenance through data-driven decisions and optimized activities. Continuous research and innovation are encouraged to enhance road infrastructure sustainability and resilience.

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