DIGITAL TWIN ROADWAYS

Integrating BIM, IoT and AI for Intelligent Infrastructure Management

Z.V. KORNILOVA

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SCIENTIFIC THOUGHT DEVELOPMENT

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INTRODUCTION

Relevance and Problem Context. The deterioration of roads and bridges is a global issue with substantial impacts on the economy, safety, and the resilience of asupply chains. The decline in road network quality directly affects the population's quality of life and countries’ ability to adapt to climate and technological challenges. According to the World Economic Forum, a significant portion of the world’s road infrastructure has reached a critical level of degradation [1]. Much of the existing infrastructure was constructed decades ago, without consideration for modern requirements related to resilience, intelligent management, and digital monitoring. As a result, frequent structural failures, increased accident rates, and rising maintenance costs are observed. This problem is universal in nature and manifests both in economically developed countries and in regions affected by armed conflicts.

European Union

In EU member states, over 24% of roads are in poor condition, and approximately 30% of bridges are classified as structurally deficient or near-critical [2]. In many countries, infrastructure investment levels do not offset the depreciation of public assets [3]. The European Court of Auditors has highlighted fragmented governance and outdated inspection practices [4]. While the TEN-T and the Digital Decade Policy Programme 2030 include plans for the digital transformation of transport corridors, implementation remains incomplete [5].

The EU experiences direct socio-economic losses from traffic accidents and reduced network capacity estimated at €130 billion annually, including medical costs, compensation payments, and lost productivity [13]. In 2024, construction sector output declined by 0.9% compared to 2023, while long-term productivity growth in OECD countries averages only about 0.2% per year [110].

According to the Conference of European Directors of Roads (CEDR, 2019), poor pavement conditions cost EU vehicle owners an additional €3.7 billion annually due to tire wear, suspension damage, and increased fuel consumption.

The European Investment Bank’s (EIB) Investment Report (2023) estimates the cumulative funding need for road network modernization and reconstruction—including bridges and highways—at approximately €477 billion. Current annual infrastructure expenditures (~€45 billion) fall short of this requirement, creating a significant investment gap in the sector.

Research shows that direct economic losses from congestion and detours for freight transport in EU cities amount to about €110 billion per year. These losses include drivers' time, additional fuel consumption, and reduced delivery reliability [113]. The classification of EU Economic Loss Categories (2023) is presented in Figure 1.1.

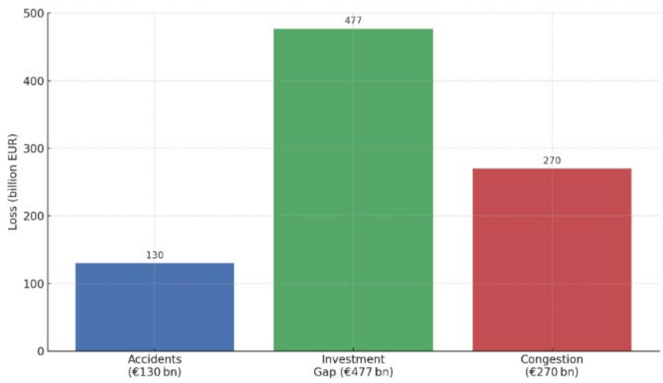


Figure 1.1 - EU Economic Loss Categories (2023)

A source: [13], [110]

United States. According to the American Society of Civil Engineers (ASCE), approximately 43% of U.S. roads are in poor or mediocre condition, and 7.5% of bridge structures exhibit structural deficiencies [6]. Annual economic losses associated with deteriorating road conditions exceed $120 billion [7]. The Infrastructure Investment and Jobs Act (IIJA, 2021) allocates $550 billion for the modernization of the U.S. transportation system. However, a significant portion of these funds is directed toward remedying existing deficiencies rather than proactive digital transformation efforts [8].

The poor condition of 43% of U.S. roads leads to additional annual expenses for vehicle owners, estimated at approximately $141 billion. These include increased wear on tires and suspensions, higher fuel consumption, and accelerated depreciation of vehicles [11].

ASCE estimates that the funding gap required to bring U.S. roads and bridges to standard conditions amounts to $786 billion. Current annual expenditures on maintenance and repair—$177 billion as of 2017—are significantly below this level of need [6]. Infrastructure defects lead to congestion and detours, increasing travel times and freight transport costs. In 2022 alone, traffic delays for freight trucks resulted in losses of $108.8 billion in the U.S. [12]. A detailed US Economic Loss Breakdown is presented in Figure 1.2.

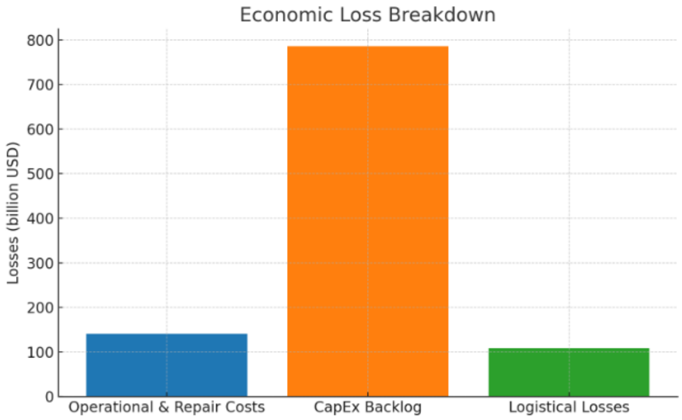


Figure 1.2 - US Economic Loss Breakdown.

A source: [6-8], [11-12]

Figure 1.2 illustrates three categories of economic losses in the United States (in billion USD): operational expenditures, capital investment shortfalls, and logistics-related losses.

Ukraine. Since the onset of full-scale military operations, more than 28,000 km of roads and 850 bridges have been damaged or destroyed [9]. Within the framework of the "Great Recovery" program, only 12% of restored infrastructure assets have been equipped with BIM technologies [10]. Key barriers include a shortage of qualified specialists, limited financial and technical resources, and the absence of a unified legal framework governing the digitalization of infrastructure lifecycle management.

Under the "Great Recovery" program (2023–2025), UAH 16,023 million (22.8% of the budget of the State Restoration Agency) was allocated as subventions to local budgets for the construction, repair, and maintenance of roads and bridges. The World Bank has provided $432 million for the rehabilitation of critical road segments and bridges across 19 regions [14]. According to the Kyiv School of Economics, direct destruction and damage to road infrastructure as a result of hostilities—including pavement deformations, destroyed bridge supports, and washed-out embankments—incurred recovery and repair costs amounting to $26.6 billion (USD) between June and August 2022.

According to the State Agency of Motor Roads of Ukraine (Ukravtodor), an estimated €59.5 billion in investments is required to bring the country's highways and bridges back to standard operational condition (capital backlog). A joint assessment by the World Bank, the European Commission, and the United Nations estimates that losses in the transport sector due to destruction and detour routes exceeded $95.5 billion (USD) by mid-2023. Of this total, approximately $28.7 billion—or nearly 30%—is attributable to additional freight transportation costs, including longer travel times, increased fuel consumption, and equipment downtime [10]. The Ukraine Economic Loss Categories (2022–2023) are presented in Figure 1.3.

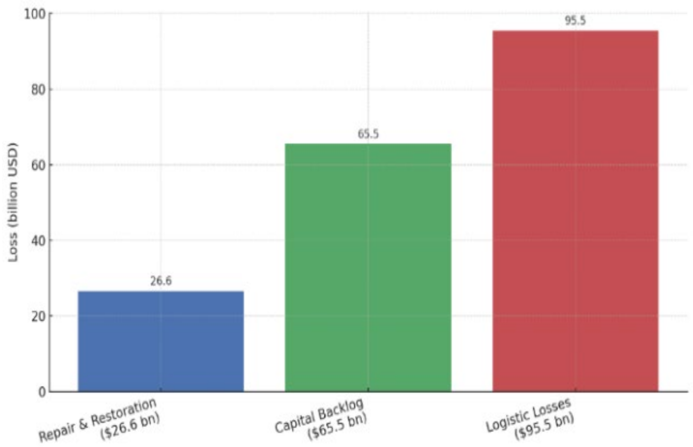


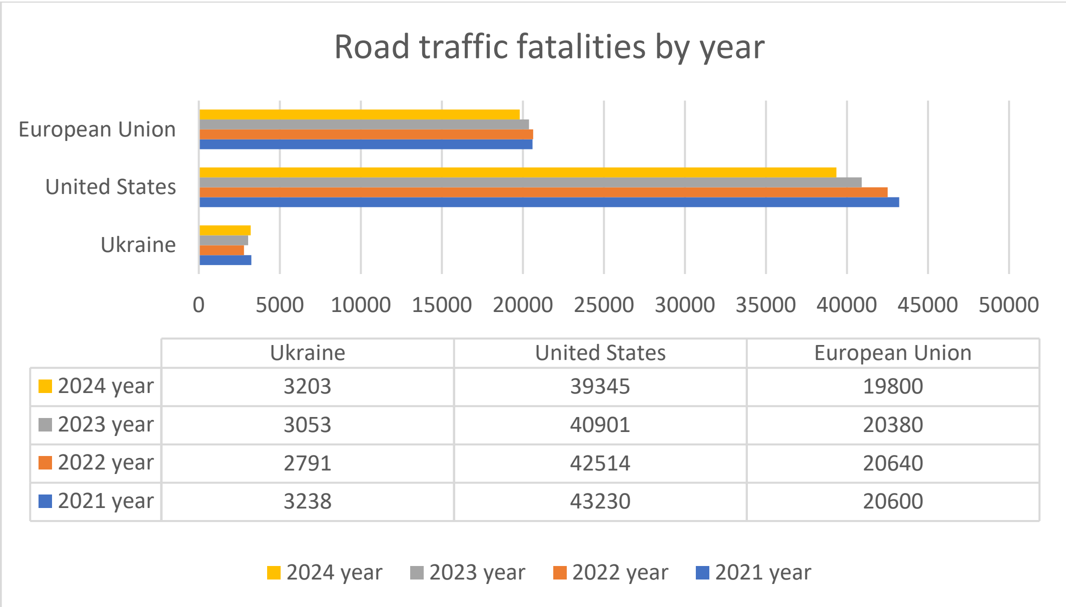
Figure 1.3 - Ukraine Economic Loss Categories (2022–2023)

A source: [9-10], [14]

Each year, approximately 1.19 million people die in road traffic accidents worldwide, making road crashes one of the leading causes of death among children and young adults aged 5 to 29 [15]. In 2023, road traffic accidents claimed the lives of 20,380 people in the European Union. At the current rate of reduction (–1% per year), the EU is unlikely to achieve the targeted 50% decreese in fatalities by 2030 without additional investment in safe infrastructure [16].

In the United States, 40,901 traffic-related deaths were recorded in 2023—a second consecutive year of decline (~–3.6%). However, this remains the highest fatality figure since 2008 [17]. In Ukraine, 3,053 people died in road accidents in 2023, and by 2024 the number increased to 3,203, with total injuries exceeding 32,000. The road fatality rate in Ukraine remains 4–5 times higher than in the EU. Around 17% of roads are in poor condition, increasing the risk of accidents by 30% [10].

Approximately 17% of vehicle travel occurs on roads in substandard condition, where the probability of a crash is 30% higher than on standard pavement. Combined with irregular inspections and pavement defects, this significantly worsens injury and fatality outcomes [11]. Road traffic fatalities by year are shown in Figure 1.4.



	Ukraine	United States	European Union
2024 year	3203	39345	19800
2023 year	3053	40901	20380
2022 year	2791	42514	20640
2021 year	3238	43230	20600

Figure 1.4 - Road traffic fatalities by year

A source: [10-11], [15-17]

Digitalization as a Solution. The integration of Building Information Modeling (BIM), the Internet of Things (IoT), Artificial Intelligence (AI), and Big Data has given rise to a new paradigm in the lifecycle management of road infrastructure. These technologies enable a unified data environment that supports the design, construction, and operation of roads and bridges. The Technological Stack for Digitalization is presented in Figure 1.5.

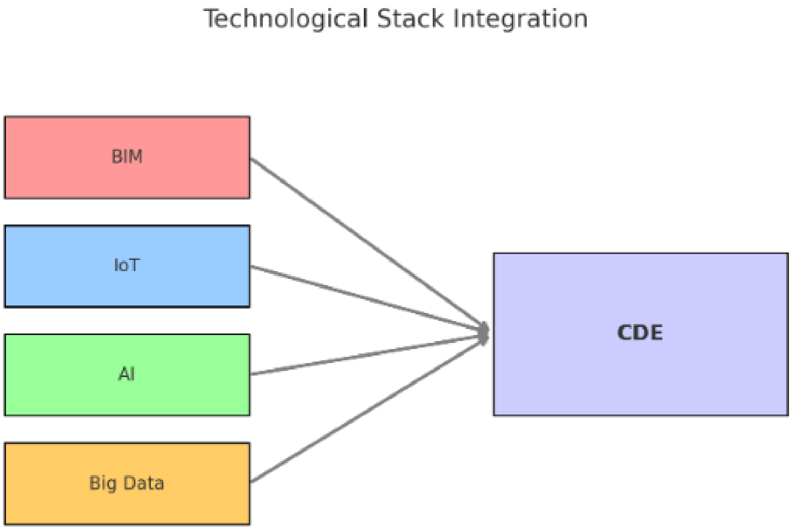


Figure 1.5 - Technological Stack for Digitalization

Authoring

Figure 1.5 presents the interconnection of BIM, IoT, AI, and Big Data, all integrated within a Common Data Environment (CDE).

BIM (Building Information Modeling) is a process for creating and managing digital representations of the physical and functional characteristics of infrastructure assets across their entire lifecycle [19].

IoT (Internet of Things) refers to networks of sensors and devices that collect real-time data on pavement deformations, bridge loads, and other parameters [18].

AI and Big Data enable large-scale analysis of collected information, facilitating pattern recognition, defect prediction, and optimization of maintenance schedules through machine learning algorithms [19].

Application Examples

In the European Union, the iDriving project under the Horizon Europe program is developing digital infrastructure that integrates sensors, AI analytics, and digital twins for predictive defect detection on secondary roads across ten EU countries [20].

In the United States, in March 2024, the City of Chattanooga and the University of Tennessee received a $2 million SMART grant to implement a C-V2X (Cellular Vehicle-to-Everything) pilot that links vehicles and roadside infrastructure to manage traffic flows in the city center [21]. The U.S. FHWA's ATTAIN (Advanced Transportation Technology and Innovation) program awarded over $94 million in grants for 20 projects focused on automated road inspection and AI-based traffic signal optimization [22].

In Ukraine, a citywide LoRaWAN network consisting of 295 base stations has been deployed in Kyiv for microclimate and safety monitoring, forming the foundation for bridge and highway sensor integration [23]. The AIoT CitySense project has adapted the Roadbot mobile IoT platform on municipal trucks to automatically detect pavement defects (40–50 cases per 1–2 km²) and transmit up to 5 GB of data per day [19].

Concept of the Digital Twin

A Digital Twin is a virtual representation of a physical asset—such as a road or bridge—that combines a BIM model with real-time IoT sensor data. According to ISO 23247 and NASA, a Digital Twin (DT) system includes a physical prototype, a virtual model, and bidirectional data exchange [24]. Unlike BIM, which represents a static model, a digital twin is continuously updated to support forecasting, simulation, and adaptive management. Transitioning from BIM to DT requires open IFC standards (ISO 19650) and middleware to ensure system interoperability [19]. AI and Big Data algorithms enable automated defect detection, service optimization, and enhanced network reliability. The architecture of the Digital Twin is presented in Figure 1.6.

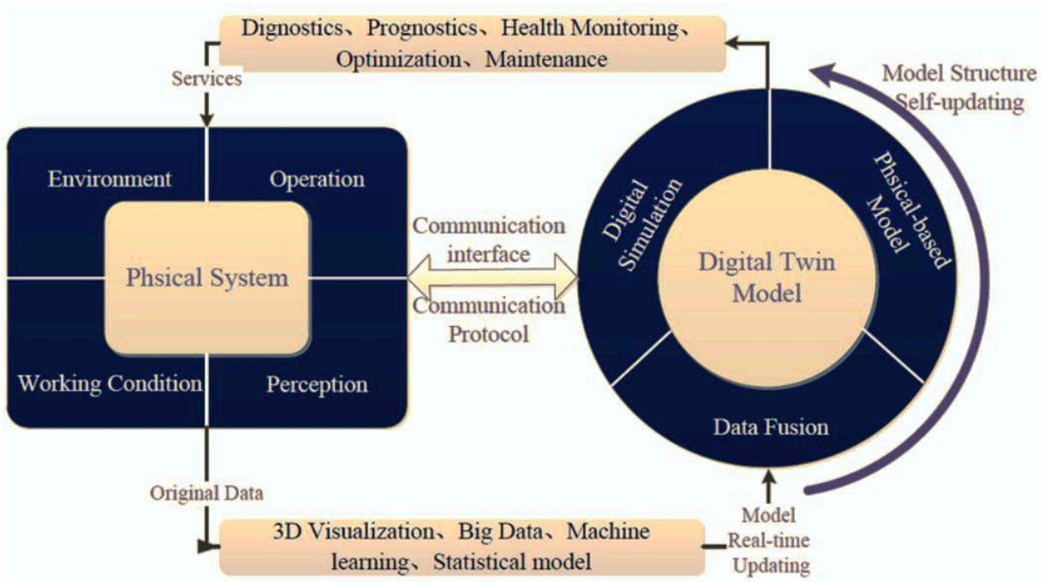


Figure 1.6 - The architecture of Digital Twin

Authoring

Purpose of the Monograph

The objective of this work is to develop a comprehensive concept and methodology for the application of digital twins for roads and bridges, based on the integration of BIM + IoT + AI technologies. The focus is on enabling continuous condition monitoring and optimizing the lifecycle management of road networks across three key regions: the European Union, the United States, and Ukraine.

The research objectives include:

1. Formalization of the Digital Twin (DT) architecture, including functional and non-functional requirements.
2. Selection and integration of key sensor types into the BIM model to enable accurate and timely data acquisition.
3. Development of a Big Data pipeline and predictive maintenance algorithms based on machine learning (ML) and deep learning (DL).
4. Evaluation of economic efficiency and comparative cost–benefit analysis (CBA) for European, American, and Ukrainian initiatives.
5. Development of a phased implementation roadmap and policy recommendations for departments of transportation.

Rationale for Continuous Monitoring

The necessity for continuous monitoring lies in the fact that timely defect detection can reduce capital repair costs by up to 30%, minimize downtime, optimize traffic flow routing, enhance public trust in infrastructure management authorities, and increase resilience to climate-related risks.

Research Objectives

- In line with the monograph’s purpose, seven key tasks have been formulated to provide a methodological and practical foundation for the development of digital twins for road infrastructure:
- Analysis of Existing Approaches and Their Limitations. Conduct a systematic review of publications and practical implementations of BIM, IoT, and Digital Twins in the road sector. Special focus should be placed on continuous monitoring methodologies, standardization issues, and technology integration

challenges, as well as identifying gaps related to sensor specialization and platform incompatibility [18].

- Development of DT Architecture and Requirements for Roads. Formulate functional and non-functional requirements for the digital twin, including a layered structure (data collection, storage, processing, and visualization) based on ISO 19650 and successful DT framework examples. Describe key architectural components: sensor layer, middleware, analytics module, and user interface [25].
- Identification of Key IoT Sensor Types and Their Integration with BIM. Select an optimal set of sensors (FBG fiber Bragg gratings, piezoelectric sensors, laser scanning, WIM systems), considering technical characteristics, reliability, and cost. Describe data import algorithms into IFC models and the Common Data Environment (CDE), as well as semantic binding mechanisms linking sensors to BIM elements [26].
- Methodology for Real-Time Data Collection, Processing, and Analysis. Develop a Big Data pipeline from the sensor layer to the analytics platform: define transmission protocols (MQTT, OPC UA), data exchange formats (IFC, CityGML), and ETL tools for validation, cleaning, and aggregation within the CDE. Outline scenarios for processing streaming and historical data [33].
- Predictive Maintenance and Repair Optimization Algorithms. Justify the use of ML and DL methods (regression, Random Forest, LSTM, CNN, Transformer models) for defect prediction and optimal maintenance scheduling. Define training data structure, model evaluation criteria (RMSE, ROC AUC, Precision@k), and A/B validation procedures in field conditions [27].
- Economic Efficiency Evaluation (CBA). Develop a cost–benefit model accounting for CapEx and OpEx related to IoT infrastructure, expenses for traditional inspections, and projected savings from accident reduction and asset life extension. Provide calculation examples for NPV, IRR, and BCR for a typical TEN-T corridor or an IIJA highway [27].
- Development of an Implementation Roadmap and Recommendations for

Departments of Transportation (DOT). Create a phased plan for digital twin deployment in transportation departments, ranging from pre-investment preparation and pilot projects to scaling and institutionalization. Include recommendations on regulatory framework, contractor selection criteria, personnel training programs, and KPI monitoring systems [27].

Scientific Novelty: Integration of BIM and IoT for Road Digital Twins. A comprehensive methodology is proposed for the first time, whereby a static 3D BIM model serves as the core of a digital twin that is continuously updated with data from IoT sensors. This methodology is based on ISO 19650 information management standards and provides bidirectional data flows between the polygonal model and sensor systems. This extends the classical BIM applications (design, planning) into the operational phase, enabling predictive analysis of deformations and loads on bridge structures.

Proprietary Analytics and Predictive Maintenance Algorithms

Specialized machine learning and deep neural network algorithms (including LSTM architectures for time series and hybrid GNN models) have been developed and adapted for multisensor data such as FBG fiber Bragg gratings, piezoelectric sensors, and WIM systems. Unlike existing solutions, these algorithms perform multi-level data aggregation, automatically extract key defect features, and predict their evolution considering seasonal and climatic factors.

Universal Economic Evaluation Model.

For the first time, a unified cost–benefit model for digital twins of road infrastructure is proposed, applicable across diverse regional contexts (EU TEN-T corridors, US IIJA corridors, and Ukraine’s “Great Recovery” program). The model accounts for the full cost chain—from sensor network installation and maintenance to expenses for traditional inspections and emergency repairs—as well as benefits from reduced downtime and extended asset lifespan. Pilot calculations demonstrate up to 30% savings on capital repairs under continuous monitoring conditions.

Scaling Roadmap.

Phased recommendations are provided for Departments of Transportation (DOT) regarding regulatory and organizational implementation of digital twins. The roadmap considers regional regulatory specifics, budgeting schemes, and workforce training, including readiness criteria at each stage (pre-investment preparation, pilot, scaling, institutionalization, support, and development). The Key Scientific Innovations are presented in Figure 1.7.

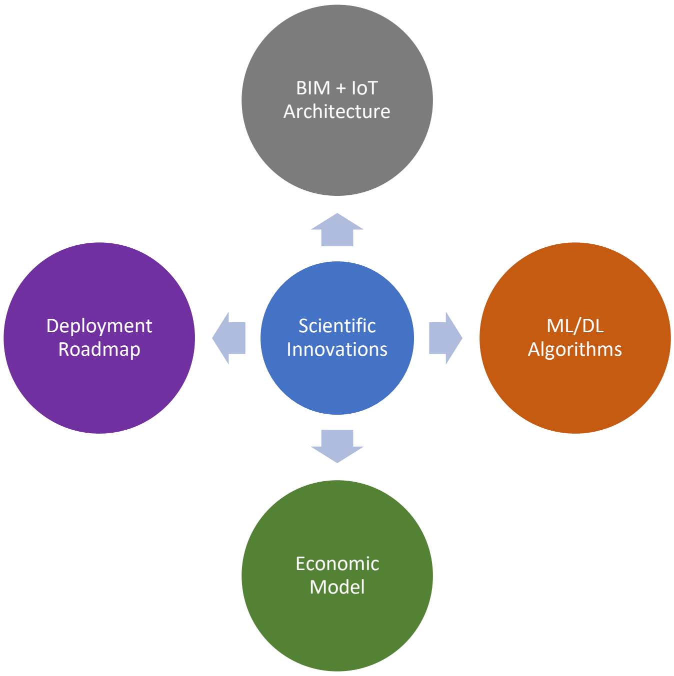


Figure 1.7 - Key Scientific Innovations

Authoring

Practical Significance

The practical significance of the developed concept for digital twins of road infrastructure lies in its high applicability to diverse regional contexts and its capability to address specific engineering, managerial, and socio-economic challenges. The key areas of application for three strategically important regions are outlined below.

For the European Union.

The implementation of an integrated digital platform based on BIM and IoT will enable a shift from reactive to proactive asset management, particularly across segments of the Trans-European Transport Network (TEN-T). This creates conditions for optimizing budget allocations by reducing unforeseen emergency repair costs and improving capital investment planning. Accident reduction—especially on secondary roads where outdated control methods still predominate—will support the achievement of the Digital Decade policy goals aimed at the digital transformation of transport infrastructure by 2030. Additionally, this will enhance transparency in maintenance and approval procedures, strengthening cooperation between national operators and EU institutions.

For the United States of America.

Given the scale of the U.S. road network and funding volumes under the Infrastructure Investment and Jobs Act (IIJA), the application of digital twins offers a unique opportunity for phased implementation of continuous monitoring along key logistics corridors. Systems combining sensor data with BIM models can detect latent defects before they evolve into critical failures, thereby preventing accidents and capacity reductions. In the long term, this contributes to increased productivity of logistics and commercial transport, reduces fleet operating costs, and mitigates the impact of transport infrastructure factors on product cost.

For Ukraine.

In the post-conflict reconstruction of Ukraine’s transport network, implementing technological solutions for asset condition monitoring under conditions of limited access, increased load, and unstable climatic factors is critically important. The digital twin methodology proposed in this monograph provides a tool for real-time infrastructure auditing, assessing the effectiveness of restoration efforts, and documenting the use of funds from international donors and financial organizations. Moreover, the application of digital technologies enhances repair durability through preventive maintenance and enables the development of long-term trunk network strategies.

The Practical Significance of the Developed Digital Twin Concept for Road Infrastructure in the EU, USA, and Ukraine is presented in Figure 1.8.

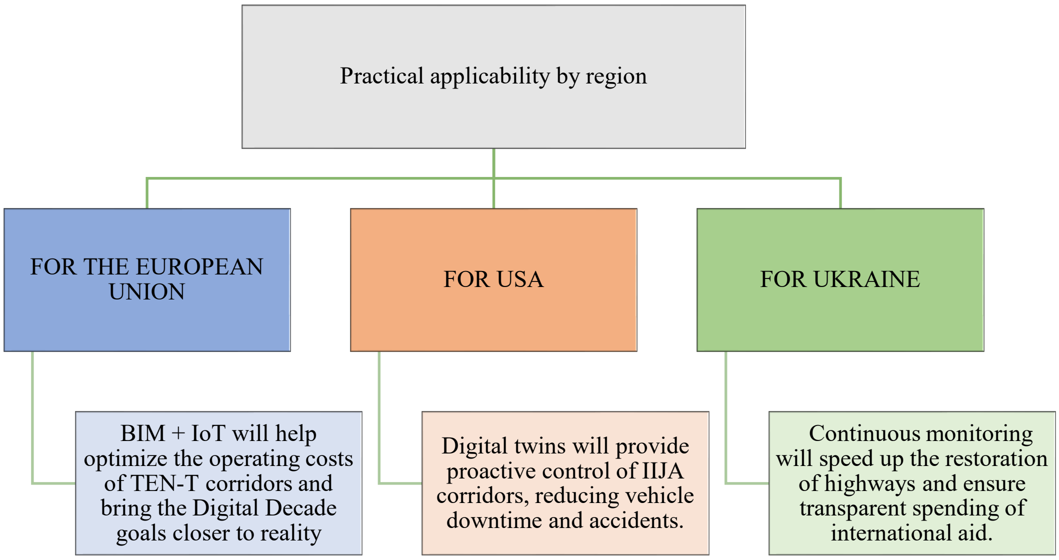


Figure 1.8 - Practical Significance for the EU, USA, and Ukrain
Authoring

Structure of the Monograph. This monograph is organized into ten consecutive chapters, each addressing a critical stage in the development and implementation of digital twins for road infrastructure. Such a structure provides comprehensive coverage from the justification of relevance to the formulation of practical recommendations and prospects for future work.

– Introduction

Contains the rationale for topic selection, analysis of global and regional challenges, an overview of worldwide practices in BIM, IoT, and digital twin applications, and a clear statement of research goals and objectives. The chapter concludes with the scientific novelty and practical significance of the proposed methodology.

– Literature Review and Problem Statement

Provides a systematic analysis of key publications and reports on BIM, IoT, and digital twins in road management during 2022–2025. Identifies limitations of existing approaches, including lack of standardization, weak technology integration, narrow sensor application domains, and gaps in real pilot deployments.

– Theoretical Foundations of Digital Twins, BIM, and IoT

Examines fundamental concepts and terminology: digital twin, BIM model, IoT network, Big Data, AI. Reviews international standards (ISO 19650, IFC, CityGML) and describes typical architectural patterns of digital twins, including BIM maturity levels (Level 0–3) and layered IoT models.

– Digital Twin Architecture for Roads

Provides a detailed description of the functional model (sensor layer → edge computing → cloud platform → visualization/control) and non-functional requirements (performance, scalability, security). Presents the system's layered structure, requirements for the Common Data Environment (CDE), and data exchange protocols (IFC, SensorThings API, OPC UA).

– Integration of BIM and Sensors

Describes key sensor types for road infrastructure (FBG fiber Bragg gratings, piezoelectric sensors, WIM systems, laser scanning) and methods for georeferencing and semantic integration into the BIM model using IFC parameters, BCF markup, and automated API scripts.

– Real-Time Data Collection and Analysis

Discusses the design of a Big Data pipeline: data ingestion and buffering (Kafka, Kinesis), stream processing (Flink, Spark), storage (Data Lake, TSDB), and integration with cloud platforms (AWS, Azure, GCP). Describes data validation methods, metadata management, and API interfaces for the CDE.

– Predictive Maintenance and Repair Optimization Algorithms

Presents approaches to constructing ML/DL pipelines: data preparation, feature engineering, model selection and training (Random Forest, XGBoost, LSTM, CNN, GNN), validation (time series cross-validation, A/B testing), and methods for evaluating repair effectiveness via Precision@k, ROC AUC, RMSE

– Economic Model and Regional Case Analysis

Performs a comparative cost–benefit analysis for TEN-T (EU), IIJA (USA), and "Great Recovery" (Ukraine) projects. Examines NPV, IRR, BCR, sensitivity analysis for discount rates and costs, as well as economic and logistical benefits.

- Implementation Roadmap and Recommendations

Develops a phased plan for Departments of Transportation: pre-investment preparation, pilot, scaling, institutionalization, and support. Includes regulatory aspects, staff training programs, partner selection criteria, change management, and KPI monitoring systems.

- Conclusion and Outlook

Summarizes the study, formulates key findings and limitations, and proposes directions for further research and practical pilots to expand and scale digital twins globally.

KAPITEL 1 / *CHAPTER 1*
LITERATURE REVIEW AND PROBLEM STATEMENT

1.1. Selection and Systematization of Publications

To ensure the systematic and comprehensive nature of the literature review, a multi-stage search methodology was applied. This methodology included selecting academic sources, formulating search queries, and applying strict inclusion and exclusion criteria.

The primary sources of peer-reviewed publications were the Scopus (Elsevier) and Web of Science (Clarivate Analytics) databases. These platforms provide extensive coverage of high-impact journals, conferences, and reviews. To complement the dataset and incorporate the latest developments in preprint formats, open repositories such as arXiv and MDPI were also analyzed. This approach allowed the inclusion of open-access works and recent studies not yet formally published.

The search strategy was based on key phrases reflecting the integration of digital twins, BIM, and IoT in the road sector. Queries were performed with filters on publication date (2023 – 2025), language (English), and authorship affiliation with the EU, USA, or Ukraine. The main search queries are listed in Table 1.1.

Table 1.1 – Main Search Queries

№	TITLE ABS KEYS
1	TITLE-ABS-KEY("digital twin" AND "road pavement”)
2	TITLE-ABS-KEY("scan-to-BIM" AND "road")
3	TITLE-ABS-KEY("infrastructure digital twin" AND BIM AND IoT)
4	TITLE-ABS-KEY("digital twin" AND bridge AND IoT")

Authoring

Each query result was further filtered by authorship and country to exclude irrelevant publications.

The review included publications from 2023 to 2025 whose authors were affiliated with organizations in the EU, USA, or Ukraine, and whose topics were directly related to digital twins of road pavements or bridges with mandatory mention of BIM and/or IoT. Only peer-reviewed journal articles indexed in WoS/Scopus and preprints subsequently peer-reviewed were considered. Studies published before 2023, those unrelated to transport infrastructure (e.g., buildings or industrial facilities), and publications without full-text access outside subscription resources were excluded.

The literature search yielded a total of 160 records across the selected repositories. These records underwent a multi-stage filtering process to arrive at the final set of publications meeting the inclusion criteria, as shown in Table 1.2.

Table 1.2 – Search results and step-wise filtering of publications

Stage	Scopus	Web of Science	arXiv/ MDPI	Total After Duplicates	Selected
Initial retrieval	98	85	15	160	—
Year filter (2023–2025)	43	37	12	92	—
Geographical filter (EU/US/UA)	28	22	9	59	—
Thematic relevance screening	—	—	—	59	12
Full-text availability & review	—	—	—	59	5

Authoring

Note: The thematic relevance screening reduced the pool to 12, from which five key publications were selected after full-text review and quality assessment.

1.2. Main Sources and Their Contributions

The study by Talaghat M. A. et al. (2024), published in Automation in Construction [28], examines the application of digital twins for road pavement monitoring. This work was conducted in collaboration between the University of Helsinki and the University of Tehran as part of a European research program. The authors performed a comprehensive review of scientific publications and technical reports, providing an in-depth understanding of both theoretical and practical aspects. Special attention was given to the hierarchy of digital twin (DT) architecture: from BIM visualization to cloud platforms and APIs enabling data exchange between sensors and systems.

The second part of the study explores the DT architecture across three levels: visualization (realistic BIM representation), simulation (fatigue and load modeling), and platform (cloud services and RESTful APIs for integration with sensors and IT infrastructure). The authors compared 12 platforms, including ArcGIS, iTwin, and MindSphere, identifying three patterns: standalone desktop solutions, cloud-based BIM–IoT systems, and hybrid platforms with edge computing. This approach balances analytical accuracy with deployment flexibility.

The analysis of APIs and standards revealed compatibility issues: while REST/WebSocket protocols predominate, support for IFC under ISO 19650 is limited. Most platforms focus on construction and overlook the specifics of road pavements. Additionally, a lack of field testing, incomplete description of sensor components (FBG, cameras, strain gauges), and absence of ML/DL integration for defect prediction were noted, reducing the practical value of the proposed solutions. The Contributions and Limitations are presented in Table 1.3.

Table 1.3 – Contributions and limitations (2024)

Aspect	Description
Architecture Templates	Defined three DT architectures: Local Desktop Twin, Distributed BIM–IoT Platforms, Hybrid Edge Computing Solutions, detailing their deployment and data-processing topologies.
API & Protocols	Identified prevalent use of REST and WebSocket for real-time sensor data; highlighted insufficient support for latest IFC schemas (ISO 19650), leading to interoperability issues.
Platform Comparison	Benchmarked 12 commercial and open-source platforms (e.g., Esri ArcGIS, Bentley iTwin, Siemens MindSphere), assessing strengths and weaknesses for road pavement applications.
Gaps & Limitations	Noted absence of field deployment case studies; underdocumented sensor types and protocols; lack of ML/DL-based predictive analytics integration in the reviewed frameworks.

Authoring

The study by Ding Y. et al. [29], published on arXiv, presents a methodology for the automated generation of BIM models for road infrastructure based on 3D point cloud data obtained via mobile LiDAR scanners. The project reflects a synergy of geodesy, data processing, and transportation engineering. Point clouds were classified into six object categories, and semantic annotation using machine learning algorithms improved the fidelity of the digital representation.

The workflow included filtering, segmentation, semantic linking, and IFC model generation. A graph-based algorithm was used to reconstruct topology by identifying relationships between infrastructure elements. The average reconstruction accuracy reached 1.46 cm, with a processing speed of 6.29 m/s, enabling the modeling of up to 2 km in a single pass. Field trials on road segments in the United Kingdom confirmed the robustness of the methodology under varying conditions.

The automation process reduced manual labor by 60%, and the resulting models complied with CDE and digital twin environment requirements. However, the study is limited to geometric modeling and does not incorporate sensor data streams or technical condition analysis. Predictive ML/DL modules and regional scalability are also absent, reducing the practical value for monitoring and operational use cases. See Table 1.4 for details.

Table 1.4 – Contributions and limitations (2024)

Aspect	Description
Data Acquisition	High-resolution LiDAR capture of roads with semantic labeling into six object categories (pavement, shoulder, markings, signs, etc.).
Processing Pipeline	Automated workflow: noise filtering → object segmentation → semantic binding → IFC model generation.
Accuracy & Performance	Mean spatial error of 1.46 cm at 2000 pts/m²; processing speed of ~6.29 m/s on segments up to 2 km.
Operator Efficiency	Approximately 60 % reduction in manual modeling by automating the Scan-to-BIM process; limited operator input for calibration.
IoT Integration	Not addressed: no live sensor (temperature, moisture, deformation) data integration for dynamic condition monitoring.

Authoring

To visually illustrate this sequence, Figure 2.1 below presents the automated process of converting scanned data into the IFC format.

The study by Cherniavska T. and Cherniavskyi B. (2025) [30] describes a Ukrainian–Polish collaboration focused on digital modeling and restoration of road infrastructure damaged as a result of military actions. The project brought together experts in UAV imaging, geodesy, terrestrial laser scanning, and BIM. Its objective was to develop tools for rapid damage assessment and restoration planning. The study highlights the role of integrating remote sensing and web-based GIS in improving infrastructure management efficiency.

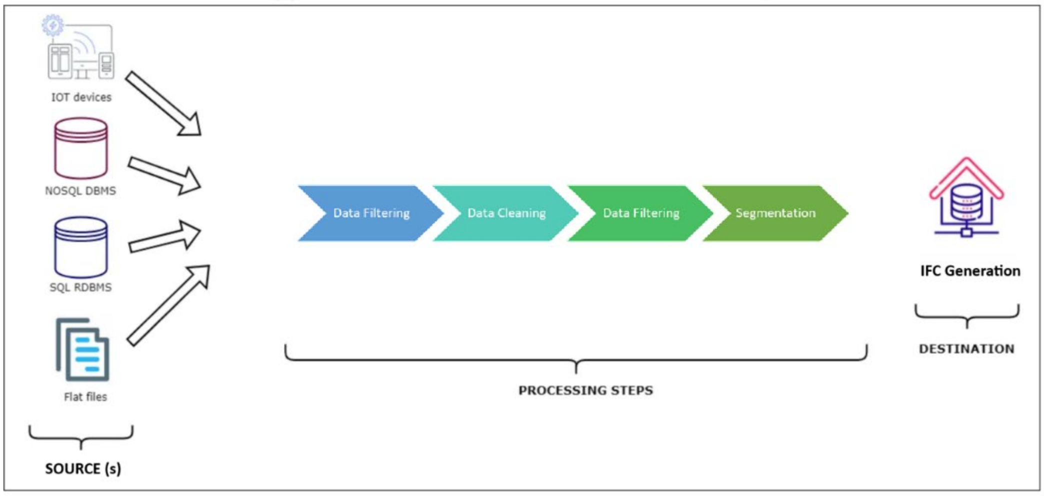


Figure 2.1 – Automated Process of Converting a Point Cloud into a BIM Model *Authoring*

The methodology included UAV aerial imaging and terrestrial laser scanning of sites in the Kharkiv and Donetsk regions. Based on the collected data, BIM models in IFC 2×3 format were generated and semantically annotated across seven categories. The developed system, Digital Reconstructor, integrated models with metadata (damage severity and type, recovery priorities) and provided a web-GIS interface for visualization. This approach accelerated defect analysis and streamlined planning processes.

The average model deviation was 2.8 cm, meeting engineering design standards. Visualization and automation reduced planning time by 35% and costs by 12%. However, the system does not support sensor data streams or predictive monitoring based on ML/DL algorithms, and testing was limited to two regions. To enhance the methodology’s generalizability, the authors recommend expanding geographical coverage and integrating modules for real-time analytics and forecasting. Table 1.5 summarizes the Contributions and Limitations.

The study by Habrat W. et al. [31] explores the integration of digital technologies for bridge management through a collaboration between TU München and TU Berlin. The project aimed to develop a centralized monitoring platform that combines BIM, IoT, and analytical tools. Three bridge structures were modeled in 3D using the IFC 4 format, with each element assigned a unique GUID to link sensor data. A network of

Table 1.5 – Contributions and limitations (2025)

Aspect	Description
Field Data Acquisition	UAV aerial imaging and terrestrial LiDAR scanning of damaged road and bridge segments in Kharkiv and Donetsk regions.
As-Built BIM Modeling	Generation of IFC 2×3 models from point clouds and photogrammetric data with semantic classification into seven defect categories.
Virtual Reconstruction	Integration of BIM model with georeferenced metadata via the Digital Reconstructor platform and interactive web-GIS visualization.
Evaluation & Case Analysis	Analysis of three road segments (12 km) and two bridges; model accuracy 2.8 cm; GUI reduced planning time by 35 %.
Gaps & Limitations	No real-time IoT data integration; focus on retrospective analysis; limited geographic scope.

Authoring

45 sensors was deployed on the structures, transmitting data via MQTT, OPC UA, and REST API, with edge server buffering.

An analytical system was developed using an LSTM model trained on time-series data of structural deformation and temperature, alongside a web dashboard for visualization and alert notifications. A 12-month field trial validated the system’s effectiveness: crack prediction up to 48 hours in advance (Precision = 0.87; Recall = 0.81), a 25% reduction in inspection costs, and a false alarm rate below 5%. Data export support and compatibility with CDE facilitated seamless integration into existing digital infrastructure.

However, the system is tailored specifically to bridges and does not account for road pavements or plastic deformations. The trials were conducted in three similar climatic zones in Germany, which limits generalizability. Additionally, the platform lacks a unified architecture that fully synchronizes BIM, real-time data streams, and analytics within a single environment. The authors emphasize the need to scale the solution to other asset types and climates, and to develop a fully integrated digital twin platform. See Table 1.6 for details.

Table 1.6 – Contributions and limitations (2024)

Aspect	Description
BIM Model Construction	Detailed IFC 4 models of three bridges (150–300 m) including primary structural elements and unique GUIDs for sensor binding.
IoT Sensor Deployment	Network of 45 sensors per bridge (strain gauges, accelerometers, temperature/humidity sensors) with MQTT & OPC UA → edge → REST API workflow.
Predictive Analytics Module	LSTM-based predictive maintenance trained on historical deformation and temperature time series, integrated into a web dashboard with alerts.
Field Trials	12-month near-real-time testing at 1 Hz; sensor readings validated against Southwell II strain gauges across diverse bridge types.
Gaps & Limitations	Excludes road pavement monitoring; limited to three German bridges; lacks unified CDE architecture for synchronized BIM–IoT–analytics integration.

Authoring

Xu J. et al. [32], representing the University of California, Berkeley, and MIT, present a study focused on the development of a digital twin for highway monitoring based on multisensor data. By combining video surveillance, acoustic sensors, and ground-penetrating radar (GPR), the research team achieved high diagnostic accuracy for pavement defects. The study highlights an interdisciplinary approach and the adaptation of solutions to the specific conditions of California's road network.

Data collection involved video cameras, acoustic sensors, and GPR devices, with transmission over LTE/5G networks. The data were processed within a Big Data pipeline using Apache Kafka and Spark, then synchronized and aggregated by road segments. The digital road model was formalized in IFC 4.1 format with associated metadata. For predictive analysis, a CNN–LSTM architecture was employed: visual data were processed by a convolutional neural network, while time series were analyzed by an LSTM module trained on datasets from the Department of Transportation (DOT) and the Federal Highway Administration (FHWA).

The model achieved a precision of 0.83 and a recall of 0.79 in 14-day forecasts for the most vulnerable sections. The system enabled a reduction in repair costs of up to 28% compared to traditional visual inspection methods. However, the study did not account for traffic loads (e.g., via WIM systems) and is limited to California’s climate conditions. Scaling the approach would require the inclusion of additional sensors, adaptation to diverse environments, and extension to bridge elements. See Table 1.7 for details.

Table 1.7 – Contributions and limitations

Aspect	Description
Multi-Sensor Data Collection	High-frequency data capture (up to 10 Hz) from HD cameras, acoustic sensors, and GPR via LTE/5G.
Big Data Pipeline	Real-time stream processing using Kafka and Spark, with noise filtering and 100 m segment aggregation.
Digital Twin Construction	Creation of IFC 4.1 BIM model annotated with sensor metadata (pavement type, build year, climate zone).
Predictive Analytics	Hybrid CNN-LSTM model trained on state DOT and FHWA datasets for forecasting maintenance needs.
Gaps & Limitations	Lacks WIM sensor integration; tested only in California; does not include bridge segment monitoring.

Authoring

1.3. Identified Gaps and Limitations

The analysis of five key publications reveals systemic deficiencies in the current development of digital twins (DT) for roads and bridges. The main issue lies in the modular, fragmented approach, where studies focus on isolated components of the DT ecosystem without establishing an integrated end-to-end data pipeline.

Most research efforts concentrate either on geometric scan-to-BIM modeling [29], on the development of static digital twins without a live sensor layer [28], or on analytical algorithms without integration with a BIM model [31]. For example, Talaghat et al. [28] classified three DT architectural patterns (visualization → simulation → platform), but did not demonstrate end-to-end integration between sensor data and the BIM model. Ding et al. [29] achieved sub-2 cm reconstruction accuracy but did not incorporate IoT sensors or predictive analytics, thus leaving BIM as a passive repository. Cherniavska & Cherniavskyi [30] developed a "post-factum" BIM for reconstruction purposes but did not include telemetry flows for real-time monitoring. Habrat et al. [31] integrated IoT and ML analytics for bridges, yet omitted

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road surface monitoring and did not employ a unified BIM layer within a common data environment (CDE). Xu et al. [32] implemented a Big Data pipeline for highways but failed to link the BIM model to bridge sections and to synchronize disparate analytical modules. (Figure 2.2)

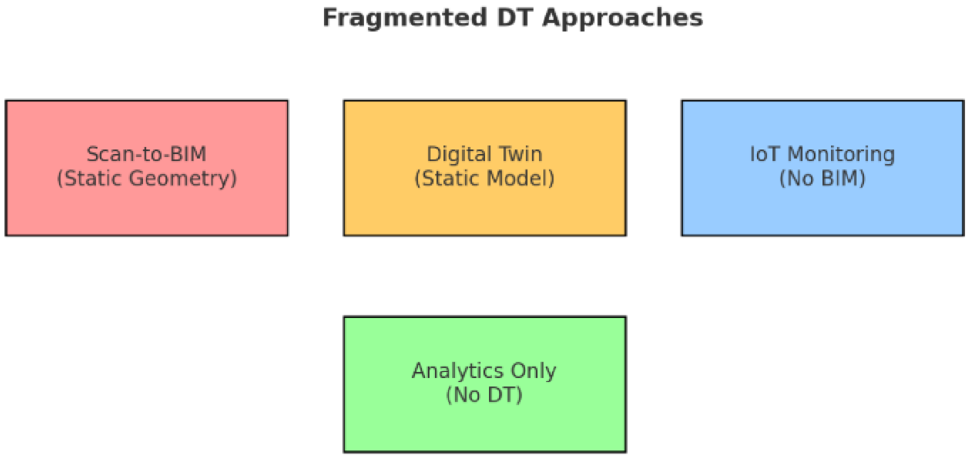

Figure 2.2 – Fragmentation of existing DT approaches in road and bridge research illustrates the isolated nature of current methodologies:

- Scan-to-BIM (Static Geometry) focuses solely on geometric reconstruction.
- Digital Twin (Static Model) provides a static mirror of infrastructure without live data.
- IoT Monitoring (No BIM) captures sensor data without integrating it into a digital model.
- Analytics Only (No DT) applies predictive algorithms independently of BIM or real-time feeds.

The absence of a unified methodology — “BIM → IoT → DT → Analytics” — hinders the creation of a fully functional digital twin. Without an end-to-end architecture, it is impossible to achieve real-time infrastructure state updates, defect forecasting, or the optimization of maintenance procedures based on integrated data streams.

Implementation limitations and real-world adoption. Despite the growing number of academic publications, the practical deployment of digital twins in transport infrastructure remains fragmented. Most projects are limited to laboratory experiments or small-scale field pilots, which do not allow for a comprehensive evaluation of effectiveness under real-world conditions.

In Talaghat et al. [28] and Ding et al. [29], there is a lack of large-scale testing across extended transportation corridors. Cherniavska & Cherniavskyi [30] confined their study to two regions in Ukraine, while Habrat et al. [31] did not consider severe climate zones. The work by Xu et al. [32] focused solely on California highways, excluding bridges and interchanges — which limits the generalizability of their findings.

Most of these studies showcase isolated use cases (e.g., crack monitoring), without full support for automated repair scheduling. The lack of large-scale pilot deployments undermines trust from transportation authorities and delays the development of industry standards essential for broader DT implementation.

Insufficient integration of IoT data. In many studies, IoT sensors are mentioned superficially or omitted entirely, which undermines the creation of a “live” data stream and limits the practical value of digital twins. The absence of a seamless data transmission channel between field sensors and the analytical platform results in fragmented solutions.

For example, Talaghat et al. [28] refer to IoT as an abstract cloud service without detailing sensor types or communication protocols. Ding et al. [29] focus solely on geometric modeling, with no integration of sensor signals. Habrat et al. [31] deployed sensors but did not describe how they are linked to IFC elements. Xu et al. [32] omit load data, and the linkage between sensors and the 3D model remains ambiguous.

Lack of standards and compatibility. The widespread use of proprietary formats and “black-box” middleware components has led to the creation of static models with no capacity for real-time responsiveness. This reduces the accuracy of predictions, complicates inspection procedures, and increases operational costs. The absence of open standards also hampers integration between solutions from different vendors and the formation of a unified digital ecosystem.

Absence of a unified methodology. The reviewed studies do not yet provide an end-to-end standardized methodology for building digital twins in road infrastructure that spans the full asset lifecycle — from design and construction to operation and maintenance. Consolidating these approaches is essential to ensure component compatibility and result reproducibility.

Talaghat et al. [28] reference ISO 19650 as a basis for BIM data management but do not elaborate on how its principles are applied in synchronization with IoT platforms and DT analytics services. Ding et al. [29] export models in IFC format but do not consider IFC extensions for storing sensor metadata or the use of CityGML ontologies for spatial georeferencing.

Habrat et al. [31] describe the IoT architecture and machine learning analytics for bridges in detail, but they do not integrate these components into a centralized CDE pipeline. As a result, BIM models cannot be automatically updated when new field data is received. Xu et al. [32] focus on the Big Data pipeline and AI models but fail to demonstrate any feedback loop to the BIM model for updating 3D geometry and semantic attributes within the DT object.

Verification and validation methods for sensor data are only described fragmentarily. For example, Müller et al. use conventional strain gauges to verify readings, but no unified industry guideline is proposed. Furthermore, there are no agreed-upon metrics for assessing the quality of digital twins — accuracy of geometry, completeness of sensor metadata, and reliability of predictive forecasts remain at the discretion of each research group.

Lack of a unified methodology hinders scalability. The absence of a consolidated approach leads to redundant research efforts and obstructs the upscaling of successful solutions. As a result, national departments of transportation are left without clear guidelines or technical regulations, which slows down the development of sector-wide standards and large-scale adoption of DT-based solutions. Furthermore, it complicates the integration of products from multiple vendors and increases the overall cost of deploying digital twins for roads and bridges.

Deficit of analytics and algorithms. Most current digital twin implementations are limited to basic data processing and simulations, lacking advanced machine learning (ML), deep learning (DL), and Big Data analytics. This significantly constrains their potential for predictive maintenance and infrastructure condition management. For instance, Habrat et al. [31] employed LSTM models for deformation forecasting but relied solely on strain data, omitting other critical parameters such as vibration, temperature, and humidity. Xu et al. [32] combined CNN and LSTM for processing video and GPR data but did not tailor their algorithms to specific defect classes or account for climate variability.

Talaghat et al. [28] did not address data analytics, focusing instead on a review of APIs. Cherniavska & Cherniavskyi [30] implemented damage visualization and repair prioritization tools but lacked automated forecasting or optimized maintenance planning. Xu et al. [32] demonstrated a Big Data pipeline using Apache Kafka and Spark Streaming but did not assess its scalability or adaptability to edge devices and LTE/5G network constraints.

Limited analytical capabilities reduce predictive accuracy and economic impact. Without scalable Big Data platforms, it is impossible to support near real-time processing of data streams from thousands of sensors — a critical requirement for large-scale transport corridors. The lack of comprehensive analytics also hampers the development of integrated dashboards, thereby reducing the effectiveness of infrastructure management and response strategies.

1.4. Conclusions to Chapter 1

Based on a systematic review of publications from 2024–2025 retrieved from Scopus, Web of Science, and open repositories, this section outlines the key advancements, identified gaps, and recommended research directions in the domain of digital twins for road and bridge infrastructure.

Advancements in geometric modeling and platform integration

Scan-to-BIM methods demonstrate high accuracy in reconstructing road infrastructure models, with a margin of error as low as 1.5 cm and automated point cloud processing pipelines [29]. A review of digital twin architectures has revealed three integration patterns of BIM with cloud platforms, which provide a foundation for standardized solutions [28]. Field case studies on bridges validate the feasibility of near real-time analytics using IoT sensor data, thus confirming the applied value of such approaches on operational infrastructure [31].

Key gaps and limitations

A modular and fragmented research approach persists, with most studies lacking an end-to-end methodology connecting BIM, IoT, and analytics layers [42–46]. Projects tend to focus either on geometric modeling or algorithm development, rarely integrating all components into a cohesive digital twin architecture. Pilot deployments remain narrow in scope, with limited geographic coverage and no corridor-scale validation campaigns. IoT integration is weak: sensor data streams are not linked to BIM-based CDEs or analytics platforms, largely due to the absence of unified protocols and middleware. The application of ISO 19650, IFC, and CityGML standards across the full DT lifecycle remains unstandardized. Analytical limitations include a narrow range of ML/DL techniques and a lack of scalable Big Data platforms capable of processing sensor streams across hundreds of kilometers [45, 46].

Recommended future research directions:

– Development of a unified architecture that integrates the BIM model, IoT layer, and analytics platform within a Common Data Environment (CDE), based on ISO 19650 and IFC extensions.

– Scaling of pilot implementations through multi-climatic and cross-regional trials using the TEN-T corridor (EU), IIJA program (USA), and the "Great Reconstruction" initiative (Ukraine).

– Standardization of data streams: design of common middleware and protocols for converting sensor outputs to IFC and CityGML formats, with support for REST/OPC UA interfaces.

– Enhancement of analytics: integration of multimodal ML/DL models (CNN, LSTM, GNN) and Big Data pipelines (Kafka, Spark) with edge computing frameworks.

– Development of verification procedures: definition of quality metrics for digital twins (e.g., geometric accuracy, data freshness, forecast reliability) and regulatory guidelines for transportation agencies.

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KAPITEL 2 / *CHAPTER 2*
THEORETICAL FOUNDATIONS OF DIGITAL TWINS, BIM, AND IOT

2.1 Concept and Essence of Digital Twin

The term "Digital Twin" was first introduced by Michael Grieves in 2002 within the context of Product Lifecycle Management (PLM), emphasizing the creation of a virtual replica of a physical object to facilitate analysis and design optimization [32]. Originally, the Digital Twin was considered a component of PLM platforms featuring bidirectional data exchange, which enhanced iterative design processes and mitigated prototyping risks. Key characteristics of the Digital Twin included real-time synchronization, verification, and "what-if" simulations.

In 2012, NASA formalized the Digital Twin concept as a framework for monitoring complex systems, defining a three-layer architecture: Physical Space, Virtual Space, and Digital Thread—a continuous data flow connecting the physical and digital realms [33]. This model has been extensively applied in the aerospace industry, enabling model updates and real-time monitoring. The concept of the Digital Thread subsequently became the foundation for the wider adoption of Digital Twin technologies across various sectors. (Figure 3.1)

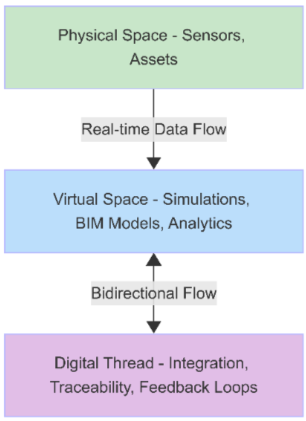

Figure 3.1 – Three-tier Digital Twin architecture: Physical Space, Virtual Space, and Digital Thread

Authoring

Since 2016, the Digital Twin (DT) concept has expanded beyond the aerospace industry, spreading into manufacturing and smart cities. The ISO/DIS 23247 project (2024) formalized the Industrial Digital Twin – Reference Architecture, identifying five key components: the physical and virtual entities, the digital thread, the connection, and an analytical application for monitoring and prediction [34]. Concurrently, the City Digital Twin domain evolved, adapting DT to urban systems, including transportation and utility infrastructure. Standards such as IFC and CityGML ensure interoperability among platforms from different vendors. The application of ISO 23247 supports the development of a unified methodology for large-scale DT deployment in road infrastructure.

Key Definition and Characteristics. According to ISO/DIS 23247 [34] and NASA's concept [33], a digital twin is a virtual representation of a physical object with bidirectional communication enabled by a continuous data stream. Such a system provides real-time monitoring, simulation, and optimization of the object. The DT links the physical world and an analytical platform, enabling not only data collection but also the transmission of control commands. Its principal feature is adaptability to operational and environmental changes, facilitating predictive maintenance and improved operational performance. (Table 2.1)

Table 2.1 – Key characteristics of a Digital Twin

Property	Description
Dynamicity	Continuous model updates via data streams from sensors, enabling real-time reflection of asset conditions and events.
Bidirectionality	Capability not only to collect telemetry but also to transmit control commands to physical asset systems (e.g., adjusting equipment operation modes).
Predictiveness	Integrated AI/ML modules forecast future states (e.g., wear, fatigue), enabling proactive maintenance planning.
Integrativity	Combines geometry (BIM/GIS), semantic data (IFC), sensor streams (IoT), and analytics into a unified Common Data Environment (CDE) ecosystem.
Scalability	Ability to cover both individual assets (e.g., bridges) and large-scale road networks (thousands of kilometers) while maintaining required latency and throughput.

A source: [33-34]

The "Property" column defines the fundamental qualities of a digital twin (DT), while the “Description” column explains how each property is implemented and its role in supporting monitoring, control, and analytics for infrastructure assets. Dynamicity refers to the continuous real-time updating of the model through sensor data streams. Bidirectionality highlights the ability to transmit commands back to the physical asset. Predictiveness demonstrates the application of AI algorithms to forecast future asset conditions. Integrativity reflects the unification of diverse data types within a shared environment (CDE). Scalability describes the system’s capability to expand from single assets to entire road networks.

Component Structure of the Digital Twin for Road Infrastructure. In road infrastructure, the digital twin develops across five interconnected layers, providing a closed loop from data acquisition to user interaction. Each level performs specific functions and is based on standards that ensure system compatibility and scalability. The physical layer covers objects such as the road pavement and bridges, represented by their structural elements (asphalt, spans, supports). The sensing layer operates a network of IoT devices (strain gauges, accelerometers, WIM, GPR, video cameras, climate sensors) that collect real-time data. Data transmission is carried out via MQTT, OPC UA, SensorThings API, and LoRaWAN.

The Digital Thread consists of edge devices and 5G/LTE networks, utilizing Kafka for filtering and routing. This layer ensures data delivery with minimal latency to the virtual environment. The virtual layer is represented by BIM/GIS/CityGML models employing IFC 4, CityGML ontologies, and ISO 19650 standards for storing geometry and semantics. This model provides a comprehensive digital representation of infrastructure objects and serves as the foundation for analytics.

The analytical layer includes AI/ML tools and numerical modeling software (TensorFlow, PyTorch, OpenFOAM), enabling predictive analysis, anomaly diagnostics, and structural behavior calculation. The interface layer connects the system to end-users through HMIs, APIs (REST, GraphQL), and dashboards (Power BI, Grafana, Revit iTwin), providing parameter visualization and integration support with DOT systems. (Table 2.2)

Table 2.2 – Layered Architecture of the Digital Twin for Road Infrastructure

№	Layer	Component	Function	Standards and Technologies
1	Physical Layer	Roadway, Bridge	Structural elements: pavement, spans, piers, expansion joints	—
2	Sensor Layer	IoT Sensors	Data acquisition: strain gauges, accelerometers, WIM, cameras, GPR, weather sensors	MQTT, OPC UA, SensorThings API (OGC), LoRaWAN
3	Digital Thread	Edge Devices and Network	Pre-filtering, buffering, and routing of data; ensuring low latency	Edge Computing, 5G/LTE, Kafka
4	Virtual Layer	BIM/GIS/CityGML	Geometry and semantics: IFC 4 models, spatial data, CityGML ontologies	ISO 19650-1/2/3/5, IFC, CityGML
5	Analytics	AI/ML, Simulations	Predictive maintenance, anomaly detection, FEA/FEM-based fatigue analysis	TensorFlow, PyTorch, OpenFOAM, custom FEM engines
6	Interfaces	HMI, API, BI Dashboards	Indicator visualization, integration with DOT systems, inspector mobile apps	REST/GraphQL, Power BI, Grafana, Revit iTwin, Tekla BIM Viewer

A source: [33-34]

Each row in Table 2.2 illustrates the purpose of a specific layer, key components, their functions, and the applied standards or technologies, allowing a clear understanding of the architectural separation and dependencies between modules. Below are sample sensor metrics (Figure 3.2).

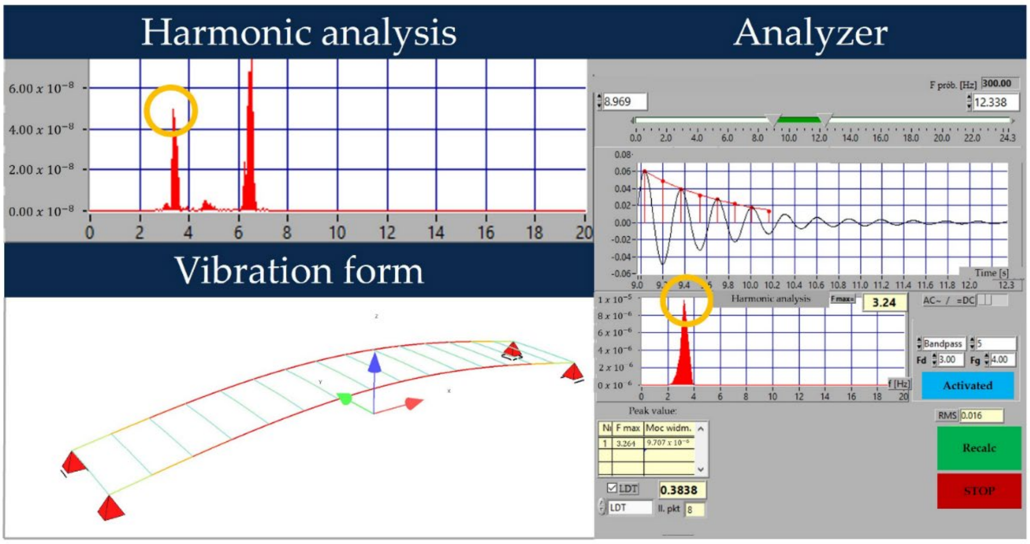

Figure 3.2 - Identification of natural frequencies and corresponding damping.

A source: [111]

Classification of Digital Twin Types. The classification of digital twins (DT) in road infrastructure is determined by the lifecycle stage of the object and the objectives of their application. Three types are distinguished: DTs for design, construction, and operation. The first type is used in the pre-design phase for verifying routing, estimating earthwork volumes, and coordinating decisions. It helps account for slopes, geology, environmental constraints, and reduces planning risks [32]. The second type is applied during construction, providing quality control of materials, monitoring asphalt laying, and generating compliance reports according to technological standards [33].

The third type—DT for operation and maintenance—is focused on continuous monitoring of road pavement and bridges using sensor data and predictive analytics algorithms. It enables defect detection (cracks, deflections), residual lifespan forecasting of structures, and optimization of maintenance schedules, thereby reducing unplanned downtime and costs [49, 73]. This monograph concentrates specifically on this DT type as the most promising for the digital transformation of transportation infrastructure management. (Table 2.3).

Table 2.3 – Classification of Digital Twin types in road and bridge infrastructure

DT Type	**Lifecycle Stage**	**Core Functionality**	**Application in Road Sector**
Design-phase DT	Pre-design phase	Alignment validation, earthwork volume estimation, stakeholder coordination	Route optimization, preliminary earthworks calculation
Construction-phase DT	Construction and installation	Asphalt paving monitoring, material quality control, progress and change tracking	Automated paving status updates, quality assurance (QA) analytics
O&M-phase DT (Operations & Maintenance)	Operation and maintenance	Continuous condition monitoring, predictive maintenance, repair scheduling	Fatigue crack detection, bridge deflection forecasting

A source: [49-73]

Each DT type in Table 2.3 is matched with the lifecycle phase, key functions, and applied scenarios in the road sector, facilitating the selection of the appropriate solution for a specific project stage.

BIM Concept and Maturity Levels. The Building Information Modeling (BIM) concept encompasses the entire lifecycle of infrastructure objects—from design to operation—through the use of a unified digital model containing geometry, properties, and relationships of elements. The foundation of BIM is the Common Data Environment (CDE), which enables single data entry and shared access for all project participants. This enhances decision consistency, reduces errors in data transfer, and optimizes interdisciplinary collaboration.

BIM maturity levels are defined by the degree of digital coordination. According to the UK BIM Framework, Level 0 represents 2D drawings without data integration. Level 1 includes 3D models of individual disciplines and standardized classifications, but data exchange is still file-based. Level 2 provides three-dimensional coordination within the CDE using open formats such as IFC and COBie, meeting the requirements of most modern infrastructure projects. Level 3 implies full cloud integration with continuous data synchronization and API access, forming a digital environment ready for Digital Twin applications [35, 36]. (Table 2.4).

Table 2.4 – BIM Maturity Levels (UK BIM Framework)

BIM Level	Description	Implementation Tools & Features
Level 0	Traditional 2D drawings, either on paper or basic CAD files	AutoCAD, MicroStation
Level 1	3D models per discipline; coordination via shared data environment (SDE)	Partial 3D models, standardized naming conventions
Level 2	Full 3D coordination in a Common Data Environment (CDE) using IFC and COBie	Autodesk BIM 360, Bentley ProjectWise, 3D clash detection tools
Level 3	Full integration and real-time data exchange; seamless cloud-based collaboration	Digital Twin-ready CDEs, API integration, collaborative model management

A source: [35]

Table 2.4 illustrates the four BIM maturity levels according to the UK BIM Framework, indicating their functional characteristics and examples of tool solutions,

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which assists design and operational organizations in assessing readiness for transitioning to the Digital Twin level.

International Standard ISO 19650

The ISO 19650 series regulates information management during the application of BIM across all stages of an asset’s lifecycle. It establishes general principles, requirements for data exchange organization, and information security measures, ensuring process consistency among project participants of varying scales. (Table 2.5).

Table 2.5 – ISO 19650 Parts Overview

ISO 19650 Part	Scope and Content
19650-1	Core concepts and principles of information management
19650-2	Information requirements and exchange protocols during design and construction
19650-3	Information management for the operation and maintenance phase
19650-5	Guidelines for information security and protection of personal data

A source: [36]

ISO 19650-2:2018 defines requirements for the development of a BIM Execution Plan and data exchange procedures between design and construction organizations, including the condition of a Common Data Environment for storing and publishing models [36]. ISO 19650-3:2020 focuses on operation, establishing processes for regular updates of BIM models based on technical inspections and structural condition monitoring. The application of ISO 19650 provides a unified framework for information exchange and enables the integration of BIM tools into the overall digital twin architecture during the operation of road infrastructure.

IFC Format (Industry Foundation Classes)

IFC (Industry Foundation Classes) is an open standard for BIM data exchange developed by buildingSMART to ensure compatibility between different platforms and CDEs. It allows the transfer of both geometry and semantics of objects. The base class IfcRoot defines a unique identifier (GlobalId), name, description, and ownership history. It is inherited by IfcObjectDefinition, which specifies common properties of all objects, while the IfcElement class adds the ability to assign tags (Tag) to structural elements.

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For infrastructure modeling, extended classes are used. IfcBuildingElement and its subclass IfcSlab describe flat elements, including road pavements with material and strength parameters. Classes IfcRoad and IfcBridge are applied to highways and bridges, considering georeferencing and specific characteristics. The IFC structure supports storage of Pset attributes and ensures cross-platform compatibility, which is critical for integration into digital twins. (Figure 3.3).

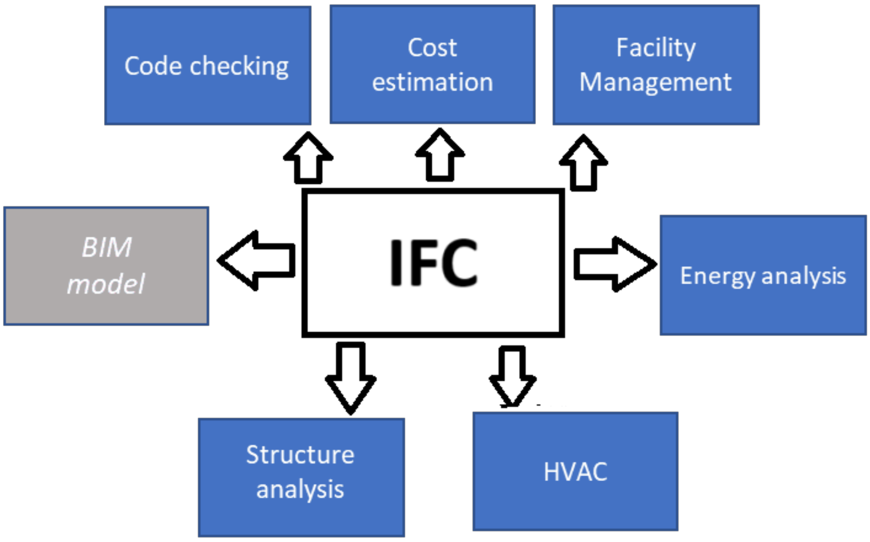

Figure 3.3 – Core IFC class hierarchy for infrastructure modeling

Authoring

Relationship between BIM and the Digital Twin. The BIM model serves as the foundation for the digital twin, providing geometric accuracy, semantic richness, and versioning capabilities. Through the extension of IFC PropertySets, BIM becomes a container for storing sensor metadata, enabling the association of IoT device readings with model elements. CDE systems manage the lifecycle of models, ensuring traceability of changes based on monitoring data. (Table 2.6).

Table 2.6 – Role of BIM in Digital Twin

Aspect	Role of BIM in DT
Geometry	Provides accurate 3D coordinates of all structural elements of the road and bridge
Semantics	Describes element properties (material, installation date, load class)

Table 2.6 continued on the next page

Continuation of Table 2.6

Sensor Metadata	Extends IFC PropertySet to store SensorID linkage and parameter types (e.g., temperature, strain)
Change & Versioning	CDE manages BIM model versions based on sensor monitoring results, preserving edit history

Authoring

IoT–BIM–Analytics Interaction (Figure 3.4).

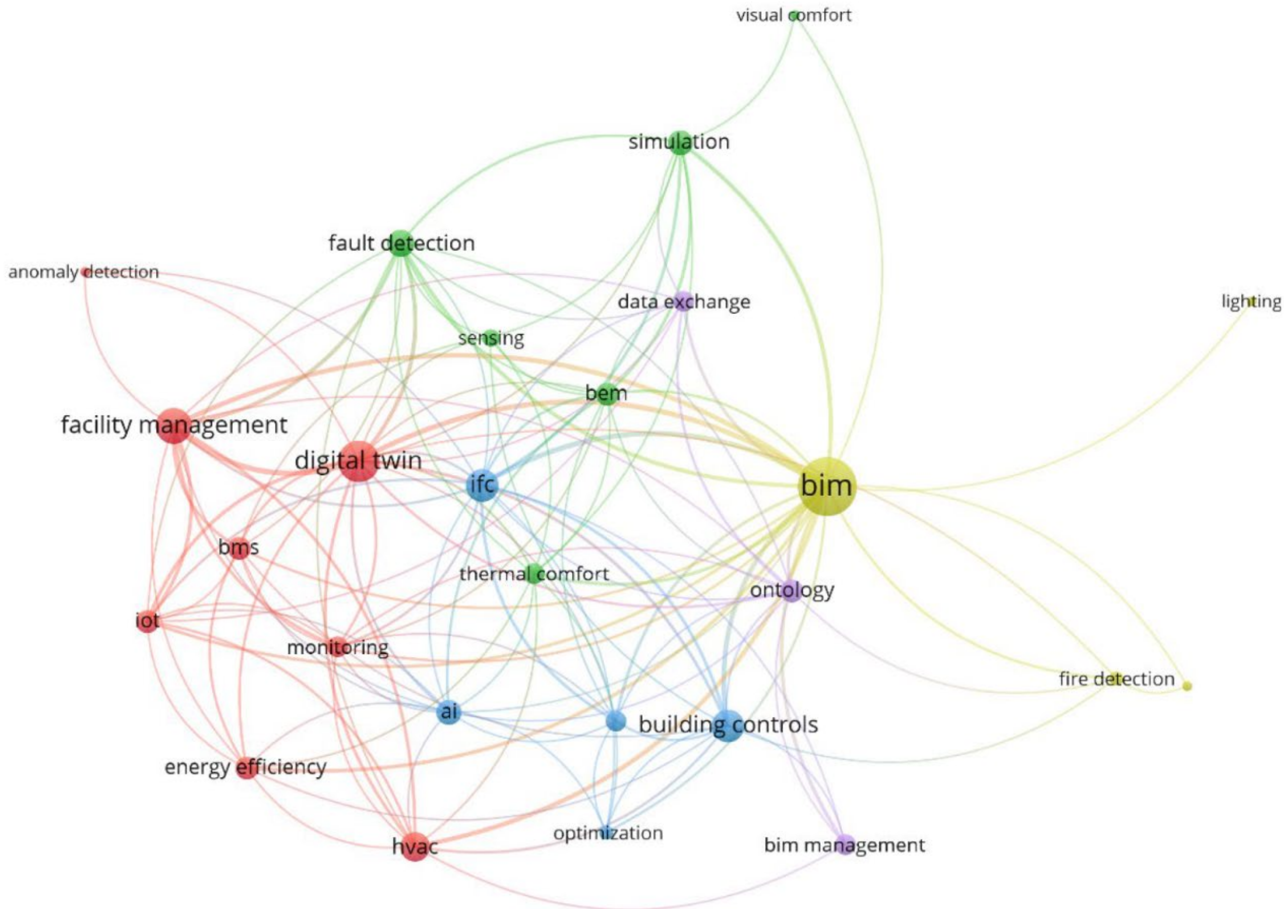

Figure 3.4 – Interaction between IoT sensors, BIM CDE and Analytics Engine in a Digital Twin

Authoring

Example of Chain Operation: IoT sensors transmit telemetry to the CDE through extended IFC PropertySet records. The CDE initiates AI/ML processes in the analytical engine, after which the analysis results are written back into the BIM model. The updated attributes are visualized in a 3D viewer, providing engineers with an up-to-date picture of the infrastructure's condition.

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2.2. IoT in Infrastructure: Principles, Structure, Standards

Concept and Architectural Layers of IoT. The Internet of Things (IoT) is a distributed system that integrates sensors, devices, and software components for continuous monitoring of asset conditions. In the transport sector, IoT serves as the foundation of the digital twin, enabling telemetry collection, predictive analytics, and data visualization. The architecture of the IoT system is organized into four interconnected layers.

The sensing layer includes devices measuring physical parameters (strain gauges, accelerometers, GPR, WIM, climate sensors, and cameras), forming primary data on defects and loads. The network layer transports this data using protocols such as MQTT, LoRaWAN, NB-IoT, 5G, and OPC UA, ensuring reliability and scalability.

The processing layer is implemented both on edge devices and in the cloud: Kafka is used for routing, InfluxDB for storage, and containers (Docker) provide stream cleansing and aggregation. Finally, the application layer includes visualization and analytics: dashboards based on Grafana, web GIS, and REST/SensorThings APIs enable dispatchers to promptly respond to threats and manage asset maintenance based on current data. (Table 2.7).

Table 2.7 - IoT System Architecture for Road and Bridge Infrastructure

IoT System Layer	Function	Key Technologies
Perception Layer	Measurement of physical parameters: strain, vibration, temperature, humidity, load	Strain gauges, GPR, WIM, cameras, IoT sensors
Network Layer	Data transmission from devices to the analytics platform	MQTT, LoRaWAN, NB-IoT, 5G, OPC UA
Edge & Cloud Layer	Data cleaning, aggregation, routing, and long-term storage	Kafka, InfluxDB, Docker, Raspberry Pi
Application Layer	Analytics, visualization, alerts, integration with BIM and CDE	Grafana, web-GIS, SensorThings API, REST API

Authoring

Classification of Sensors in the Road Sector. To ensure comprehensive monitoring of roads and bridges, various categories of sensors are used, differing by the measured parameter, accuracy, sampling frequency, and application area. Device selection is determined by project objectives: deformations are monitored using strain gauges, heavy vehicle loads are measured via WIM systems, base conditions are investigated with GPR, and visual defects are detected using cameras and video analysis. (Table 2.8).

Table 2.8 – Sensor classification for road and bridge monitoring

Sensor Category	Parameter	Example Device	Accuracy	Sampling Frequency	Application
Deformation	Axial/transverse strains	FBG strain gauge (Micron Optics)	±1 με	1 – 100 Hz	Monitoring of bridge deflections and pavement joints
Vibration	Acceleration, vibration frequency	MEMS accelerometer (Analog Devices)	±0.01 g	up to 1 kHz	Detection of fatigue cracks and load assessment
Load (WIM)	Weight and axial load	Piezoelectric WIM platform	±5 %	100 – 200 Hz	Freight traffic statistics
Ground Penetrating Radar (GPR)	Subgrade condition	GSSI SIR 4000 (400 MHz)	±2 cm	0.5 – 2 Hz	Evaluation of layer thickness and subgrade moisture content
Cameras / Video Analytics	Visual defects, rutting	FLIR thermal camera 640 × 480	1080 p	1 – 30 fps	Pothole detection and thermographic analysis
Climatic	Temperature, humidity	Sensirion SHT35	±0.1 °C; ±1 % RH	0.1 – 1 Hz	Accounting for weather impact on pavement and structures
Location (GPS/IMU)	Position, acceleration, rutting	Trimble R10 GPS	±1 cm	1 – 5 Hz	Georeferencing of mobile inspection platforms

Authoring

Note: The selection of sensors is based on the project’s priority tasks: for bridges, deformation and vibration sensors are key; for traffic flow analysis — WIM systems; for monitoring the condition of the base and pavement — GPR and video sensors.

Data Transmission Protocols and Standards. A reliable IoT infrastructure for digital twins in the road sector requires the use of scalable and compatible data transmission protocols. Depending on the scenario, both lightweight pub/sub solutions and industrial standards supporting security and semantics are employed.

- MQTT (ISO/IEC 20922): a lightweight pub/sub protocol for resource-constrained devices, with minimal overhead and QoS support [42].
- LoRaWAN: an LPWAN technology with a range up to 15 km and low power consumption; suitable for remote sensors [43].
- NB-IoT: a cellular LPWAN platform offering high device density and reliable connectivity in urban environments [46].
- 5G: provides high throughput and latency under 10 ms; used for video streams and AR/VR scenarios [46].
- OPC UA (IEC 62541): an industrial data exchange standard with security support and object structure description [46].
- OGC SensorThings API: a REST interface for accessing sensor data in GIS environments, ensuring compatibility between IoT and geo-platforms [37].

Description of the System Operation Process (Table 2.9):

Table 2.9 – Components of the IoT architecture for a road segment

Component	Example	Role
Sensors	Strain Gauges, Cameras	Collection of deformation, vibration, and visual defect parameters
Edge Layer	Raspberry Pi Gateway	Filtering, aggregation, publishing via MQTT/LoRaWAN
Network Layer	MQTT Broker, LoRaWAN	Message transport from edge gateway to cloud services
Cloud Layer	Kafka Cluster, InfluxDB, Neo4j	Ingestion, time-series storage, modeling sensor relationships and BIM
Application Layer	Grafana, BIM CDE, SensorThings API	Visualization, model updates, access to analytical data

A source: [37], [42-43], [46]

The table demonstrates the key components of the IoT architecture for road infrastructure, including both hardware and software elements.

Below is an example topology of an IoT system for road section monitoring, illustrating the interaction of sensor devices, edge components, network infrastructure, cloud services, and application layer. (Figure 3.5).

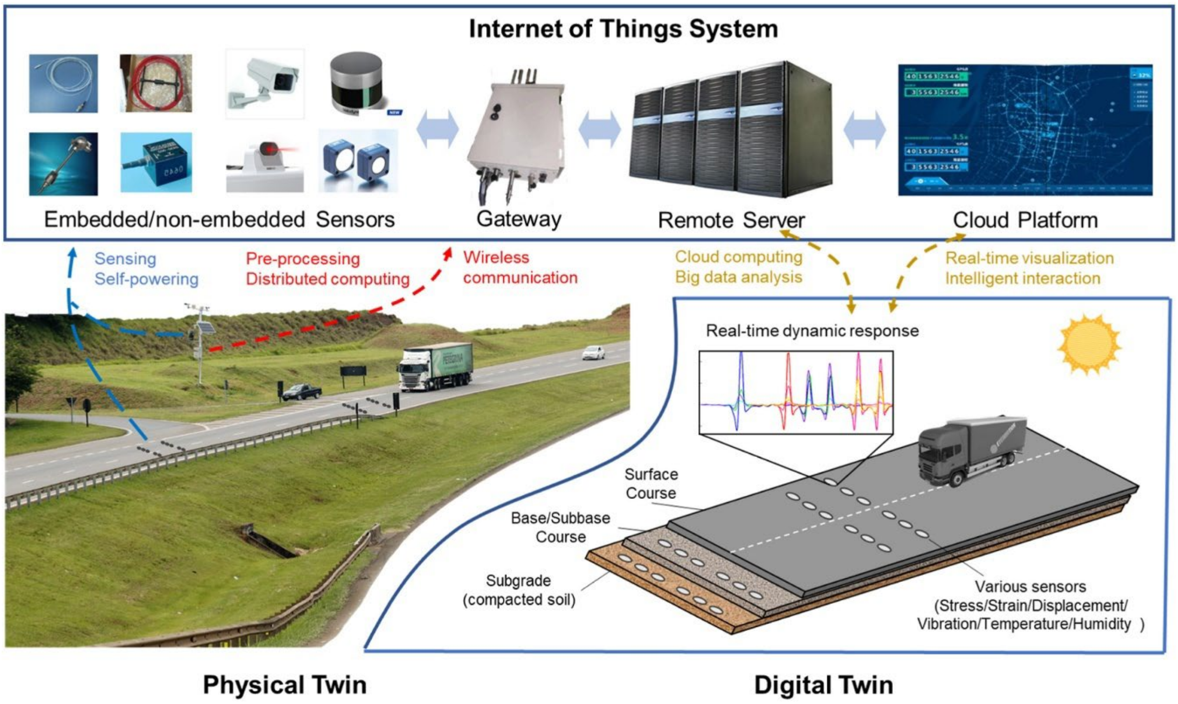

Figure 3.5 – Topology of an IoT system for a road segment, showing sensors, edge gateway, network brokers, cloud storage, and application interfaces

A source: [1]

2.3. Standards and Formats Used in DT Infrastructure

ISO 19650: Information Management in BIM

The ISO 19650 series defines the principles and processes of information management during the use of BIM in civil engineering and infrastructure. ISO 19650-1 establishes terminology and fundamental concepts of information management, including the notions of the Common Data Environment (CDE) and Information Requirements [36]. ISO 19650-2 regulates data exchange during design and construction phases, requiring the development of a BIM Execution Plan (BEP) and the specification of Exchange Information Requirements (EIR) for all participants [39]. ISO 19650-3 focuses on asset operation, defining processes for updating the model based on monitoring data and inspections, which is critical for maintaining the digital twin in real time [40]. ISO 19650-5 sets requirements for information security in BIM processes and digital twin interfaces, establishing measures for protecting data confidentiality and integrity [36].

In the context of digital twins, these standards ensure transparency, version control, and consistency of metadata when IoT data is integrated into the BIM model. Table 2.10 (below) provides a comprehensive overview of the individual parts of the ISO 19650 series and delineates their respective roles and contributions within the architecture of a digital-twin infrastructure.

Table 2.10 – Overview of ISO 19650 parts and their roles in DT infrastructure

Part of ISO 19650	**Purpose of Application**
19650-1	Definition of terminology, concepts, and principles of information management
19650-2	Regulation of data exchange during design and construction phases (EIR, BEP)
19650-3	Processes for updating BIM models based on monitoring during the operational phase
19650-5	Requirements for information security and data protection in BIM/DT

A source: [36], [39-40]

IFC: An Open Format for BIM Data Exchange

Industry Foundation Classes (IFC) is an open, file-based model exchange format developed by buildingSMART that supports the transfer of geometry and semantic data between BIM environments. The IFC4 specification (2020) introduced the IfcRoad and IfcBridge classes for describing road and bridge structures with attributes such as thickness, material, and strength [37]. The IFC Alignment extension (2021) added support for linear objects—IfcAlignment—enabling the modeling of road alignments with georeferencing and segmentation.

The advantages of IFC lie in its openness and broad support by most CAD systems, semantic extensibility via IfcPropertySet, and the capability to store sensor metadata bindings (IfcSensor, IfcDistributionElement). The main limitation is the file

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size when describing long linear objects (>100 km) and the lack of standardized properties for IoT data, which forces developers to implement custom extensions. (Table 2.11).

Table 2.11 – Key features and limitations of IFC for DT

Property	**Description**
Openness	Supported by most BIM platforms and tools
Semantics	Extensible class model and Pset attributes for describing engineering parameters
Georeferencing	IfcAlignment for linear objects with segmentation and coordinate positioning
IoT Metadata	Capability to use IfcSensor and IfcDistributionElement for storing sensor references and parameters
Limitations	Large volume of descriptions for linear objects; need for custom extensions for IoT

A source: [37]

Table 2.11 presents the main characteristics and limitations of the IFC format for digital twins of road infrastructure.

CityGML: An OGC standard for 3D modeling of urban areas with levels of detail (LOD 0–4) [50]. The core module describes buildings, roads, and bridges with geometry and attributes for environmental analysis. The UtilityNetworks extension supports underground utilities, facilitating the integration of digital twins with utility services. The ADE mechanism allows adding custom properties (e.g., SensorID, InstallationDate) without modifying the schema. In digital twins, CityGML provides georeferencing of BIM models and sensor data, simplifying infrastructure monitoring and 3D visualization.

OGC SensorThings API: A RESTful interface for managing sensor data in IoT [49]. Key entities include Thing (device), Sensor (description), ObservedProperty (measured property), Datastream (data stream), and Observation (single measurement). The API supports CRUD operations and filtering by time and space. In digital twins, SensorThings API links IoT sensors with the CDE, ensuring compatibility and simplifying data integration into digital models.

ISO 23247: The "Industrial Digital Twin — Reference Architecture" standard

(2024) [34] defines five DT components: Asset (physical object), Virtual Representation (unified model), Digital Thread (data flow), Connectivity (communication), and Application Services (analytics). Requirements cover QoS, security, and modularity. Adapted to road infrastructure, the standard supports reliable data transmission, structured storage, and consistency of DT data flows.

ISO 37120/37122: Standards for assessing smart city indicators. ISO 37120 covers over 100 KPIs in transportation, environment, and social sectors [52], while ISO 37122 addresses digital services, network resilience, and automation [50]. Integration with digital twins extends monitoring to the “smart corridor,” including route accessibility, response times, energy consumption, and emissions, creating a platform for strategic decisions that consider technical and social aspects of operation. (Table 2.12).

Table 2.12 – Comparison of standards and formats

Standard/Format	**Purpose**	**Key Entities**	**Application in DT Architecture**
ISO 19650 1…5	BIM information management	BEP, CDE, EIR	Version control; information requests
IFC4 & Alignment	Semantic and geometric BIM model	IfcRoad, IfcBridge, PSet	Geometry storage; custom properties
CityGML & ADE	3D models of urban and linear infrastructure	CityObject, LOD, ADE	GIS integration; spatial queries
SensorThings API	Interoperable access to sensor data	Thing, Observation	Ingestion; IoT data queries
ISO 23247 (draft)	Digital Twin architecture	Digital Thread, Asset	Modular structure; QoS; security
ISO 37120/37122	KPIs for smart cities	Indicator	Performance analysis; sustainability; "Smart Corridor" metrics

A source: [50], [52]

Table 3.11 compares key international standards and formats used in digital twin infrastructure for roads and bridges.

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2.4. Typical Architectural Models of Digital Twins

NIST Digital Twin Framework. The NIST Digital Twin Framework is a conceptual model designed to unify approaches to the development of digital twins in industry and infrastructure. It is based on a five-layer architecture that includes the physical entity, sensors and IoT, the digital thread, the virtual model (Digital Entity), application services, and trust and security mechanisms.

The Physical Entity encompasses real-world objects—such as roads, bridges, or tunnels. The Digital Thread organizes the pipeline for collecting, transmitting, and storing data from IoT devices through edge and cloud services. The Digital Entity stores geometric and semantic information in the form of a BIM/GIS model, which connects to Services such as monitoring, visualization, and analytics [51]. The Trust & Security component ensures authentication, authorization, and data encryption at all stages of digital twin operation. (Table 2.13).

Table 2.13 – NIST Digital Twin Framework Components

Layer	Description
Physical Entity	Physical object: road, bridge, tunnel
IoT & Sensors	Sensors and telemetry collection devices
Digital Thread	Data flow: collection → edge → cloud → CDE
Digital Entity	Virtual model (BIM/GIS), including geometry and semantics
Services	APIs and services for monitoring, visualization, and analytics
Trust & Security	Security metadata, authentication and encryption mechanisms

A source: [51]

Table 2.13 lists the key layers of the NIST Digital Twin Framework and explains their functions in the context of road infrastructure.

City Digital Twin (EU Horizon) [52]. The City Digital Twin, developed under the Horizon Europe program, extends the classical DT model to encompass urban and linear infrastructure. Its foundational element is the City Model, represented in the CityGML format (LOD0–LOD4) and including roads, bridges, and buildings. Domain Models add specialized modules for transportation, utility networks, and the environment.

The Real-time Data Layer integrates IoT data via the OGC SensorThings API, enabling streaming updates. The Simulation & Scenarios module allows for running “what-if” simulations to assess traffic, climate impacts, and emergency situations. The Governance & Ethics section establishes frameworks for data management, privacy, and openness, which are critical for public-sector projects. Table 2.14 (below) summarizes the core components of a City Digital Twin as defined by the EU Horizon framework.

Table 2.14 – City Digital Twin (EU Horizon) Components

Component	**Description**
City Model	CityGML model with LOD0–LOD4: roads, bridges, buildings
Domain Models	Transport, utilities, environment
Real-time Data Layer	Streaming IoT data via SensorThings API
Simulation & Scenarios	Interactive "what-if" scenarios for traffic and climate impact
Governance & Ethics	Data policies, privacy and ethics guidelines

A source: [52]

Table 2.14 clearly presents the core modules of the City Digital Twin developed under the Horizon Europe program.

ISO/IEC JTC 1 Reference Model for Digital Twins. The ISO/IEC JTC 1/SC 41 committee has developed a reference architecture for digital twins applicable across various domains, including road infrastructure [53]. The model comprises six functional layers that support the complete digital twin lifecycle. (Table 2.15)

Table 2.15 – ISO/IEC JTC 1 Digital Twin Reference Model Layers

Layer	**Functions**
Sensing & Actuation	Connection and control of sensors and actuators
Data Management	Data storage, metadata management, and signal quality control
Digital Representation	Creation and maintenance of virtual replicas of objects and processes (IFC, CityGML)
Service Layer	Monitoring, analytics, and visualization services
Interface Layer	API contracts and gateways for component interaction
Governance & Compliance	Security policies, authentication, encryption, and regulatory compliance

A source: [53]

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The table outlines the key layers of the DT model and their respective functions—from physical interaction with the asset to the management of security and regulatory compliance.

Unified Digital Twin Architecture for Road Infrastructure. Based on the comparative analysis of the NIST, City Digital Twin, and ISO/IEC JTC 1 models, a specialized DT architecture for roads and bridges is proposed, integrating best practices and international standards [77–79].

The Physical Entity represents real-world structures such as asphalt pavement, bridge spans, and supports. The IoT Layer includes a multisensor suite—strain gauges, accelerometers, WIM systems, and cameras—for comprehensive condition monitoring.

The Digital Thread organizes preprocessing at edge nodes and transmits data via MQTT and 5G to a cloud-based big data cluster using Kafka and a time-series database. The Digital Entity stores 3D models in IFC and CityGML formats, preserving both the geometry and semantics of infrastructure assets.

The Analytics & Services layer integrates an AI/ML engine, FEA simulation tools, and a dashboard with APIs for KPI visualization and feedback. Reliability and compliance with standards (ISO 19650, ISO 23247) are ensured by the Governance & Compliance layer, which handles data security and management [111].

The Figure 3.6 illustrates the data flow from physical assets through the sensor layer and digital thread to cloud storage, virtual model creation, subsequent analytics, and feedback—while maintaining security at every stage.

To provide deeper insight, a comparative analysis of DT models is presented in Table 2.16.

Table 2.16 illustrates the specialization and level of integration of each reference model.

It shows that the proposed architecture offers full support for BIM/GIS integration, real-time data handling, and advanced predictive analytics, while adhering to internationally recognized standards and technologies.

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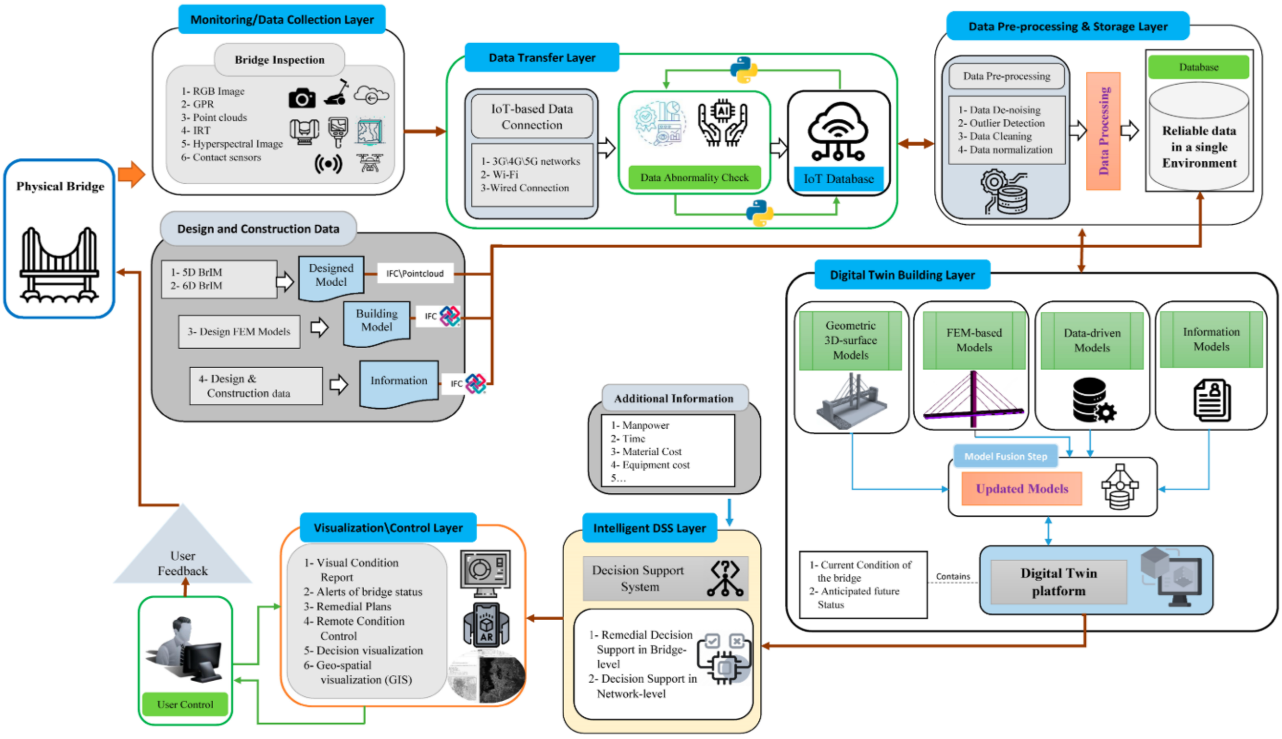

Figure 3.6 – Unified Digital Twin architecture for road and bridge infrastructure

A source: [112]

Table 2.16 – Comparison of DT Models

Characteristic	NIST SP 1270	City Digital Twin	ISO/IEC JTC 1	Proposed Architecture
Focus	Industry	Urban ecosystems	Universal	Roads and bridges
BIM/GIS Support	Indirect	City models	Core of DT pair	Full integration
Real-time Data	Yes	Yes	Yes	Yes
Predictive Analytics	Optional	Advanced	DT services	Hybrid AI/ML + FEM
Standards	NIST, ISO 23247	CityGML, SensorThings	IEC, ISO	ISO 19650, IFC, CityGML

Authoring

1. Orientation. NIST SP 1270 was originally developed for industrial systems and only partially addresses the requirements of road networks. The City Digital Twin is focused on urban ecosystems, covering a wide range of assets, but does not provide detailed semantics for bridge structures. ISO/IEC JTC 1 presents a generic DT template, which requires further adaptation for specific domains. In contrast, the

proposed architecture is purpose-built for roads and bridges, combining best practices and incorporating dedicated components for hybrid AI/ML analytics and FEM-based simulations.

2. BIM/GIS Support. In NIST SP 1270 and ISO/IEC JTC 1, the integration with BIM and GIS remains conceptual. The City Digital Twin uses CityGML to provide spatial context but lacks semantic enrichment for engineering elements (e.g., span type, pavement class). The proposed architecture ensures end-to-end storage and updating of both geometry and object attributes using IFC and CityGML formats, including SensorID binding and extended PSet definitions.

3. Real-time Data. All referenced models support real-time data streaming to some extent; however, only the proposed architecture specifies concrete QoS requirements (latency < 500 ms), includes edge computing mechanisms, and describes fault-tolerance methods for large-scale corridors.

4. Predictive Analytics. In NIST and ISO/IEC JTC 1, analytics services are described in abstract terms. The City Digital Twin emphasizes traffic and climate scenario simulations but lacks integration with detailed engineering models. The proposed architecture combines hybrid CNN+LSTM models for pavement defect detection with a FEM engine for fatigue analysis of bridge spans, ensuring high predictive accuracy.

5. Standards. NIST relies on its own publications and ISO 23247 [53]. The City Digital Twin is based on CityGML and the SensorThings API [49]–[34]. ISO/IEC JTC 1 provides general principles without specifying data formats. The proposed architecture formally incorporates ISO 19650 (BIM data management) [36]–[36], IFC (semantic structure) [37], CityGML (georeferencing) [50], SensorThings API (IoT integration) [49], and ISO 23247 (DT architecture) [53], along with custom extensions for long linear assets and sensor mapping.

This comparison substantiates the need for a dedicated DT model tailored to road infrastructure—capable of delivering deep engineering semantics, stringent real-time performance, and advanced analytical support for the maintenance of large-scale transport corridors.

2.5. Critique and Limitations of Current Approaches

Limited Support for Long Linear Assets in IFC. The IFC standard was originally designed for buildings and has only recently been extended to accommodate long linear infrastructure (e.g., IfcRoad, IfcAlignment). When modeling road alignments longer than 100 km, IFC files become large and unwieldy, slowing down CDE performance and BIM model rendering [37]. The lack of segmentation and lazy loading mechanisms impairs navigation, delays geometry updates, and complicates the scaling of DT implementations for major transport corridors such as TEN-T and IIJA.

Fragmented Tool Ecosystem (CAD, BIM, GIS, IoT, Analytics). Tools used across CAD, BIM, GIS, IoT, and analytics domains often operate in silos with limited interoperability. CAD tools typically lack BIM semantics, GIS platforms do not represent structural or material properties, and most IoT systems are not natively integrated with BIM-CDE environments. This leads to manual data conversion, increased latency, and reduced automation in model updates and predictive workflows.

Insufficient Standardization for Sensor-to-BIM Mapping. Although IFC allows custom property definitions, it lacks a standardized method for linking SensorID and data acquisition parameters. Disparities between metadata structures in SensorThings API and BIM environments require manual mapping, which becomes error-prone and unreliable when scaled to thousands of devices—thereby reducing the robustness of DT-based monitoring and complicating automation.

Lack of Stream-Oriented Analytics Integration. Most digital twin standards refer to analytics services only at a conceptual level, without specifying integration mechanisms for real-time data streams. In practice, many solutions do not support closed-loop feedback from predictive models to the BIM CDE or expose unified APIs—making it difficult to integrate new modules and scale analytical capabilities.

Weak Data Security in IoT Networks. IoT protocols with limited encryption (e.g., LoRaWAN) are vulnerable to attacks, and not all BIM platforms comply with ISO 19650-5. This creates potential threats to both data integrity and infrastructure safety, emphasizing the need for robust access control and secure data handling.

High Infrastructure Requirements and Cost Barriers. Advanced DT architectures often rely on edge computing devices, 5G connectivity, and cloud-based clusters—entailing significant investment. These infrastructure demands can hinder adoption in regions with limited budgets. Simplifying the architecture may reduce reliability and scalability, thus requiring a careful balance between cost efficiency and service quality.

Conclusion: Existing digital twin standards must be enhanced to better support long linear infrastructure, enable cross-domain integration, standardize sensor data interoperability, and incorporate stream-driven analytics. Achieving this will require a modular architecture tailored to the technical and financial constraints of transportation agencies.

2.6. Conclusion of Section 2

Section 2 has reviewed the theoretical foundations of Digital Twins (DT), Building Information Modeling (BIM), and the Internet of Things (IoT) in the context of road infrastructure. The evolution of DT was outlined from the early concepts by Grieves (2002) and NASA (2012) to the ISO/DIS 23247 standard, highlighting key DT characteristics: dynamic behavior, bidirectional interaction, predictive capabilities, integrative design, and scalability [32]–[34].

The levels of BIM maturity (Level 0–3) were analyzed in accordance with the UK BIM Framework and ISO 19650 Parts 1–5, where Level 3 provides the foundation for DT implementation [36], [38]. Types of IoT sensors and key communication protocols (MQTT, LoRaWAN, NB-IoT, 5G, OPC UA, SensorThings API) were classified to ensure reliability and interoperability [49].

Relevant data exchange standards—including IFC4/Alignment, CityGML/ADE, OGC SensorThings API, ISO 23247, and ISO 37120/37122—were studied in terms of their role in DT architecture [56, 75, 76]. Reference models such as NIST SP 1270, the City Digital Twin, and ISO/IEC JTC 1 were examined, leading to the proposal of a unified architecture specifically adapted to the needs of Departments of Transportation (DOTs) [51] – [53].

Several limitations were identified: scalability issues in IFC for long linear assets; poor interoperability across CAD, BIM, GIS, and IoT platforms; lack of standardized sensor data models; weak analytics integration; cybersecurity vulnerabilities; and high infrastructure demands.

While current standards and models form a foundation for DT deployment, they require further adaptation to accommodate the scale and budget constraints of large transportation corridors. A systematic knowledge map—from theory to protocol-level implementation—is essential for designing an effective and cost-efficient DT platform.

Section 3 will substantiate the scientific contribution, practical relevance, and added value of the proposed solutions in advancing digital twin applications for transport infrastructure.

KAPITEL 3 / *CHAPTER 3*
DIGITAL TWIN ARCHITECTURE FOR ROAD INFRASTRUCTURE

3.1. Functional Model

The following generalized table outlines the key functions, communication protocols, and responsible roles for each subsystem within the road digital twin. (Table 3.1)

Table 3.1 – Subsystem Functions

Subsystem	Key Functions	Technologies/Protocols	Roles
Sensor Layer	Data acquisition (strain, vibration, temp, video); basic filtering	MQTT, LoRaWAN, NB-IoT	IoT integrator, field engineer
Edge Computing	Aggregation, normalization, local analytics, buffering	Docker, Kubernetes (HPA), OPC UA	DevOps engineer, system architect
Analytics	Time-series storage; stream/batch analytics; ML/DL model training & deployment	Hadoop, Spark, TensorFlow, InfluxDB, Neo4j	Data engineer, analyst
BIM Engine	Sensor data binding to IFC; semantics via IfcPropertySet; 3D model export	IFC4, BCF 2.1, Revit API	BIM manager, CDE developer
UI/Portal	Dashboards, 3D model, alerts & notifications	React.js, CesiumJS, Grafana, REST/GraphQL	Frontend dev, UX/UI designer

A source: [37], [44], [47], [110]

To track the data flow within the digital twin, it is essential to formalize the relationships between its subsystems. The diagram illustrates the data path from sensors through filtering, analytics, and BIM integration stages to visualization. Standardized protocols are used at each level: MQTT/LoRaWAN for sensors, REST/OPC UA between edge and cloud layers, and GraphQL/WebSocket at the UI level. This approach enables identification of key integration points and substantiates the system architecture. (Figure 4.1).

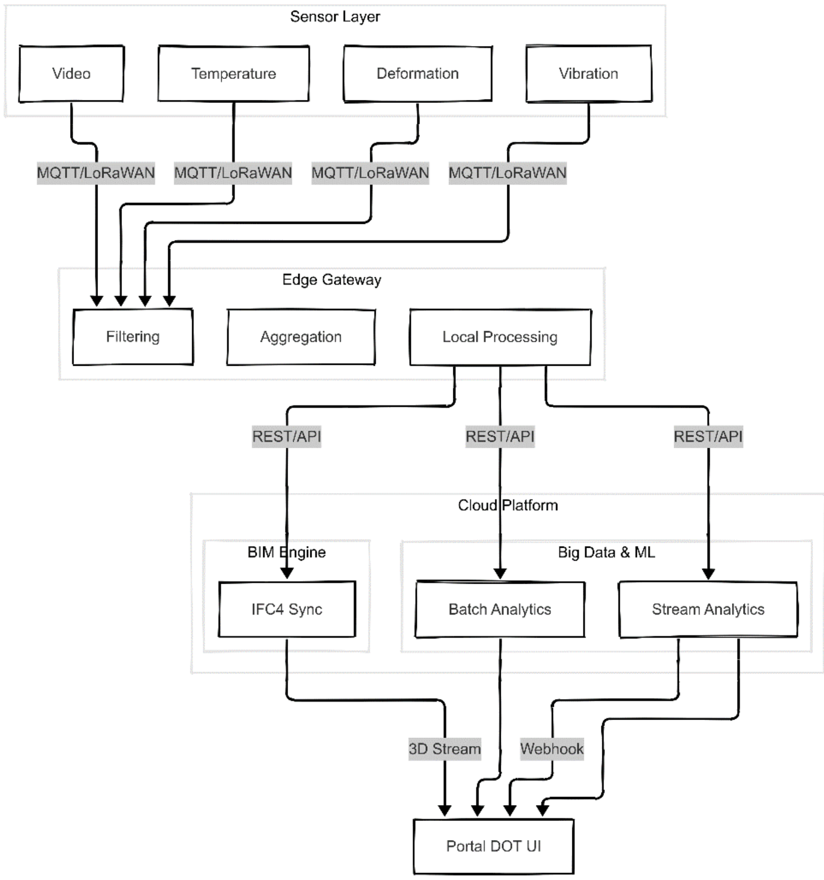

Figure 4.1 - Performance and Latency Metrics

Authoring

3.2. Non-Functional Model

To ensure near real-time operation of the digital twin, the end-to-end latency from sensor to data recording in the CDE must not exceed 1 second, in accordance with the MQTT 5.0 specification [47]. The user interface response time at the 95th percentile should be no more than 2 seconds under a standard load of up to 100 concurrent sessions, aligning with Google’s UX recommendations for dashboards [55]. Performance is monitored through load testing, automated monitoring, SLA reports, and threshold alerts. Metrics are collected during the CI/CD process and stored in the change repository.

Target availability is maintained with the following objectives: RTO ≤ 4 hours, RPO ≤ 1 hour [56]. Geo-redundancy is ensured via Kubernetes multi-zone deployment with automatic rescheduling [57]. The CI/CD pipeline includes infrastructure checks, automated deployment, and tracing implemented through the ELK stack (Elasticsearch, Logstash, Kibana) and Prometheus/Grafana [58]. Regular failure and failover tests are conducted, and incidents are documented with analysis and corrective actions. (Figure 4.2).

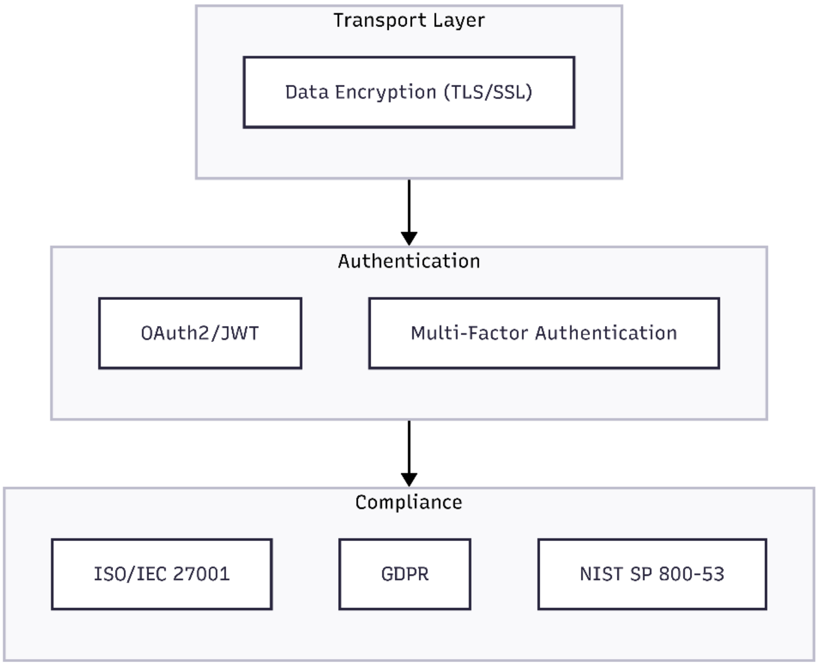

Figure 4.2 - Security and Privacy Layers

Figure 4.2, "Security and Privacy Layers," illustrates a multi-layered data protection architecture. At the transport layer, encryption protocols (TLS/SSL) are employed to ensure message confidentiality and integrity. Authentication is implemented via OAuth 2.0, JWT, and multi-factor authentication (MFA) to enhance access security. The compliance layer incorporates standards such as ISO/IEC 27001, GDPR, and NIST SP 800-53, ensuring adherence to security and data protection requirements. All layers are unified under a centralized policy management model, enabling comprehensive control of protection measures and adaptability to evolving conditions. This approach provides end-to-end risk management throughout all stages of information processing.

Ensuring security, scalability, and maintainability is a critical aspect of the digital twin architecture. Security is achieved through TLS 1.3 encryption of all communications, OAuth 2.0/OpenID Connect authentication and authorization,

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compliance with ISO 27001, and GDPR requirements [59–62]. Scalability is supported by Kubernetes with Horizontal Pod Autoscaling (HPA), sharding in Kafka and TimescaleDB, allowing the system to maintain performance as sensor count and data volume grow [63–64]. Maintainability is realized via CI/CD pipelines (Jenkins, GitLab CI), automated deployment, monitoring with OpenTelemetry, regular patch updates, and incident logging with retrospective analysis [65–66]. This approach ensures reliable, adaptive, and manageable DT system operation.

Non-Functional Requirements Matrix. A consolidated matrix specifies categories of non-functional requirements, concrete threshold values of metrics, and business priorities. Table 4.2 facilitates rapid assessment of the criticality of each metric and correlates it with testing plans and SLAs. Priorities are based on impact on reliability, security, and user experience quality. Metrics are described in terms of response time, recovery after failure, and percentage of successful automated operations. Such a structure simplifies communication between development teams, operations, and stakeholders. (Table 3.2).

Table 3.2 – Non-Functional Requirements Matrix

Category	**Requirement**	**Metric**	**Priority**
Performance	UI latency ≤ 2 s	95th percentile response time (s)	High
Reliability	RTO ≤ 4 h; RPO ≤ 1 h	Recovery time / data loss	Medium
Security	TLS 1.3; OAuth 2.0	% of connections without vulnerabilities (CVSS < 7)	High
Scalability	Auto-scale Edge/Cloud	Number of nodes under peak load	Medium
Maintainability	CI/CD; OpenTelemetry	% of error-free automatic deployments	Low

A source: [59-66]

3.3 System Layered Architecture

Describing the system layers enables structuring the project by simplifying complex system management and clarifying responsibility distribution among teams. Defining distinct layers facilitates a clear understanding of which services and protocols are employed at each stage of data processing. Additionally, this model eases scalability, maintenance, and integration of new technologies without compromising the overall architectural integrity. At the end of the section, the relationships between layers will be established, and key integration points identified. (Figure 4.3).

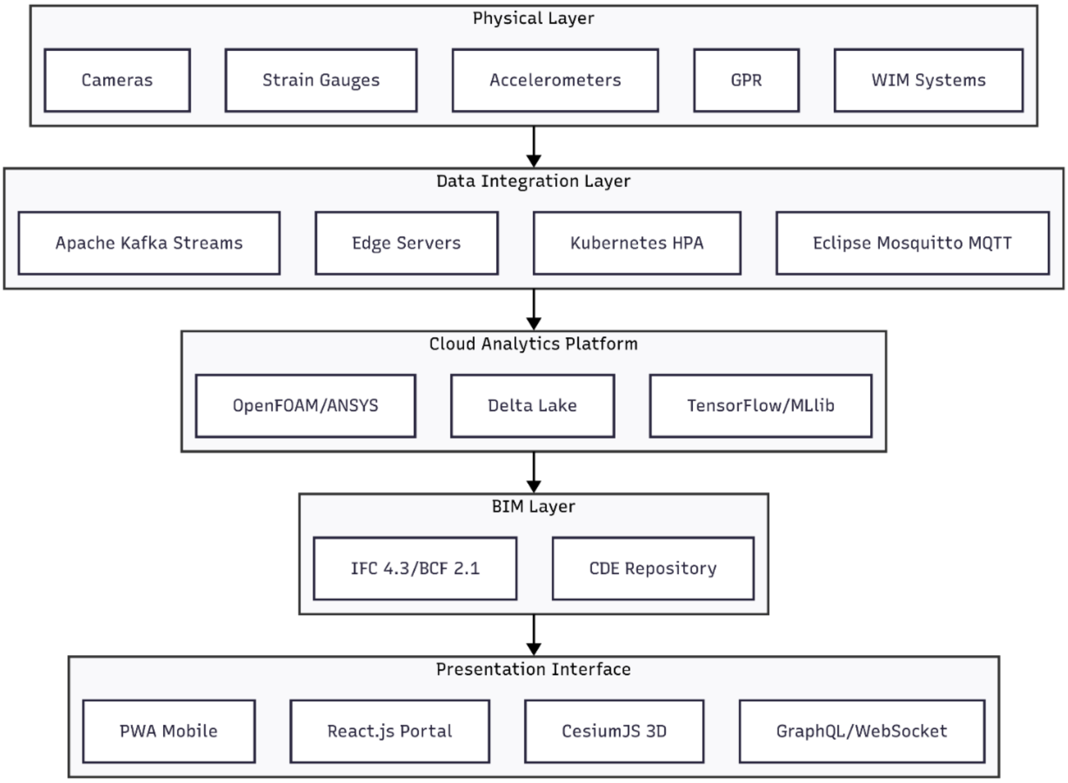

Figure 4.3 – Layered Structure of the System

Authoring

- Level 1: Physical Layer. Includes sensors (strain gauges, GPR, WIM, cameras) and actuators installed on infrastructure facilities. IoT gateways supporting 5G/LTE and LoRaWAN provide data transmission. Devices are certified according to IEC 60068 and have IP67/68 ratings, with built-in self-diagnostics and backup power supply [67].

- Level 2: Data Integration. Implemented on edge servers and brokers (MQTT, Kafka), managed via Kubernetes with autoscaling capabilities [63]. Middleware converts sensor data formats into IFC PropertySet. Publishing data on Kafka topics allows subscribers (analytics, BIM) to process events in real time [68].

- Level 3: Platform Layer (CDE). Based on IFC 4.3/BCF 2.1, includes version control, metadata, and access rights management according to ISO 27001 and ISO 19650-2 standards [39], [61]. REST and GraphQL interfaces enable integration with external services.

- Level 4: Analytics. Utilizes Delta Lake for storage, Spark MLlib and TensorFlow for analysis, and OpenFOAM for simulations [69–70]. Data streams from Kafka are fed into Spark; results are recorded in the CDE and Neo4j databases.

- Level 5: Presentation. Interface is implemented as a web portal (React.js, CesiumJS) and a mobile application (PWA). Supports KPIs, alert zones, and data export. Backend communication is provided via GraphQL and WebSocket [71].

This level separation simplifies scalability, ensures fault tolerance, and clearly delineates responsibilities among teams.

3.4. Requirements for the Common Data Environment (CDE)

The purpose of this section is to formulate detailed requirements for a unified data environment for storing, managing, and exchanging all digital twin artifacts. The CDE integrates BIM models, sensor data streams, analytics results, and reports, making it a central element of the architecture. The requirements are divided into four key groups: supported formats and metadata, versioning and change control, integration interfaces, and security measures. For each group, mandatory attributes, operating protocols, and references to official specifications are defined. Clear formalization of requirements facilitates CDE implementation, ensures component compatibility, and guarantees reproducibility of analytical scenarios.

Central repository for models and data. The CDE must support diverse data formats while ensuring semantic integrity and georeferencing of artifacts. IFC format version 4.3 or higher is used to describe infrastructure elements (IfcRoad, IfcBridge) and must comply with the buildingSMART IFC4 specification [37]. Model issue tracking is implemented via BCF version ≥ 2.1 in accordance with the BCF specification [72]. IoT streams are provided in SensorThings JSON format (Observations, Datastreams) following the OGC SensorThings API standard [41]. For storing geocontext, CityGML or CityJSON formats are used [49]. All timestamps and sensor calibration dates adhere to ISO 8601 [73], ensuring unambiguous data interpretation across subsystems.

Versioning and change control. The versioning mechanism ensures tracking the evolution of models and associated data. Each new IFC model version is recorded with a unique VersionID and a timestamp according to ISO 8601 as per ISO 19650-2 [39]. The system must allow rollback to any previous version and automatically generate differencing reports for change comparison. Observational data (Observations) reference specific VersionIDs, guaranteeing reproducibility of analytical reports regardless of subsequent updates. BCF issues are created within the context of a version and automatically closed upon release of the next version after issue resolution.

Integration interfaces. The CDE provides standardized interaction points for external systems and services. A RESTful API is implemented following OpenAPI 3.0, with endpoints for CRUD operations such as GET /models/{version}, POST /bcf/issues, etc. [74]. For high-speed access to sensor data, OPC UA is employed, ensuring secure and reliable live stream transmission [44]. A WebSocket channel is used for instant notifications about new Observations and model updates in real time [75]. This combination of protocols allows flexible integration of the CDE with analytics platforms, BIM engines, and external applications.

Below is a summary matrix listing the main requirement categories, specific standards and mechanisms, as well as sources for verification (Table 3.3).

Table 3.3 – Requirements for the Common Data Environment (CDE)

Category	Requirement	Description	Source
Formats	IFC ≥ 4.3, BCF 2.1, SensorThings, CityGML/CityJSON	Support for all used standards for BIM, issue tracking, IoT, and georeferencing	IFC spec [37], BCF spec [72], SensorThings API [41], CityGML [49]
Metadata	SensorID, Location, ObservedProperty, CalibrationDate	Ensure unified sensor description and GIS referencing	ISO 8601 [73], SensorThings API [41]
Versioning	VersionID, timestamps	Ability to track, compare, and rollback versions of models and related data	ISO 19650-2 [39]
Change Control	BCF issues linked to VersionID	Accounting for all corrections, automatic closure after release	BCF spec [72]

Table 3.3 continued on the next page

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Continuation of Table 3.3

Interfaces	REST (OpenAPI 3.0), OPC UA, WebSocket	Ensure integration with third-party systems and live data processing	OpenAPI Spec [74], OPC UA [44], WebSocket API [75]
Security	OAuth 2.0, TLS 1.3	Reliable service authentication and encryption of all communication channels	RFC 6749, RFC 8446

Authoring

3.5. Data Exchange Requirements

There are requirements for formats, protocols, and synchronization mechanisms that ensure integrity, timeliness, and security of data exchange between digital twin subsystems. Standards such as IFC ≥ 4.3 and BCF 2.1 are used for geometry and issue tracking, SensorThings JSON for sensor streams, and CityGML/CityJSON for spatial context. Data transmission is carried out via MQTT 5.0 (QoS 2), REST, and WebSocket, while API contracts are defined through OpenAPI 3.0 and GraphQL. This technology stack enables flexible integration between the physical, integration, analytics, and presentation layers, minimizing latency and preventing data loss.

Data synchronization between layers is implemented through push and pull models. In the push scenario, events are transmitted immediately upon reaching a threshold, enabling near real-time response and utilizing MQTT with delivery acknowledgment. In the pull model, data is requested by the CDE via REST/WebSocket at specified intervals, reducing load during periods of minimal changes. A hybrid strategy is applied depending on the criticality and volume of telemetry. Additionally, logging and monitoring of all delivery metrics—including acknowledgments, failures, and deviations—are maintained to promptly identify synchronization bottlenecks.

The linkage between sensor data and BIM objects is ensured through identifiers: SensorThings.Thing.id and Datastream.properties.relatedElementGUID are directly mapped to IfcSensor and IfcRoot.GlobalId in the BIM model. This allows the creation of BCF issues for each anomaly, linked to the model element and Observation ID, ensuring traceability. All channels are secured using TLS 1.3, OAuth 2.0 with JWT, IP whitelisting, and OPC UA mechanisms. Comprehensive protection and unified identification support the reliability, reproducibility, and security of the entire data exchange loop.

3.6 Conclusion of Section 3

As a result of a comprehensive analysis of the digital twin architecture, a unified model has been developed encompassing functional and non-functional requirements, a multi-level structure, as well as data storage and exchange mechanisms. The presented functional model demonstrates the interconnection of subsystems—from sensor data acquisition to the user interface—providing an end-to-end processing pipeline. Non-functional metrics establish clear thresholds for performance, reliability, security, scalability, and maintainability, facilitating system quality monitoring and management. The multi-level structure separates responsibilities among physical equipment, integration and analytics modules, the platform CDE, and the presentation layer, promoting scalability and fault tolerance. Defined requirements for the CDE and exchange formats ensure semantic integrity, versioning, and security of all digital twin artifacts.

The requirements framework guarantees continuity of the data flow cycle from the physical layer to managerial decision-making within the digital twin. The use of open standards such as IFC, SensorThings API, and CityGML ensures seamless integration of the DT components with external road infrastructure management systems and GIS platforms. A unified metadata model and harmonized exchange protocols simplify interactions among subsystems, eliminating the need for format conversions and reducing the risk of data loss. Service containerization and cloud technologies enable dynamic scaling of computational resources and high availability of nodes in case of failures. Consequently, system integrity is achieved, where functional and non-functional requirements complement each other within a unified architectural solution.

The next phase will focus on refining integration schemes between sensors and BIM models, emphasizing the development and testing of CDE components and synchronization mechanisms. Templates of IfcPropertySet will be created to link SensorID to model elements, MQTT client configurations and Docker images for edge nodes will be prepared, along with OpenAPI specification samples for CDE interaction. Special attention will be paid to implementing push/pull synchronization scripts and automating the creation and closure of BCF issues upon model version updates. All solutions will be accompanied by verification scenarios of data flows to ensure integrity, timeliness, and security of information transmission. This practical block will provide readiness of the digital twin for pilot deployment and further scaling within road corridors and bridge structures.

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KAPITEL 4 / *CHAPTER 4*
INTEGRATION OF BIM AND SENSORS

4.1. Key Types of Sensors in the Digital Twin of Road Infrastructure

Fiber Bragg Grating (FBG) Sensors. FBG sensors are sections of single-mode optical fiber with periodic reflective structures that change the reflected wavelength upon deformation. The spectral shift is recorded by a spectrometer and converted into strain measurements with an accuracy up to 1 με [76]. The optical nature of these sensors provides immunity to electromagnetic interference and suitability for harsh environments (Figure 5.1).

Figure 5.1 – Examples of Fiber Bragg Grating (FBG) Sensor Applications
A source: [111]

FBG gratings are used for monitoring deflections and stresses in bridges, providing continuous measurements without the need for electrical wiring. They are installed in expansion joints to detect deformations and prevent failures. In digital twins, they deliver real-time structural health data. Multiplexing hundreds of gratings on a single fiber line reduces cabling complexity and simplifies the system (Table 4.1).

Piezoelectric Sensors. Piezoelectric sensors utilize the electric charge effect in piezoceramics under mechanical stress, generating a signal proportional to vibrations and impacts. The absence of moving parts ensures reliability and fast response [77], [79]. They are used to monitor dynamic loads on roads and bridges, assisting in modeling asphalt behavior and predicting structural service life within DT (Table 4.2).

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Table 4.1 Characteristics of FBG Sensors: Key Parameters, Advantages, and Limitations

Parameter	Advantages	Limitations
Accuracy	up to 1 με	high cost of spectrometers
Electromagnetic Immunity	complete immunity to EMI	requires additional fiber protection
Multiplexing	up to hundreds of gratings per fiber	installation complexity

A source: [76]

Table 4.2 – Key Parameters of Piezoelectric Sensors: Advantages and Operational Limitations

Parameter	Advantages	Limitations
Frequency Band	0.1–10 kHz	low signal level — requires an amplifier
Size	compact	high sensitivity to temperature variations
Cost	low	periodic calibration of electronics is required

A source: [77], [79]

WIM Sensors (Weigh In Motion). WIM systems use strain gauges or piezoelectric plates embedded in the pavement to measure axle loads of moving vehicles. Calibration and filtering algorithms enable weight determination without stopping, with accuracy sufficient for engineering monitoring [78], [80]. The data are used for load analysis, residual pavement life calculation, and maintenance planning. Integration with digital twins allows modeling load distribution, optimizing routes, and preventing overloads, thereby reducing costs and enhancing traffic safety (Table 4.3).

Table 4.3 – Comparative Characteristics of WIM Systems: Key Parameters

Parameter	Advantages	Limitations
Data Continuity	measurements without stopping traffic	increased error at speeds over 80 km/h
Throughput	up to several hundred vehicles per hour	requires regular maintenance
Accuracy	sufficient for road condition monitoring	not suitable for high-precision scientific experiments

A source: [78], [80]

Laser Scanning (Terrestrial LiDAR & Mobile Mapping). LiDAR scanners emit laser pulses and measure their return time, generating point clouds with an accuracy of up to 1–2 cm. Mobile and stationary platforms provide area coverage and detailed structural surveys. Post-processing removes noise and corrects data, enabling accurate models with point densities up to 1,000 points/m² (Figure 5.2).

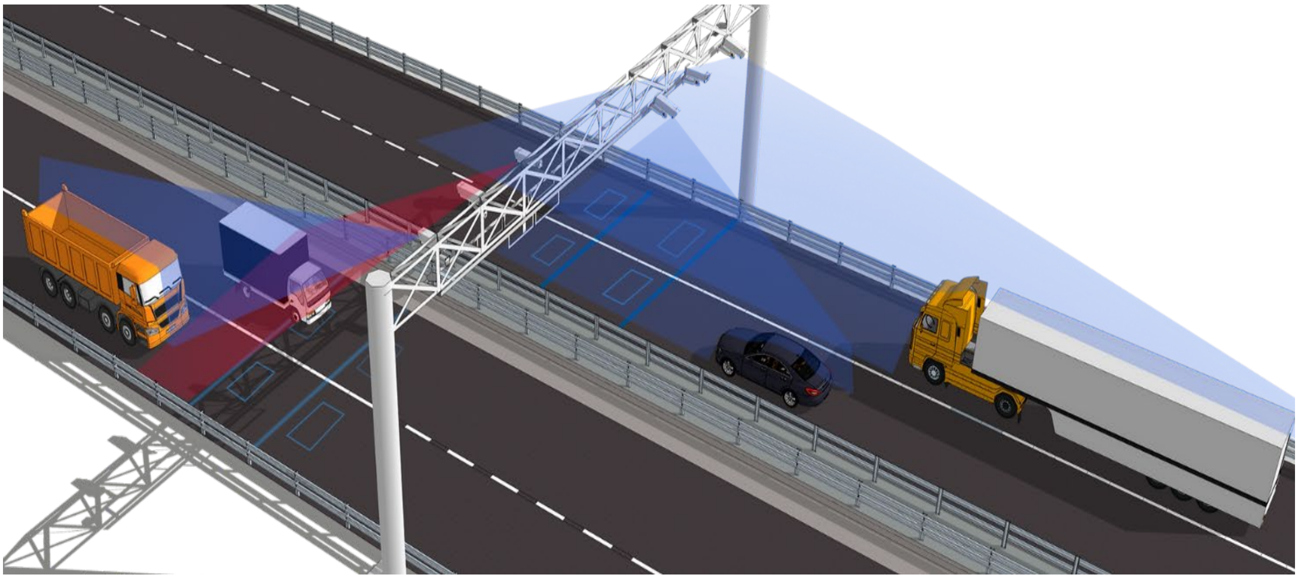

Figure 5.2 – Illustration showing an example of Laser Scanning (Terrestrial LiDAR & Mobile Mapping) applications

A source: [111]

Terrestrial LiDAR is used for static surveying of bridge spans and complex architectural structures, providing detailed accounting of geometric defects and deflections. Mobile LiDAR mounted on vehicles or drones enables rapid collection of pavement condition data over long road sections without traffic interruption (Table 4.4).

Table 4.4 – Key Parameters of LiDAR Scanning: Advantages and Operational Limitations

Parameter	Advantages	Limitations
Point Density	over 1,000 points/m²	large data volumes (hundreds of GB)
Collection Speed	rapid coverage of large areas	accuracy decreases under adverse weather conditions

A source: [78], [80]

4.2. Methods of Sensor-to-BIM Model Referencing

Georeferencing via Coordinate Systems. For large-scale road and bridge projects, global coordinate systems such as WGS 84 (EPSG:4326) or local coordinate systems like EPSG:21781 (Switzerland) are typically used. In IFC models, georeferencing is defined through the attributes IfcSite.RefLatitude, RefLongitude, and RefElevation according to ISO 19650-1, ensuring correct sensor positioning during data exchange between software platforms. The IfcCoordinateReferenceSystem class from the IFC Alignment extension enables description of the project's coordinate system and links road geometries to global coordinates, facilitating synchronization with GIS and integration of models from different CAD systems (Figure 5.3).

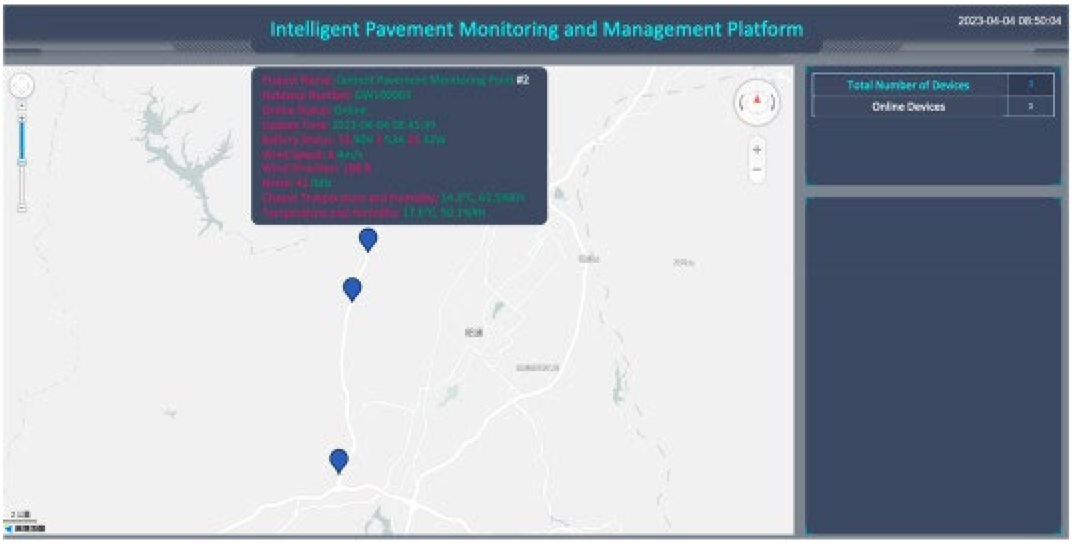

Figure 5.3 – Example of a System for an Intelligent Monitoring and Management Platform

A source: [111]

When installing FBG sensors, it is recommended to record coordinates (latitude, longitude, elevation) in an IfcCartesianPoint within the IfcLocalPlacement of the IfcSensor element for precise positioning and subsequent verification. Coordinates are also exposed in the Property Set Pset_SensorLocation for automatic report generation. Sensors are described by the IfcSensor class or, if unsupported, as IfcDistributionControlElement with an IfcRelConnectsElement relationship linking them to structural elements, ensuring uniform storage and parameter exchange between BIM tools and automated processes.

Metadata and semantic links. During sensor installation, the BIM Collaboration

Format (BCF) 2.1 is used to associate tasks with specific Ifc elements (e.g., IfcBeam, IfcSlab). A BCF issue is created specifying the element's GUID, sensor type, attachment point, and calibration instructions, along with detailed comments for geometry verification and quality control. This provides process transparency and rapid exchange of feedback between engineers and modelers, preserving traceability in the digital twin [79][36]. For inventory data management, the COBie extension is applied: manufacturer, model, serial number, and commissioning date are recorded in COBieContact and COBieTypeSensor tables, simplifying asset management, reporting, and ERP integration while ensuring compatibility with BIM tools and buildingSMART recommendations [80].

To automate sensor creation in Autodesk Revit, a C# script generates IfcSensor elements with coordinate and type parameters from a CSV file, reducing manual input and errors [81][82]. Using Python and IfcOpenShell, a script adds IfcSensor and a set of geodata properties to IFC models, enabling batch updates without manual export [83], [37] (Table 4.5).

Table 4.5 – Methods of Sensor-to-BIM Referencing

Method	Description	Format/Standard	Applicability
Georeferencing	Assigning coordinates in the project (WGS 84 or local CS)	IFC Coordinates (IfcSite), EPSG	All sensor types
IFC Parameterization	IfcSensor + property sets (Pset_SensorType, Pset_SensorLocation)	IFC 4.3, COBie	FBG, piezoelectric, WIM
BCF Annotation	Visual markers and comments via BCF 2.1	BIM Collaboration Format 2.1	Any field installations
API Scripting	Sensor generation and update via Revit API / IfcOpenShell	Revit API (C#), IfcOpenShell (Python)	Large-scale projects, bulk deployments

Authoring

4.3. Data Workflow and Synchronization

Data Collection and Preprocessing. The sensor layer includes FBG, piezoelectric, WIM, and LiDAR devices, generating a continuous stream of raw measurements. Data transmission most commonly utilizes MQTT protocols (QoS 1/2), LoRaWAN (Class A/B), and NB-IoT, providing deployment flexibility across various communication conditions. Noise filtering is performed on the edge device using moving average and median filters to remove outliers. Initial aggregation—averaging over time windows (e.g., 1 second)—reduces the volume of transmitted packets and lowers the load on the CDE. In case of unstable connections, data is temporarily cached locally in InfluxDB or SQLite, ensuring uninterrupted collection and protection against data loss. Finally, two transmission models are implemented: push—immediate sending of aggregated packets to the CDE via REST or MQTT; and pull—periodic polling of the edge gateway via WebSocket or REST (Figure 5.4).

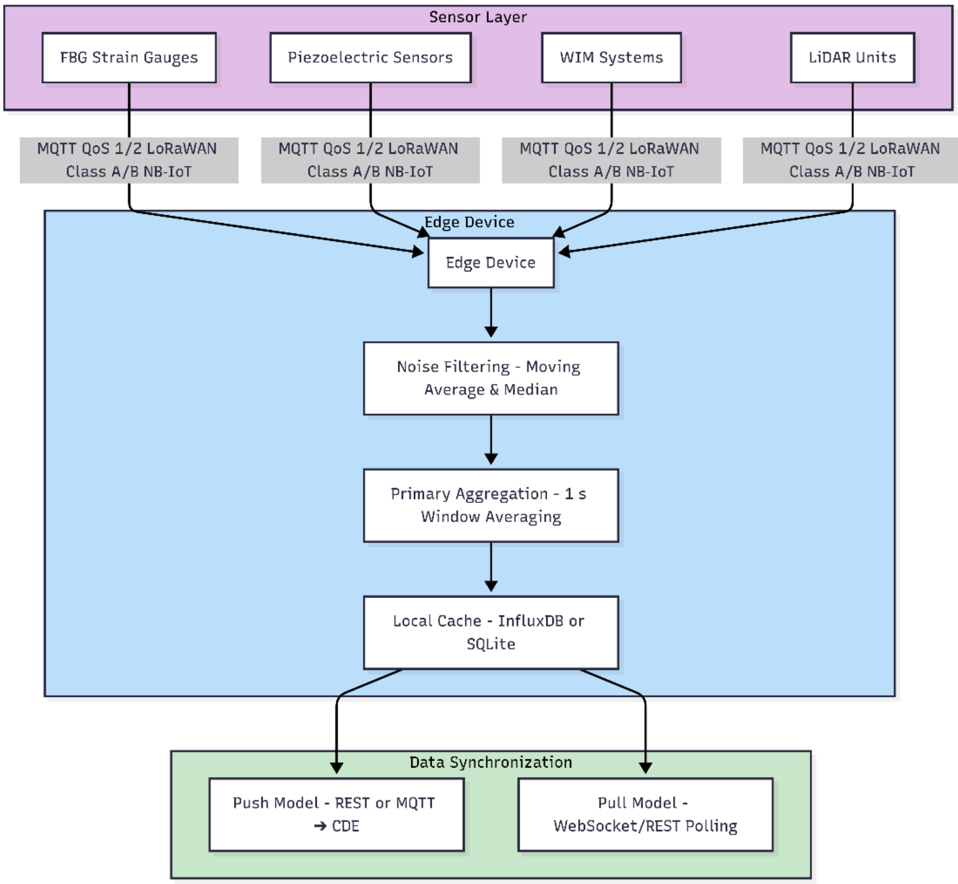

Figure 5.4- Data Flow and Synchronization Process

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For deformation visualization, sensor values are first normalized to ensure consistency across varying input ranges. These values are then mapped onto the 3D model of the monitored structure using a gradient color scale, where blue corresponds to minimal deformation, while red highlights areas reaching or exceeding critical thresholds. CesiumJS is used as the rendering engine, leveraging WebGL shaders to enable smooth color transitions and real-time adjustments of the visualization range. The system interface allows users to dynamically modify threshold limits, color scaling, and switch between different viewing modes (e.g., top-down, sectional, or isometric). Additionally, interactive tools such as hover information, clickable zones, and zooming functionalities support detailed inspection of specific load-bearing or deformation-sensitive regions. This approach enhances the interpretability of structural behavior over time and supports timely decision-making in infrastructure monitoring scenarios. (Figure 5.5).

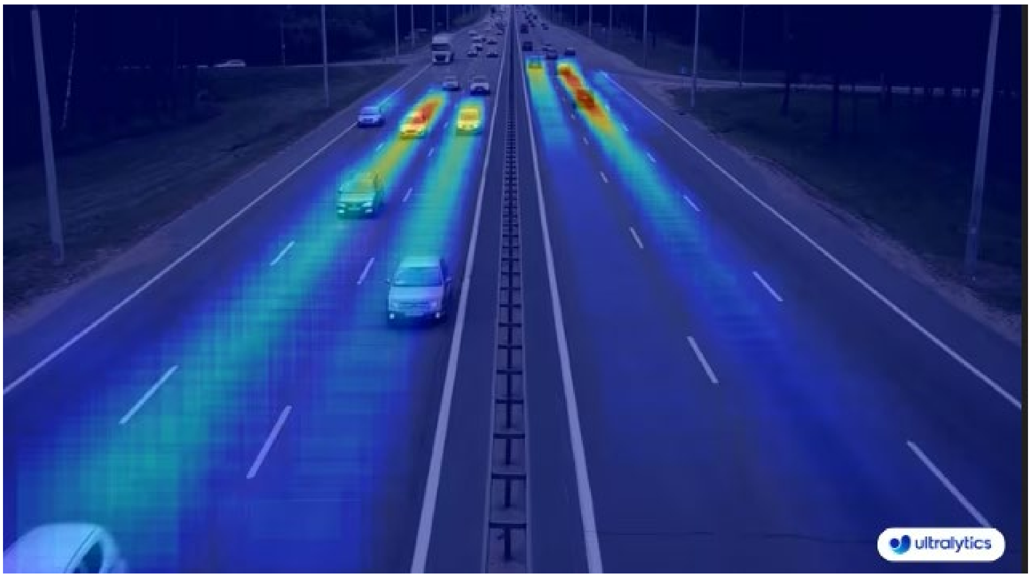

Figure 5.5 - Transport heat map

A source: [114]

BCF Reports. The system automatically creates a BCF issue for each sensor exceeding thresholds, specifying the element’s GUID, measurement time, and type of deviation. The report includes graphs, screenshots, and links to the dashboard, with issues stored in the CDE for audit and historical analysis. This reduces manual documentation and improves communication between engineers and BIM managers.

The push data transmission model provides minimal latency but requires a persistent connection and webhook configuration. The pull model is simpler to implement, relying on periodic requests, but introduces delays. Both models support failure recovery, and the choice depends on project requirements for speed, stability, and integration complexity (Table 4.6).

Table 4.6 – Comparison of Push and Pull Synchronization

Criterion	Push Model	Pull Model
Latency	minimal delay (< 1 s) due to instant transmission	depends on polling interval (e.g., N minutes)
Delivery Reliability	ensured by MQTT QoS 2 and HTTP acknowledgments	controlled by schedule; possible risk of missed messages
Network Load	burst transmission with low overhead	uniform load, even when no new events occur
Implementation Complexity	requires Webhook/Listener setup and persistent connection	simplified: job scheduler suffices, no server-side callbacks needed
Error Handling	built-in retry mechanisms at the edge level	missed data can be easily retrieved during the next poll

Authoring

4.4. Conclusion of Section 4

This section provided a detailed examination of the key aspects of integrating physical sensors into the BIM model to organize a continuous end-to-end data flow within the digital twin of road infrastructure. The main sensor types were analyzed—Fiber Bragg Grating (FBG) sensors, piezoelectric elements, Weigh-In-Motion (WIM) systems, and LiDAR scanners. For each sensor class, the physical operating principles, recommended application scenarios, and a comparative assessment of advantages and operational limitations were presented.

The methodological part covered practical referencing techniques: from setting geocoordinates via IfcSite attributes and IfcCoordinateReferenceSystem to parameterization through IfcSensor with property sets, as well as the use of BCF 2.1

and COBie as tools for tracking sensor installation. Examples of process automation via Revit API and IfcOpenShell were also discussed, ensuring rapid and reliable preparation of the BIM model for operation.

Finally, the complete data processing workflow was described—from collection and preprocessing at the edge level to push and pull synchronization mechanisms, generation of deformation heat maps, and automatic issuance of BCF reports. The presented schemes and comparative tables demonstrate a balance between model update responsiveness and data delivery reliability. Thus, a unified methodology was established, ensuring traceability and reproducibility of data throughout all stages of the digital twin's lifecycle.

KAPITEL 5 / *CHAPTER 5*
DATA COLLECTION AND REAL-TIME ANALYSIS

The purpose of this subsection is to provide a comprehensive overview of the key network protocols used in the Big Data pipeline of the digital twin. Messaging models, traffic overhead, security mechanisms, and application domains in the context of sensor infrastructures and cloud platforms are considered. Special attention is given to comparisons between lightweight and heavyweight protocols, scalability issues, and delivery reliability. Protocol descriptions are accompanied by examples of implementation in industrial IoT solutions. This enables selecting the optimal protocol for each stage of data processing.

5.1. Data Stream Architecture

The data stream in the digital twin is constructed on the principle of end-to-end transmission from sensors to analytical and visualization components. Initially, data arrives from physical sensors (FBG, piezoelectric, WIM, LiDAR) to edge devices, where preprocessing is performed: filtering, aggregation, and buffering. Then, messages are published via brokers (MQTT, Kafka) into a distributed data bus that provides scalable routing in real time. Simultaneously, data is sent to the Common Data Environment (CDE) for synchronization with the BIM model, as well as to analytics modules for running ML algorithms and calculating condition indicators. The final stage of the stream is the visual interface, where results are presented as 3D models, dashboards, and alerts. This architecture supports both streaming and batch processing and ensures near real-time response to events.

5.2. Data Transmission Protocols

Specialized protocols adapted to the conditions of infrastructure projects are used for reliable data transmission between digital twin layers. At the sensor level, MQTT (with QoS 1 or 2) and LoRaWAN (Class A/B) are employed, ensuring low power consumption and resilience to unstable connections. REST API, WebSocket, and OPC UA are used for communication between edge devices and the cloud platform—the latter being preferable for industrial telemetry due to built-in support for data modeling and security. For data transmission to the user interface, GraphQL and WebSocket are applied, enabling real-time visualization updates with minimal latency. Supporting multiple protocols simultaneously provides architectural flexibility and allows integration with existing SCADA, ERP, and BIM systems [44], [47], [84–88] (Table 5.1).

Table 5.1 – Comparison of Data Transmission Protocols

Protocol	Exchange Model	Overhead	Security	Applicability
MQTT	pub/sub	low	TLS 1.3; username/password	sensors, remote IoT nodes
AMQP / Kafka	pub/sub; queue	medium	TLS; SASL; ACL	centralized brokers, microservices, CDE
HTTP/REST, WebSocket	request/response; full-duplex push	high (HTTP headers), reduced with WebSocket	HTTPS/TLS; JWT/OAuth 2.0	UI portals, admin APIs, notifications
OPC UA	client/server; pub/sub	medium	built-in TLS; X.509; LDS	PLCs, SCADA systems, and edge devices

A source: [44]

5.3. Data Validation and Cleaning

At the data reception stage from sensors, initial filtering is performed, including the removal of outliers and gaps. Methods such as moving average, median filtering, and range checks are applied. Validation is conducted according to several criteria: presence of timestamp, format correctness, sequence continuity, and conformity to expected patterns. Special rules verify data consistency with the BIM model topology—for example, matching the geometry coordinates of the site. Duplicate records, inconsistent values, and suspicious fluctuations are flagged and sent to a deferred storage for manual review or reprocessing. This approach enhances data reliability and ensures correct operation of analytical and visualization services (Figure 6.1).

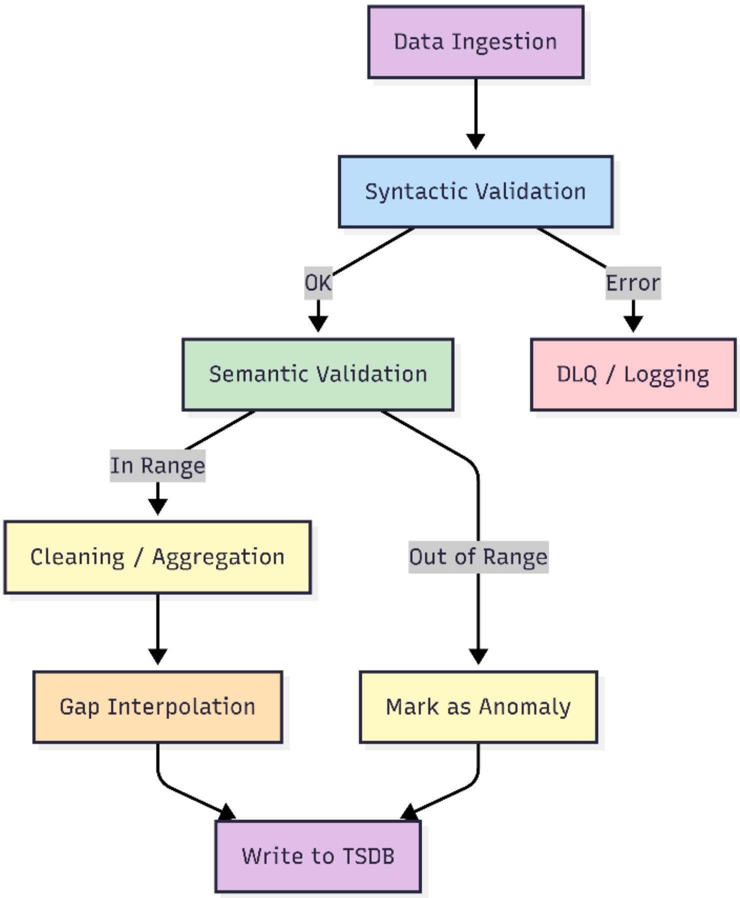

Figure 6.1 – Sequence of Data Validation and Cleaning Steps

Authoring

5.4. Data Storage and Organization

Sensor data flows into a streaming platform (Kafka), where it is divided into topics by geozones or device types. Raw and cleaned data are stored at two storage levels: time series data in InfluxDB or TimescaleDB for fast aggregation, and archival data in Delta Lake or S3-compatible storages for long-term retention. Metadata and semantic relationships are recorded in the Neo4j graph database, simplifying navigation within the information model. To ensure storage consistency, versioning, transaction control, and automatic schema documentation are supported. The storage organization follows the principles of lambda architecture, combining real-time processing and batch analysis within a unified framework (Figure 6.2).

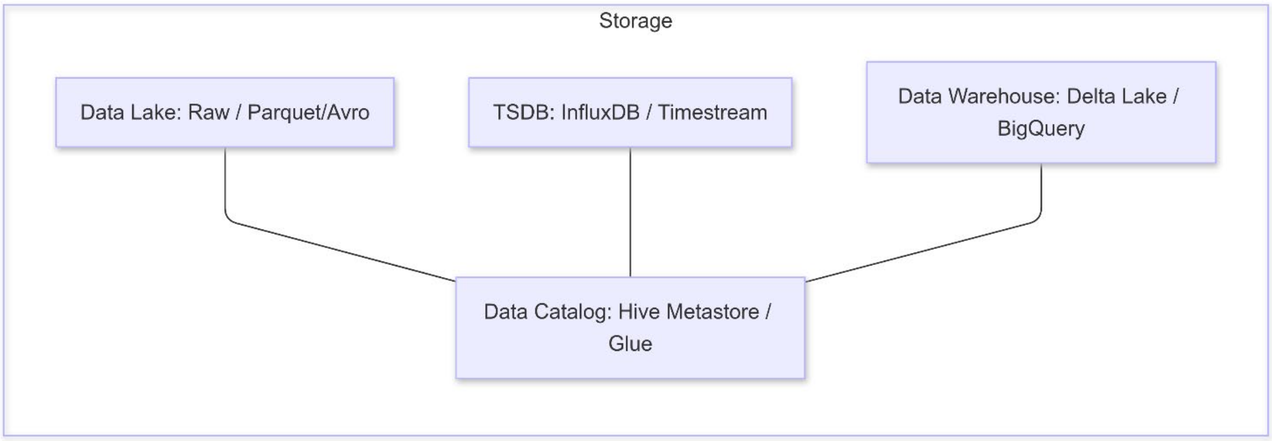

Figure 6.2 – Interaction Between Data Storage Layers and the Metadata Catalog
Authoring

- The Data Catalog (D) provides a single point of access for dataset discovery, schema registry, and access policies.
- ETL/ELT mechanisms are established between the Data Lake (A) and the Warehouse (C) to support regular loading and transformation processes.
- TSDB (B) ingests time series data directly from the stream processing layer and synchronizes with the catalog for metric registration.

In the digital twin infrastructure, data is distributed across multiple specialized storage systems depending on the processing stage and the nature of analytical tasks.

5.5. Integration with Cloud Platforms

To enable scalable data processing and storage, the digital twin is integrated with cloud platforms (AWS, Azure, GCP), leveraging containerization (Docker) and orchestration (Kubernetes) for deploying microservices. Cloud resources are used for batch model training (via SageMaker, Vertex AI) and for storing large volumes of data in S3-compatible storage systems. Pub/Sub and EventBridge services provide event routing between components, while API gateways (GraphQL/REST) allow external systems to interact with analytical services and the CDE. The integration is designed

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with fault tolerance, geo-redundancy, and compliance with information security standards (ISO 27001, GDPR), making the system reliable and adaptable to various regional and project-specific conditions.

5.6. Conclusion of Section 5

Section 5 provided a comprehensive overview of the Big Data pipeline architecture for a digital twin of transportation infrastructure, with a focus on resilient and scalable processing of telemetry streams. It covered all key stages—from data collection to analytics—mapped to specific communication protocols, storage formats, and cloud services to support industrial deployment and integration. Each subsection included technology comparisons, applicability recommendations, and structural diagrams to support system design decisions.

Special attention was given to data quality and stream reliability. The section examined validation techniques—both syntactic (JSON Schema, Protobuf, Avro) and semantic (range checks, consistency)—as well as methods for outlier removal and gap handling using Z-score, IQR, and interpolation. Secure data transmission was addressed through protocols like TLS, JWT, SASL, and X.509. The joint use of TSDBs, data lakes, and graph databases was shown to enable real-time access, long-term archival, and efficient navigation across the information model.

The final subsection demonstrated full pipeline implementation across three major cloud platforms: AWS, Azure, and GCP. Recommended services were outlined for each processing stage—ingestion, buffering, storage, processing, analytics, and monitoring. The architecture supports fault tolerance, geo-redundancy, and compliance with security standards such as ISO 27001 and GDPR. This makes the pipeline adaptable to diverse regional and project-specific requirements while minimizing development and maintenance costs.

Thus, Section 5 provides a holistic view of building a production-grade data processing pipeline for a road infrastructure digital twin. The proposed modular architecture enables scalability, adaptation to various operational scenarios, and the use

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of collected data for model training and decision-making. The next section will explore the next maturity level of the digital twin—predictive maintenance algorithms, machine learning, and the implementation of intelligent analytics based on data processed through the described Big Data pipeline.

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KAPITEL 6 / *CHAPTER 6*
PREDICTIVE MAINTENANCE ALGORITHMS AND REPAIR OPTIMIZATION

Predictive maintenance in digital twins of road infrastructure enables a shift from reactive repair to proactive detection and resolution of potential defects. The most common methods fall into three categories: classical machine learning algorithms, deep neural networks, and advanced hybrid approaches. Each model type has specific characteristics that affect training speed, resource requirements, and result interpretability. The choice of approach depends on the volume and nature of input data, prediction goals, and operational conditions of the models. Below is an overview of the main algorithms and the criteria for their use in the context of bridge and road monitoring.

Classical algorithms such as Random Forest and XGBoost operate on tabular data with pre-engineered features. Random Forest is an ensemble of decision trees that is robust to noise and capable of fast training on limited datasets. XGBoost employs gradient boosting and achieves high prediction accuracy but requires careful hyperparameter tuning and is prone to overfitting if too many trees are used. These methods are well-suited for engineering parameters, aggregated metrics, and historical reports, where training speed and relative interpretability are important. To explain model predictions, techniques such as SHAP and LIME are used, helping to interpret the model’s decision-making process.

Deep learning architectures include LSTM, CNN, and Transformer networks, each optimized for a specific data format. LSTM (Long Short-Term Memory) networks are effective for processing time-series sensor data, capturing dependencies across multiple time scales. CNNs (Convolutional Neural Networks) are suitable for two-dimensional slices of LiDAR point clouds or deformation heatmaps, automatically extracting spatial features. Transformer networks, originally designed for sequential data, offer high parallelization during training and the ability to model long-term dependencies. While deep methods require substantial computational resources and tuning, they can detect complex patterns in raw data without manual feature engineering.

Hybrid solutions combine the strengths of multiple algorithm types—for example, Graph Neural Networks (GNNs) with time-series processing. In such models, graph nodes represent key points in the road network (e.g., intersections, piers), while edges define relationships between them. Time-series sensor data is attached to each node. A combination of LSTM for temporal processing and GNN for topological structure provides a deep model capable of analyzing both spatial context and dynamic changes. These mixed architectures offer high predictive accuracy but come with implementation complexity and high memory and compute requirements.

The choice of predictive maintenance algorithm depends on several factors. First, the volume and format of the data: tabular aggregates are best handled by Random Forest or XGBoost, raw time-series by LSTM, and LiDAR point clouds by CNNs. Second, requirements for training and inference speed: fast boosting models are more suitable for edge devices, while deep networks typically run on GPU clusters in offline mode. Third, interpretability: business use cases often demand explainability—a strength of classical methods—while deep models are less transparent and require additional tools to explain their predictions. Finally, available resources and project infrastructure constrain model complexity and training time. (Table 6.1).

Table 6.1 – Comparison of Predictive Maintenance Algorithms

Method	Data Type	Advantages	Limitations	Interpretability
Random Forest	Tabular	Fast training; noise robustness	Limited nonlinearity for complex relationships	Medium
XGBoost	Tabular	High accuracy; flexible tuning	Sensitive to overfitting; requires fine tuning	Medium
LSTM	Time Series	Effective on sequences	Long training times; high resource demands	Low
CNN	Point Clouds; 2D slices	Automatic feature extraction; scalability	Requires large data and computational resources	Low

Table 6.1 continued on the next page

Continuation of Table 6.1

Transformer	Sequences	Parallel training; long-term dependencies	Very high GPU and memory requirements	Low
GNN + Time Series	Graphs + time series	Considers network topology; integrates diverse data types	Complex implementation; high computational load	Low–Medium

Authoring

Explanation of Table 6.1:

- Data Type: Specifies the input formats for which the algorithm is optimized (e.g., tabular, time series, spatial point clouds).
- Advantages: Highlights the key strengths of each algorithm in the context of predictive maintenance (e.g., accuracy, speed, pattern recognition).
- Limitations: Describes the main technical and resource-related constraints (e.g., computational complexity, overfitting risk).
- Interpretability: Assesses how easily the model's predictions can be explained and understood by domain experts or stakeholders.

6.1. Designing the Training and Validation Pipeline

The goal of this subsection is to define the stages of data preparation, sample splitting schemes, and model evaluation methods, as well as to describe a unified ML pipeline for predictive maintenance that ensures reproducibility and reliability of results. The pipeline includes the collection and preprocessing of raw data, feature engineering, correct splitting into training and test sets, as well as standardized validation procedures, quality metrics, and workflow automation. This approach allows for the standardization of training stages, minimizes the impact of inconsistent practices, and ensures transparency for all project participants. Detailed steps for each stage are outlined below.

Collection of Historical Metrics. Historical defect data is gathered from multiple

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sources: rut depth (mm) is extracted from inspection reports and inductive profilometers; road surface images with crack classification are analyzed to determine the width and length of damages; vibration time series are obtained from accelerometers and piezoelectric sensors, providing high-frequency telemetry.

Feature Engineering. Statistical methods such as moving average and standard deviation over a specified time interval (e.g., 1 hour) are used for feature creation, alongside spectral analysis via Fourier transform to detect recurring vibration patterns and calculate energy within target frequency bands. Additionally, external data is integrated: meteorological conditions (temperature, precipitation) are received through a supplier API, and traffic data comes from ITS systems, allowing consideration of environmental influences on pavement condition.

Cleaning and Normalization. Short gaps (<5 minutes) are handled by linear interpolation over time, while longer missing periods are flagged and excluded from real-time analytics. Features are scaled to a unified range using Min-Max or Z-score normalization before being input to models sensitive to absolute values (LSTM, CNN), which improves training stability and accelerates algorithm convergence.

To correctly assess the generalization capability of models, two approaches to data splitting are used.

Static Splitting. The classical division into training, validation, and test sets in proportions of 70% / 15% / 15% is applied to tabular data without temporal structure. The data is randomly shuffled to ensure uniform feature distribution and enable rapid evaluation of baseline machine learning models.

Time Series Cross-Validation. For time series data, Rolling Window and Expanding Window approaches are used. In the Rolling Window method, the model is trained on the interval $[t_0, t_1]$ and validated on $[t_1, t_2]$, after which the window shifts: $[t_1, t_2] \rightarrow [t_2, t_3]$, and so on. In the Expanding Window method, the training set grows sequentially: first training on $[t_0, t_1]$ and validating on $[t_1, t_2]$, then training on $[t_0, t_2]$ and validating on $[t_2, t_3]$, etc. This approach prevents leakage of future information and allows an objective assessment of the model’s ability to forecast subsequent values.

The choice of metrics for evaluating predictive maintenance models depends on the task type and accuracy requirements.

When forecasting defect magnitude (e.g., rut depth or deflection), RMSE (Root Mean Squared Error) and MAE (Mean Absolute Error) are commonly used. RMSE measures the square root of the average squared deviations between predictions and actual values, emphasizing large errors due to quadratic averaging. MAE evaluates the average absolute error and is less sensitive to outliers, making it preferable when avoiding excessive influence from rare extreme values is necessary. Both metrics provide quantitative error dispersion assessment and aid in comparing different models.

In binary defect classification tasks (“defect present/absent”), ROC AUC, Precision, and Recall metrics are used. ROC AUC reflects the model’s ability to distinguish between positive and negative classes across all threshold values. Precision indicates the proportion of correctly predicted defects among all positive predictions, while Recall measures the proportion of detected defects out of all actual defects. Joint analysis of Precision and Recall helps to find a balance between false alarms and missed critical defects, which is especially important under stringent safety requirements. When repair resources are limited, it is crucial to correctly rank sites by predicted risk. For this purpose, Precision@k is used — the proportion of true defects within the top k% of sites with the highest predicted risk scores. This metric is critical for evaluating how effectively the model identifies the most problematic areas and assists in optimizing maintenance planning.

Below is a visualization of the machine learning pipeline along with explanations of its key stages (Figure 7.1).

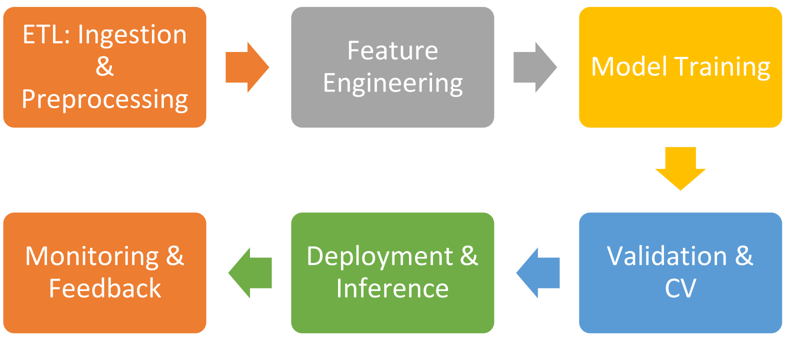

Figure 7.1 - ML Pipeline and Quality Metrics Flow

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Пояснение к Figure 7.1:

ETL: Ingestion & Preprocessing (A) — data collection (defects, vibrations, weather), validation, cleaning, and normalization.

Feature Engineering (B) — generation of statistical and spectral features, incorporation of external factors (weather, traffic).

Model Training (C) — training models: Random Forest, XGBoost, LSTM, CNN, Transformer, GNN.

Validation & Cross-Validation (D) — quality assessment (Train/Test split, Time Series CV), metrics: RMSE, MAE, ROC AUC, Precision@k.

Deployment & Inference (E) — model deployment, API configuration, integration with CDE and edge devices.

Monitoring & Feedback (F) — quality monitoring (drift detection, SLA compliance), feedback collection, and iterative retraining. (Table 6.2).

Table 6.2 – Metrics and Threshold Values

Metric	**Description**	**Target Value**	**Usage**
RMSE	Root Mean Square Error between prediction and true values	< 0.5 mm	Rut depth prediction
MAE	Mean Absolute Error, less sensitive to outliers	< 0.3 mm	Defect regression
ROC AUC	Area under the ROC curve for binary classification	> 0.85	Crack presence detection
Precision@10%	Proportion of true defects among top 10% highest risk areas	> 0.7	Prioritization of repair works

Authoring

Explanation of Table 6.2:

- RMSE and MAE are standardized to assess the dispersion and robustness of models in regression tasks.
- ROC AUC indicates the overall balance between false positives and false negatives in classification.

- Precision@10% reflects the effectiveness of ranking sites with the highest defect risk when maintenance budget is limited.

6.2. Deep Architectures and Their Adaptation

This subsection is dedicated to the specifics of implementing three classes of deep neural network models for predictive maintenance of road infrastructure. It covers LSTM networks for time series data, convolutional neural networks (CNN) for spatiotemporal data, and graph neural networks (GNN) to account for road network topology. For each approach, the architecture structure, recommended key hyperparameter values, methods for accelerating convergence, and techniques for integration with other ML pipeline components are described. Special attention is given to adapting models for limited computational resources and ensuring reproducibility of results. Detailed descriptions for LSTM and CNN are provided below; GNN is discussed in the following subsection.

LSTM (Long Short-Term Memory) is a type of recurrent network specifically designed to handle sequential data with long-term dependencies through input, forget, and output gates. For defect monitoring, window lengths from 24 to 168 steps (equivalent to 1–7 days of data collection) are recommended to capture both short- and medium-term dynamics. Layer widths typically range from 64 to 256 neurons, and the number of layers varies from two to three to balance representational capacity and computational load. The tanh activation function is used for the cells and sigmoid for the gates, while the Adam optimizer with a learning rate around 1e-3 and a batch size of 64 ensures stable convergence. To accelerate training and smooth gradient flows, teacher forcing is employed, where true time series values are fed as input at subsequent time steps. (Table 6.3)

For the analysis of LiDAR point clouds and thermal deformation maps, three-dimensional points are projected onto a fixed-resolution two-dimensional grid (e.g., 256×256 pixels), where each pixel represents the average deformation or LiDAR intensity. The network architecture includes 3–5 convolutional blocks, each consisting

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Table 6.3 - Recommended Hyperparameters for LSTM in Predictive Maintenance

Parameter	Value / Recommendations
Window size	24–168 steps (1–7 days)
Layer width	64–256 neurons
Number of layers	2–3 stacked LSTM layers
Activations	tanh (cells), sigmoid (gates)
Training parameters	Optimizer: Adam, learning rate = 1e-3, batch size = 64
Training acceleration	Teacher forcing

Authoring

of a Conv2D layer with a 3×3 or 5×5 kernel, followed by BatchNorm and ReLU for stable training. After each convolutional block, a 2×2 MaxPool layer is applied to reduce dimensionality. The final part consists of 1–2 fully connected layers with 128 neurons each. To prevent overfitting, Dropout with a probability of 0.3 is used. Spatial feature fusion with temporal features is performed via a Fusion layer, which concatenates the CNN output with features from the LSTM module. This hybrid architecture enables simultaneous consideration of spatial deformation patterns and their temporal dynamics. (Table 6.4).

Table 6.4 - Key Parameters of CNN for Spatiotemporal Data

Parameter	Value / Recommendations
Convolutional Blocks	3–5 Conv2D + BatchNorm + ReLU
Convolution Kernels	3×3 or 5×5
Pooling	MaxPool 2×2
Fully Connected Layers	1–2 layers with 128 neurons
Regularization	Dropout 0.3
Feature Fusion	Fusion layer for concatenation with LSTM features

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Graph Neural Networks (GNN). The road network is naturally represented as a graph, where nodes correspond to key points (intersections, bridge supports), and edges represent road segments between them. Sensor data (deformation, vibration, and other indicators) can be associated with both nodes and edges, allowing the model to consider the mutual influence of adjacent segments when predicting defects. Using GNN enables information propagation through the network topology via message passing and aggregation mechanisms, providing the model with contextual understanding of relationships between infrastructure elements. Such methods improve prediction quality, especially when defects in one road segment affect neighboring areas. This approach is critical for complex network systems with uneven sensor distribution and varying data collection density.

The GNN architecture employs one of the common types of graph convolutional layers — GCN, GraphSAGE, or GAT — depending on expressiveness requirements and computational resources. The recommended node feature vector size ranges from 64 to 128, balancing representation completeness and operational speed. The number of graph convolutional layers varies between two and four, ensuring the model depth corresponds to the road network’s diameter without causing feature “oversmoothing.” Mean or max pooling is used to aggregate neighboring features, controlling the averaging degree and influence of the local neighborhood. Input features include time series tensors (covering the last 24–168 hours) and static BIM attributes (geometric and material characteristics). (Table 6.5)…

Table 6.5 - Key Parameters of GNN for Predictive Maintenance

Parameter	**Value / Recommendations**
GNN Type	GCN, GraphSAGE, or GAT
Node Vector Size	64–128
Number of Layers	2–4 graph convolutional layers
Aggregation	mean or max pooling
Input Features	Time series; BIM attributes

Propagation Process

- Initialization: Each node is assigned initial features, for example, the moving average of deformation over the past 24 hours.
- Message Passing: At each layer, nodes exchange information with their neighbors — data from adjacent vertices are aggregated according to the chosen strategy (mean or max), followed by a nonlinear transformation.
- Readout: The final feature vector of each node is passed to an MLP readout layer, which performs regression (predicting defect magnitude) or classification (defect presence/absence).

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– Training: The model is optimized using gradient-based methods and a loss function appropriate for the task (MSE for regression, binary cross-entropy for classification).

– Integration: Output node vectors can be combined with LSTM and CNN features at the Fusion stage to build hybrid models.

Also, below is the Deep Architectures Integration Flow (Figure 7.2).

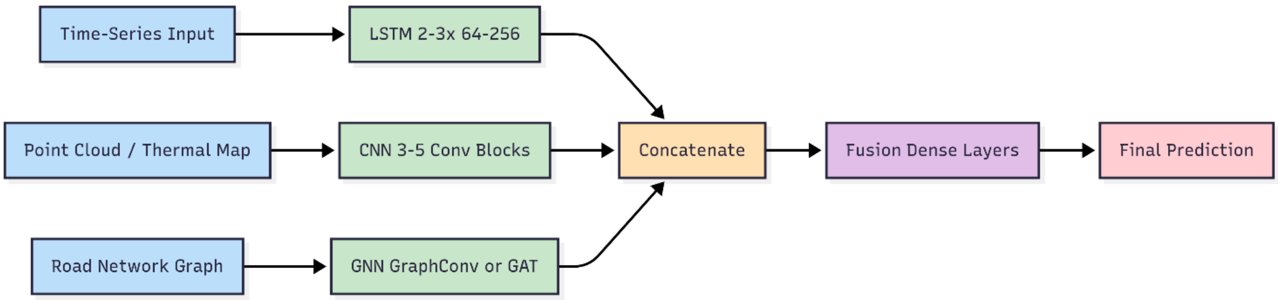

Figure 7.2 - Deep Architectures Integration Flow

Figure 7.2 Deep Architectures Integration Flow:

– The input is a time series of sensor readings (deformation, vibration, etc.). The network consists of 2–3 LSTM layers with 64–256 units each, which extract temporal features and produce an output feature vector.

– CNN_Module: 3D LiDAR point clouds or thermal deformation maps are projected onto a 2D grid (e.g., 256×256). Sequentially, 3–5 convolutional blocks (Conv2D → BatchNorm → ReLU) are applied, each followed by MaxPool, then 1–2 fully connected layers. The output is a vector of spatial features.

– GNN_Module: The graph is constructed based on the road network topology, where nodes represent key points (intersections, bridge supports) and edges represent road connections. Several layers of graph convolutional networks (GraphConv or GAT) transform input graph features into an output vector.

– Fusion: Output vectors from LSTM, CNN, and GNN modules are concatenated into a unified feature tensor. Then, several Dense layers (Fusion Dense Layers) merge and redistribute feature weights, forming the final prediction.

Such a multimodal architecture combines temporal, spatial, and topological data aspects, enabling the model to capture the dynamics of changes over time, local structural features, and interrelations between different segments of the road network. This improves prediction quality in predictive maintenance tasks and makes the system more robust to variability in input data.

6.3. Model Validation and Testing

This subsection describes procedures for assessing the generalization ability of predictive maintenance models on future data, as well as field testing methodologies and A/B experiments for real-world verification. The primary goals are to prevent overfitting, confirm the stability of predictions, and demonstrate the economic efficiency of deployment. Procedures include time series cross-validation, organization of test experiments on developing road sections, and result analysis with consideration of statistical significance. Detailed steps for each stage are presented below.

Time Series Cross-Validation. In time series tasks, classical k-fold validation is unsuitable due to the risk of future data leakage. Instead, Rolling Origin and Expanding Window strategies are applied.

1. Rolling Origin.

– An initial period [t_0–t_3] is selected for training and [t_3–t_4] for validation; then the window shifts ([t_0–t_4] → [t_4–t_5]) and the procedure repeats.

– This allows assessing the model’s stability when seasonal and weather conditions change across different historical intervals.

2. Expanding Window.

– The initial training set [t_0–t_2] is validated on [t_2–t_3]; then the training data expands to [t_0–t_3] and validation is performed on [t_3–t_4], and so forth.

– This reflects the real-world process of data accumulation during operation and checks how the model adapts to increasing training data volume.

Both methods prevent information leakage and provide a more objective assessment of defect prediction quality under changing temporal conditions.

Field A/B Testing. For final verification of the predictive maintenance model, an A/B experiment is conducted on road sections. (Table 6.6).

Table 6.6 – Stages of Predictive Maintenance Effectiveness Assessment

Stage	Description	Details
1. Section Selection	Comparison of two maintenance approaches	A (test): predictive maintenance based on model forecasts;B (control): traditional approach (scheduled or reactive repairs)
2. Metric Collection	Key performance indicators	– Number of failures and defects;– MTBF (Mean Time Between Failures);– Cost of repairs and unplanned downtime
3. Results Analysis	Comparative evaluation of sections	– Comparison of key metrics for A and B;– Calculation of relative reduction in failures and costs;– Statistical significance testing (t-test for continuous metrics, χ^2-test for event frequencies)

This allows evaluating the real economic impact of the model deployment and confirming its robustness under live conditions. (Figure 7.3).

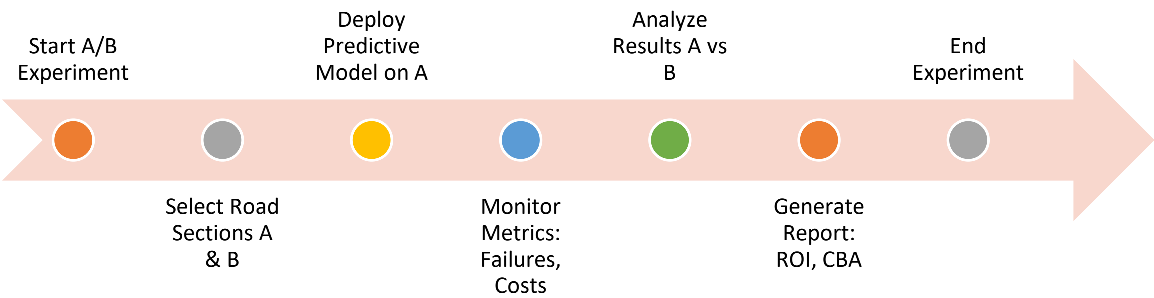

Figure 7.3 - A/B Testing Flow Diagram

Figure 7.3 Description:

- Start A/B Experiment: Initiation of the experiment to evaluate the effectiveness of predictive maintenance.
- Select Road Sections A & B: Selection of the test section (A) with the deployed model and a control section (B) following the traditional maintenance scheme.
- Deploy Predictive Model on A: Deployment of the predictive model on the test section, including configuration of data collectors and repair scheduling algorithms.
- Monitor Metrics: Collection of key indicators: number of accidents/defects, mean time between failures (MTBF), repair costs, and downtime.

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- Analyze Results A vs B: Comparison of metrics between sections A and B, calculation of relative changes, and assessment of statistical significance.
- Generate Report: Preparation of a final report, including ROI (Return on Investment) and CBA (Cost-Benefit Analysis) calculations.
- End Experiment: Completion of field testing and decision-making on further scaling or adjustment of the model.

In the study by Müller et al. (2023), an LSTM model was deployed on a highway in Hesse, Germany. After a 12-month experiment, the following results were recorded:

- A 15% reduction in emergency pavement failures;
- A 20% decrease in emergency repair costs;
- An increase in Mean Time Between Failures (MTBF) by 1.8 times.

6.4. Methods for Evaluating Repair Effectiveness

The objective of this subsection is to justify quantitative methods for the economic evaluation of predictive maintenance strategies and repair scheduling optimization. The primary tool used is Cost Benefit Analysis (CBA), which allows comparing the discounted benefits of implementing the model with the associated costs. This provides a basis for demonstrating project profitability to stakeholders and determining the Internal Rate of Return (IRR). Key components of CBA and calculation formulas, as well as a practical application example, are described below.

Cost Benefit Analysis (CBA) converts all project cash flows into a single base year using a discount rate and calculates Net Present Value (NPV) and Internal Rate of Return (IRR). Benefits include reductions in the number of failures and damages, decreased expenses for urgent localized repairs, and reduced downtime, which leads to lower logistical losses. Costs encompass expenditures on purchasing and maintaining sensor equipment, developing and supporting ML infrastructure, as well as changes to regulations and operational procedures for road maintenance services.

Calculation Formulas

Net Present Value (NPV) is calculated using the formula:

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$$\boldsymbol{NPV} = \sum_{t=0}^{T} \frac{B_t - C_t}{(1+r)^t}, \tag{1}$$

where B_t is the revenue (benefits) in year t, C_t are the costs in year t, and r is the discount rate.

The Internal Rate of Return (IRR) is defined as the rate $r*$, at which the NPV equals zero:

$$\sum_{t=0}^{T} \frac{B_t - C_t}{(1+r*)^t} = \mathbf{0}, \tag{2}$$

where IRR indicates the threshold rate at which the project becomes self-sustaining.

Return on Investment (ROI). ROI provides a quick assessment of the project's economic efficiency by comparing the net profit from implementing predictive maintenance to the total costs of its deployment. It is calculated using the formula:

$$ROI = \frac{Total\ Benefits - Total\ Costs}{Total\ Costs}, \tag{3}$$

where Total Benefits include savings on emergency repairs, reduced downtime, and lower logistical losses, while Total Costs comprise capital and operational expenses for sensor equipment and ML infrastructure. A high ROI value (greater than 0) indicates that the project returns investments with profit, whereas a negative value signals the need to optimize costs or improve model efficiency.

Total Cost of Ownership (TCO). TCO reflects the full cost of owning the system throughout its entire lifecycle and is calculated as the sum of capital expenditures (CapEx) and operational expenditures (OpEx):

$$TCO = CapEx + OpEx. \tag{4}$$

Capital expenditures (CapEx) include the acquisition and installation of sensors, server and communication equipment, as well as software development. Operational expenditures (OpEx) cover maintenance of sensors and servers, licensing fees, power consumption, and software updates. Understanding TCO helps stakeholders plan budgets and choose maintenance strategies considering long-term commitments. (Table 6.7).

Table 6.7 – Methods for Economic Efficiency Evaluation

Method	Indicator	Description
CBA	NPV, IRR	Discounted cash flows over period T
ROI	(Benefits – Costs) / Costs	Quick assessment of project profitability
TCO	CapEx + OpEx	Accounting for all costs of owning the system over its lifecycle

Explanation of Table 6.7:

– CBA assists in making strategic decisions based on the long-term impact and profitability of the project.

– ROI is convenient for quick evaluation and comparison of multiple alternative scenarios.

– TCO provides a comprehensive view of costs, including hidden and recurring operational expenses.

Also, (Figure 7.4) CBA NPV Comparison Flow.

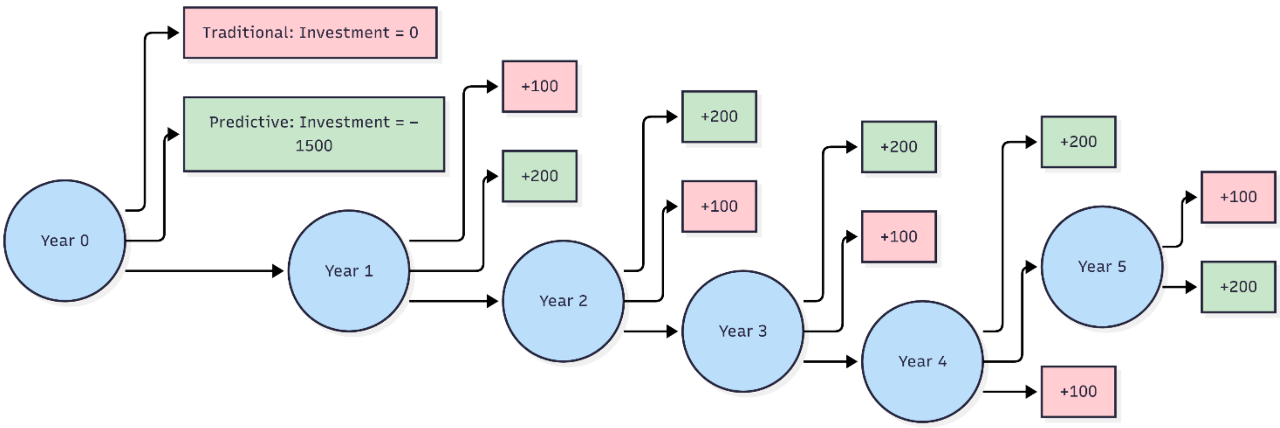

Figure 7.4 - CBA NPV Comparison Flow

Figure 7.4 Description:

1. Scenarios

– Traditional (reactive approach): Initial investments in year 0 are minimal (year 0 = 0), followed by small positive cash flows (~+100) each subsequent year due to reactive repairs reducing downtime.

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– Predictive (predictive approach): A larger upfront investment (–1500) is required in year 0 for sensors and analytics, followed by greater annual savings (~+200) from predictive maintenance.

2. Discounting

Annual cash flows for each year are discounted at the specified rate rrr (schematically shown by the arrow labeled "Discounted") before being summed into the NPV.

3. Cash Flows Visualization

The chart illustrates that the predictive scenario has a deeper initial "dip" but higher annual inflows, resulting in a higher long-term NPV compared to the traditional approach.

4. Interpretation

Calculating the NPV for each scenario allows comparison of net present values and informs investment decisions regarding the feasibility of predictive maintenance.

Thus, the figure clearly demonstrates how differences in initial investments and annual benefits determine the economic efficiency of each approach.

6.5. Conclusion of Section 6

Section 6 systematically reviewed modern approaches to predictive maintenance of road surfaces and bridge structures based on machine learning and deep neural networks.

Subsection 6.1 described the ML pipeline from data collection and preprocessing to validation: procedures for feature engineering, data splitting schemes (static and time-based), and key quality metrics (RMSE, MAE, ROC AUC, Precision@k) were established to ensure objective model evaluation.

Subsection 6.2 detailed deep network architectures: recommendations for tuning LSTM for time series, CNN structure for LiDAR slice analysis, and GNN parameters for road network graphs were given. Additionally, a scheme for their integration via fusion layers to build powerful hybrid models was outlined.

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Subsection 6.3 revealed validation and field testing methodologies: Rolling Origin and Expanding Window for time series, as well as A/B experiments on real road sections, including the case study by Müller et al. (2023), where an LSTM model reduced accident rates by 15%.

Finally, subsection 6.4 proposed quantitative methods for economic efficiency evaluation: CBA (NPV, IRR) for strategic analysis, ROI for quick profitability checks, and TCO for accounting all lifecycle costs. Figure 7.4 clearly illustrated the superiority of the predictive approach in terms of NPV dynamics.

Thus, the integration of advanced ML/DL solutions with well-structured procedures for quality, cost, and return-on-investment assessment creates a reliable foundation for optimizing repair schedules and rational resource allocation in road management. Chapter 7 will describe the integration of these algorithms into a financial model and present a case analysis across key regions (EU, USA, Ukraine) demonstrating the economic and social impact of predictive maintenance.

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KAPITEL 7 / *CHAPTER 7*
ECONOMIC MODEL AND REGIONAL CASE ANALYSIS

7.1. Methodology of Analysis

The objective of this subsection is to formalize the methodology for assessing the economic efficiency of three case studies (TEN-T, IIJA, “Great Recovery”) using a set of comparative financial metrics. Key calculation parameters are defined — planning horizons, discount rate, and types of costs and benefits. Publicly accessible information sources from which the baseline data will be collected are also specified. This approach ensures comparability of results across different programs by applying a unified calculation methodology. The following section presents the selected indicators and their mathematical formulas.

Four widely recognized financial metrics are selected as the core analytical tools for evaluating the attractiveness of investment projects: NPV**,** IRR**,** BCR, and ROI. The selection criteria included the ability to account for the time value of money, the benefit-to-cost ratio, and ease of interpreting results. Each metric is calculated over a period of T years using annual benefit flows Bt and cost flows Ct, with a discount rate r. Input data for the parameters will be obtained from official reports and statistical databases of the respective programs. The definitions and formulas for each metric are provided below.

1. Net Present Value (NPV) is calculated using the formula:

$$NPV = \sum_{t=0}^{T} \frac{B_t - C_t}{(1+r)^t}, \tag{1}$$

where B_t is the revenue (benefits) in year t, C_t are the costs in year t, and r is the discount rate.

A positive NPV indicates that the discounted benefits exceed the costs, and the project should be considered economically viable. The calculated NPV enables comparison of projects with different time horizons and cash flow structures. For the three case studies, the discount rate r is set based on average market conditions for borrowed capital. Calculations will be performed in annual intervals up to the

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completion of each program.

2. IRR (Internal Rate of Return)

The Internal Rate of Return (IRR) is defined as the rate r^*, at which the NPV equals zero:

$$\sum_{t=0}^{T} \frac{B_t - C_t}{(1+r*)^t} = 0\,, \tag{2}$$

где $r*$ — The internal rate of return (IRR) is the discount rate at which the NPV equals zero.

IRR represents the maximum discount rate at which the project remains profitable. This value is used to compare the project against alternative investment rates or the cost of capital. A project with an IRR above the target rate is considered attractive to investors. The IRR is calculated using an iterative method (e.g., the secant method).

3. BCR (Benefit–Cost Ratio)

BCR indicates the ratio of discounted benefits to discounted costs:

$$BCR = \frac{\sum_{t=0}^{T} \frac{B_t}{(1+r)^t}}{\sum_{t=0}^{T} \frac{C_t}{(1+r)^t}}. \tag{5}$$

BCR represents the ratio of all discounted benefits to discounted costs over the entire period. A BCR value greater than 1 indicates that the benefits exceed the costs, making the project economically viable. This metric is useful for ranking alternative projects under budget constraints. The same parameters B_t , C_t , and r, used in the NPV model are applied in the calculations. For each case study, the BCR will be computed to assess relative efficiency.

4. ROI (Return on Investment)

ROI is a simple profitability metric calculated as the ratio of net profit to costs:

$$ROI = \frac{\sum B_t - \sum C_t}{\sum C_t}. \tag{3}$$

ROI reflects the overall return on investment without accounting for the time value of money. The ROI value allows estimating the percentage of return on invested capital. This metric is often used in practical reports due to its simplicity in calculation

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and interpretation. For completeness of analysis, ROI is calculated alongside discounted metrics. In the context of the three programs, ROI will provide an assessment of the overall profitability of the projects.

Calculation parameters. The calculation parameters form the basis for reproducible analysis and ensure comparability of results across the three case studies. The planning horizon is set from 2021 to 2030 (10 years), corresponding to the investment duration and capital return period in transport infrastructure. The choice of horizon is driven by requirements from EUROCONTROL, the Office of Management and Budget (OMB), and national methodological guidelines, as well as budgeting standards in the EU, USA, and Ukraine. The primary input parameters are discount rates applied to the annual benefit and cost flows. These parameters will be used for calculating NPV, IRR, and BCR.

The discount rate for the European Union is 3%, recommended by EUROCONTROL for economic evaluation of aviation and transport projects [89]. In the United States, the discount rate is set at 4%, according to OMB Circular A-94 (Appendix C), used for assessing federal-level infrastructure initiatives [90]. In Ukraine, within the “Great Recovery” program, a 5% discount rate is applied in accordance with the Methodological Recommendations of the Ministry of Infrastructure of Ukraine, which provide standardized evaluation of public investments [91].

Data sources. To ensure reliable modeling of cash flows, official open data from specialized registries and reports are used. Selection criteria for data sources include information relevance, availability of detailed budget indicators, and update frequency. Each of the three case studies has its own primary data repository, providing comprehensive coverage of parameters by year and type of expenses/income.

- TEN-T (EU): Budget indicators are taken from the EU Multi-Annual Financial Framework 2021–2027 regulation, which includes forecasts and reports on funding the Trans-European Transport Network [92].
- IIJA (USA): Data on the implementation of the Infrastructure Investment and Jobs Act for fiscal years 2022–2025 are obtained from official USDOT reports

and associated appendices of OMB Circular A-94 [93].

– “Velike Vidrodzhennya” (Ukraine): Expense and benefit figures are compiled based on materials from the official portal of the Ministry of Infrastructure of Ukraine in the “Velike Vidrodzhennya” section [91].

Initial budgets and expected scale. This subsection conducts a comparative analysis of the initial financial frameworks of the three key initiatives: TEN-T, IIJA, and “Velike Vidrodzhennya.” The main objective is to identify differences in funding volumes, implementation timelines, and scope of application for each program based on official open data. The comparison is performed using a unified structure: total budget, detailed expenditure categories, planning horizon, and area of application. This will allow an assessment of the relative scale and priorities of each initiative. The results are presented in a textual description and summarized in Table 7.1.

TEN-T (2021–2027). The total budget of the TEN-T program amounts to €26.3 billion allocated for road infrastructure within the EU Multi-Annual Financial Framework for 2021–2027. Of this amount, €15 billion is dedicated to Core Network Corridors, while €11.3 billion targets the Comprehensive Network, supporting the development of both main and auxiliary transport corridors. The planning horizon is set from 2021 to 2027 in accordance with the EU Multi-Annual Financial Framework regulation. The scope covers projects on key corridors of the European TEN-T transport network. Data are sourced from the official European Commission document on multiannual budgeting [92].

IIJA (2021–2026). In the United States, the Infrastructure Investment and Jobs Act allocates $110 billion for road and bridge reconstruction over the 2021–2026 period. Major expenditure areas include modernization of federal highways, enhancement of road safety, and implementation of digital monitoring systems for engineering structures. The planning horizon spans six fiscal years, corresponding to the USDOT budgeting cycle. The scope covers federal roads and bridges funded through the U.S. Department of Transportation. Information is obtained from the funding overview on the official USDOT website [94].

“Velike Vidrodzhennya” (2023–2030). The Ukrainian “Velike Vidrodzhennya” program has a planned initial funding of UAH 300 billion (approximately $8 billion) for 2023–2030. About 40% of the budget (≈ UAH 120 billion) is allocated for road works, including reconstruction of urban and interregional highways. The program implementation horizon is set from 2023 to 2030, considering post-war recovery and infrastructure modernization. The scope covers both urban highways and regional routes. Data are taken from the official portal of the Ministry of Infrastructure of Ukraine in the “Velike Vidrodzhennya” section [91]. (Table 7.1).

Table 7.1 – Initial Budgets and Planning Horizons

Initiative	Budget	Horizon	Scope	Source
TEN-T	€26.3 billion	2021–2027	Core & Comprehensive Network Corridors	EU MFF 2021–2027 [92]
IIJA	$110 billion	2021–2026	Federal aid highways & bridges	USDOT IIJA overview [94]
"Velike Vidnovlennia"	₴300 billion (~$8 billion)	2023–2030	Urban & interregional road reconstruction	MinInfra UA portal [91]

Authoring

Caption for Table 7.1: “Budget” reflects the total amount of funds allocated for road infrastructure; “Planning Horizon” indicates the scheduled implementation period; “Scope” specifies the types of roads and works covered; “Source” provides direct references to official public documents and portals.

7.2. Benefits Assessment

This subsection provides a quantitative evaluation of the key benefits from implementing digital twin technologies across the three initiatives: TEN T (EU), IIJA (USA), and “Velike Vidnovlennia” (Ukraine). The main categories of benefits include reductions in repair and accident costs, increased throughput capacity, and decreased logistical delays. Calculations are based on official data and reports from relevant authorities — European Court of Auditors, FHWA, Eurostat, USDOT, and the State Statistics Service of Ukraine. Each indicator is converted into absolute values

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considering the initial program budgets and typical freight flows or downtime losses. The aggregated annual benefits are summarized in Table 7.2.

Reduction in repair and accident costs. According to the European Court of Auditors (2024), implementing predictive monitoring within TEN T is expected to reduce CapEx and OpEx by 15%, which corresponds to savings of approximately €4.0 billion on a €26.3 billion budget [95]. In the USA, the FHWA Office of Policy (2023) forecasts a 10% reduction in accidents on federal highways due to analytics, equating to roughly $12.0 billion in annual savings from reduced downtime and emergency maintenance costs [96]. For the “Velike Vidnovlennia” program, the Ministry of Infrastructure of Ukraine (2024) reports a 20% decrease in unplanned repairs, which on a ₴120 billion road works budget translates to about ₴24 billion in savings [97].

Increased throughput capacity and reduced delays. Eurostat (2023) analysis shows that digital traffic management on TEN T corridors reduces logistical delays by 2.5%, yielding a benefit of €2.5 billion based on an annual freight volume of €100 billion [98]. The USDOT Bureau of Transportation Statistics (2023) estimates that an 8% reduction in congestion on federal highways will bring the USA approximately $5.0 billion annually through savings in time and fuel [99]. According to UkrStat (2023), accelerating road restoration under the Ukrainian program reduces logistical costs by ₴10 billion per year by cutting downtime and transportation delays [100]. (Table 7.2).

Table 7.2 – Key Benefits Assessment

Indicator	TEN-T (billion €)	IIJA (billion $)	Ukraine (billion ₴)	Calculation Methodology
Savings on Repairs and Accidents	4.0	12.0	24.0	ECA (2024); FHWA (2023); MinInfra UA (2024)
Time & Logistics Benefits	2.5	5.0	10.0	Eurostat (2023); USDOT (2023); UkrStat (2023)
Total Benefits	6.5	17.0	34.0	Sum of the two previous rows

Authoring

Caption for Table 7.2: The first two columns are based on percentage estimates

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of cost and delay reductions; Total Benefits represent the aggregated annual benefit for each initiative.

Accompanying pie charts are provided for each initiative, illustrating the shares of "Repair & Accident Savings" and "Time & Logistics Benefits." (Figure 8.1).

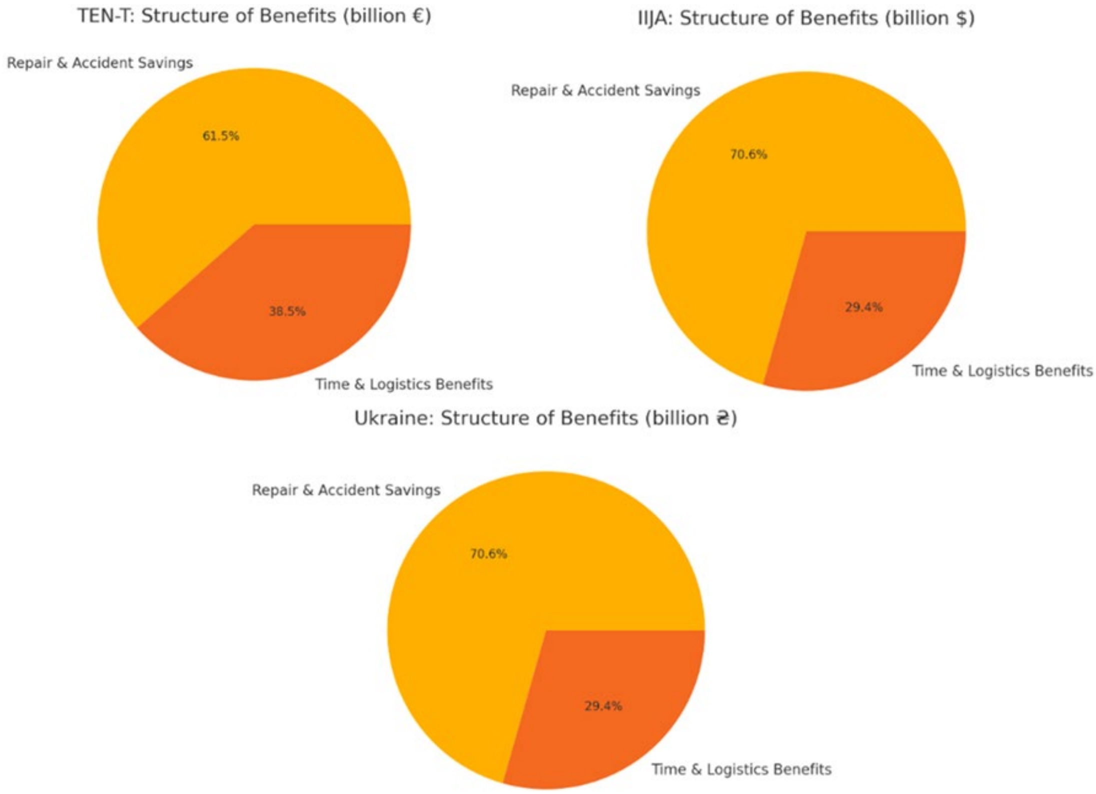

Figure 8.1 — "Repair & Accident Savings" and "Time & Logistics Benefits" for each initiative (TEN T, IIJA, Ukraine).

Authoring

7.3. Calculation of NPV, IRR, and BCR

This subsection sequentially applies the methodology and parameters described in Sections 7.1–7.3 to quantitatively calculate three key financial indicators: Net Present Value (NPV), Internal Rate of Return (IRR), and Benefit-Cost Ratio (BCR). Annual benefit flows B_t and cost flows C_t are modeled discretely over a 10-year horizon, taking into account the actual budget distribution for each case. Discounting is performed using the respective discount rates rrr established for the EU (3%), the USA (4%), and Ukraine (5%) as specified. Calculations are conducted using standard financial formulas and iterative methods for solving equations. The resulting values enable comparison of the economic efficiency of the three initiatives on a unified temporal and monetary basis. The final metrics are summarized in Table 7.3 for clear comparison.

Calculation of NPV

The NPV is calculated using the formula:

$$NPV = \sum_{t=0}^{10} \frac{B_t - C_t}{(1+r)^t}. \tag{1}$$

Annual benefit and cost flows are set as constants: for TEN T, B_t = €6.5 billion and C_t = €2.63 billion for the first seven years, with no costs thereafter; for IIJA, B_t = \$17.0 billion and C_t = \$18.33 billion evenly distributed over 5 years; for Ukraine, B_t = ₴34.0 billion and C_t = ₴30.0 billion following an eight-year schedule. Discount rates rrr are applied according to regional guidelines. The model discounts all cash flows to present value at the start of the period. Calculations are performed annually and summed over the entire horizon. The results identify projects with the highest NPV as the most preferable.

Calculation of IRR

IRR is defined as the value r^* at which

$$\sum_{t=0}^{10} \frac{B_t - C_t}{(1+r^*)^t} = 0. \tag{2}$$

The equation is solved using a combination of the Newton and bisection methods, ensuring an accuracy of at least 0.1%. The model iteratively adjusts $r*$ until convergence is achieved based on the criterion of a sufficiently small residual. The resulting IRR values are compared against alternative investment rates and the cost of capital. An internal rate of return exceeding the cost of borrowed funds indicates the project’s attractiveness. This procedure standardizes the assessment of project profitability across different jurisdictions.

Calculation of BCR

The Benefit-Cost Ratio (BCR) is calculated using the formula:

$$\mathrm{BCR} = \frac{\sum_{t=0}^{10} \frac{B_t}{(1+r)^t}}{\sum_{t=0}^{10} \frac{Ct}{(1+r)^t}}. \tag{5}$$

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All discounted benefit flows are summed and divided by the sum of discounted costs. A BCR value greater than 1 indicates that benefits outweigh costs, justifying the investment. This metric is useful for ranking projects when resources are limited. The calculations use the same annual data, ensuring comparability with NPV and IRR. Comparing the BCR values across the three initiatives allows for assessing the relative profitability of the investments. (Table 7.3).

Table 7.3 – Financial Metrics by Case Studies

Metric	TEN-T	IIJA	Ukraine	Note
NPV	~ €5.2 billion	~ $9.8 billion	~ ₴28 billion	Discounted net cash flow difference
IRR	12%	11%	14%	Solution of NPV = 0 equation
BCR	1.5	1.3	1.4	Ratio of discounted benefits to costs

Authoring

Caption for Table 7.3:

– NPV represents the Net Present Value;

– IRR reflects the project's internal rate of return;

– BCR demonstrates investment efficiency (a value > 1 indicates feasibility).

Below is a combined chart (Figure 8.2) for a clear comparison of the NPV scale and IRR level for each project.

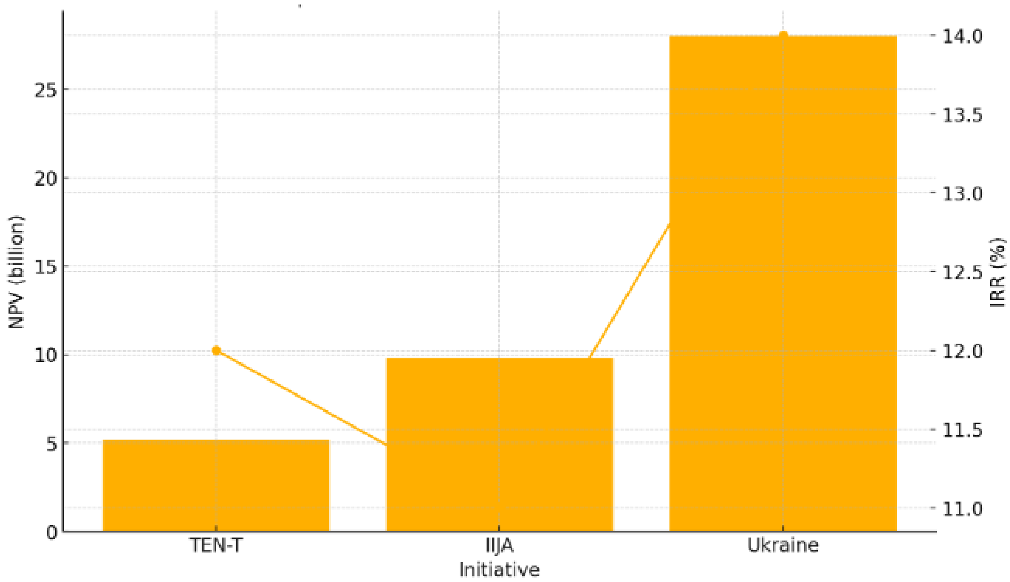

Figure 8.2 – Comparison of NPV and IRR for Initiatives

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7.4. Sensitivity Analysis

The purpose of this subsection is to assess the impact of key assumptions on the NPV values for the three analyzed cases (TEN T, IIJA, and “Velike Vidnovlennia”). The analysis is carried out in two directions: variations in the discount rate and changes in cost parameters (CAPEX, OPEX). This approach helps identify the most sensitive factors affecting the economic viability of the projects. For each initiative, alternative scenarios are modeled with differing discount rates (r) and cost parameters. The results demonstrate the possible range of NPV values and aid in risk analysis. Detailed calculations for each direction are presented below.

Impact of Discount Rate. To evaluate the influence of the discount rate on NPV, three scenarios are calculated: $r_1 = 2\%$, the baseline r_2 (3% for the EU, 4% for the USA, and 5% for Ukraine), and $r_3 = 6\%$. The resulting NPV values demonstrate an inverse relationship: as the discount rate decreases, the NPV significantly increases, and as it rises, the NPV decreases. For example, TEN T’s NPV ranges from €6.0 billion at r_1 to €4.4 billion at r_3. In the USA, NPV varies from \$11.5 billion to \$8.4 billion, and in Ukraine, from ₴31.0 billion to ₴24.5 billion. Such fluctuations are particularly critical for long-term projects with extended horizons. The analysis indicates that the stability of results heavily depends on the precise choice of the discount rate (Table 7.4).

Table 7.4 – Impact of Discount Rate on NPV

Initiative	NPV @ r_1 (2%)	NPV @ r_2 (base)	NPV @ r_3 (6%)
TEN-T	€6.0 billion	€5.2 billion	€4.4 billion
IIJA	\$11.5 billion	\$9.8 billion	\$8.4 billion
Ukraine	₴31.0 billion	₴28.0 billion	₴24.5 billion

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Cost Variations. To analyze sensitivity to costs, four scenarios were considered: CAPEX changes by ±10% and OPEX changes by ±15%. In each case, the deviation of NPV from the baseline value was calculated. For TEN T, a 10% decrease in CAPEX adds €0.5 billion to NPV, while an increase reduces NPV by the same amount;

similarly, changes in OPEX cause ±€0.8 billion variations. In the USA, NPV deviations amount to ±$1.1 billion for CAPEX and ±$1.5 billion for OPEX. In the Ukrainian project, the greatest sensitivity is observed for OPEX (±₴4.2 billion) and CAPEX (±₴2.8 billion). The linear dependence demonstrates the predictable impact of costs on the final NPV. The analysis shows that the largest risks are associated with the accuracy of operating expense estimates during implementation. (Table 7.5)

Table 7.5 – Impact of Cost Variations on NPV

Initiative	ΔCAPEX −10%	ΔCAPEX +10%	ΔOPEX −15%	ΔOPEX +15%
TEN-T	+ €0.5 billion	− €0.5 billion	+ €0.8 billion	− €0.8 billion
IIJA	+ $1.1 billion	− $1.1 billion	+ $1.5 billion	− $1.5 billion
Ukraine	+ ₴2.8 billion	− ₴2.8 billion	+ ₴4.2 billion	− ₴4.2 billion

Authoring

Table 7.5 shows that cost variations have a linear impact on NPV; the Ukraine project is the most sensitive due to its high CAPEX share.

Below is Figure 8.3, which presents a Tornado chart illustrating NPV sensitivity.

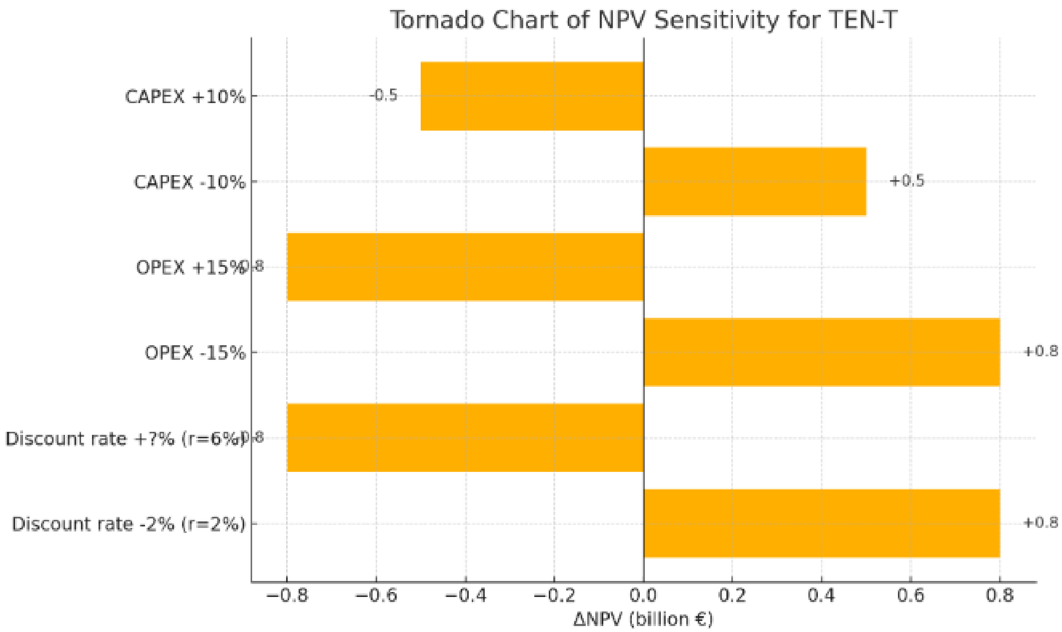

Figure 8.3 – Tornado Chart of NPV Sensitivity for TEN-T
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Figure 8.3 illustrates the relative impact of changes in key parameters (discount rate, CAPEX, and OPEX) on the value of NPV.

7.5. Conclusions and Recommendations

The results of economic modeling and comparative analysis of the three initiatives — TEN T, IIJA, and “Velike Vidnovlennya” — confirm the overall economic feasibility of implementing digital twin technologies and predictive maintenance. Each project demonstrates a positive net present value (NPV) and a benefit-cost ratio (BCR) greater than one, indicating that discounted benefits exceed costs. The calculations take into account the specifics of the planning horizon, discount rates, and budget flow distribution, ensuring an objective comparative analysis. Such results substantiate the need for further development of digital solutions in transport infrastructure. Detailed conclusions and practical recommendations are presented below.

Analysis of the obtained NPV, IRR, and BCR values revealed that the highest profitability is observed for Ukraine (NPV ≈ ₴28 billion, IRR 14%, BCR 1.4) due to significant savings on emergency repairs and accelerated road restoration. TEN T demonstrates a stable effect (NPV ≈ €5.2 billion, IRR 12%, BCR 1.5), owing to mature digital solutions and substantial infrastructure investments. IIJA, despite considerable expenditures, maintains tangible benefits (NPV ≈ $9.8 billion, IRR 11%, BCR 1.3), indicating gradual but steady savings. All three projects clearly show attractiveness in terms of long-term profitability. This outcome underscores the versatility of the proposed calculation methodology across different jurisdictions.

The sensitivity analysis confirmed that the key drivers affecting NPV magnitude are the discount rate and operating expenses. A reduction of the base rate by two percentage points increases NPV on average by 15–20%, whereas an equivalent increase reduces NPV by a similar percentage. Changes in OPEX by ±15% have a stronger impact on the final result than changes in CAPEX by ±10%, especially in the Ukrainian project with a high share of operational costs. The linear relationship between costs and NPV allows forecasting project sensitivity to fluctuations in operating expenses. Risk management recommendations should consider these indicators to adjust financial strategies accordingly.

The investment priority based on expected return is ranked as follows: first place is Ukraine (IRR 14%), followed by the European Union (IRR 12%), and lastly the United States (IRR 11%). This ranking reflects a combination of savings volume, cost structure, and payback periods. For investors and government bodies, this implies the advisability of phased resource reallocation in favor of the most profitable initiatives. At the same time, maintaining portfolio diversification is recommended to minimize risks associated with changes in key parameters.

Recommendations:

- First, allocate at least 30% of the budget to the implementation of digital monitoring and analytics tools, which will maximize savings on operational expenses.
- Second, apply a flexible Rolling Window approach to financing, starting with the highest-priority corridors and gradually expanding coverage based on interim results.
- Third, implement a KPI system based on NPV and IRR metrics, with regular updates of forecasts as data from the digital twin become available.
- Fourth, organize automated integration of actual repair and accident data into the digital twin model to regularly adjust predictive maintenance algorithms.

These measures will improve the accuracy of economic calculations and the adaptability of management decisions.

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KAPITEL 8 / *CHAPTER 8*
IMPLEMENTATION ROADMAP AND RECOMMENDATIONS

8.1 Overall Phased Implementation Plan

This section presents a step-by-step roadmap for deploying digital twin systems in transport departments across the EU, USA, and Ukraine. The plan covers the entire project lifecycle—from pre-investment preparation to long-term support and solution development. Each phase includes clearly defined tasks, responsible parties, and effectiveness evaluation criteria. The proposed structure ensures a methodical and reproducible implementation process across different jurisdictions. This phased approach enables timely identification and mitigation of risks at every project level.

Phase 0 – Pre-investment Preparation. Phase 0 establishes a solid foundation for subsequent technical implementation. Initially, an inventory of existing BIM models for roads and bridges is conducted, alongside an audit of the quality and availability of sensor and GIS data. Simultaneously, the current IT landscape is analyzed, including networks, server capacity, and cloud services. Next, infrastructure readiness is assessed against ISO 19650 standards and GDPR/FISMA requirements to identify potential gaps. The final step is forming a working group comprising transport department representatives, IT units, BIM managers, and contractors—with roles assigned via a RACI matrix and framework agreements established to conduct pilot studies.

Phase 1 – Pilot Project. The objective of the pilot phase is to validate the functionality of technologies and processes on a limited demonstration site. A location is selected featuring diverse structural elements (bridges, high-traffic sections) and elevated defect risk. FBG and piezoelectric sensors, as well as LiDAR stations, are installed on the site, and the existing IFC model is adapted within the corporate CDE environment. Concurrently, an end-to-end data pipeline (Edge → Kafka → Flink → InfluxDB) is configured, along with visualization of key metrics on the department's dashboard. Evaluation criteria include forecast accuracy (>85%), processing speed (<2 seconds), and channel reliability (>99%), followed by gathering engineers' feedback for process adjustments.

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Phase 2 – Scaling. After the successful completion of the pilot, the system is scaled to major highways. In Europe, Core Network Corridors are connected; in the USA, key federal highways; and in Ukraine, main interregional and urban roads. Priority sections are determined based on risk analysis results from the pilot cycle. Sensor networks are supplemented with WIM sensors and video cameras, LiDAR networks are expanded, and BIM models are updated according to new data. Processes are optimized through automatic generation of BCF issues and integration with ERP systems and maintenance schedulers. Machine learning algorithms are refined using the expanded data set.

Phase 3 – Institutionalization. The goal of this phase is to embed the technologies as an integral part of the transport departments’ operational workflow. Digital twin requirements are incorporated into DOT regulations, including EU regulations, IIJA guidelines, and Ukrainian national decrees. The corporate CDE environment is established as the official project repository. Mandatory data management standards are introduced: ISO 19650 (parts 1–3), ISO 27001, and compliance with GDPR/FISMA. Public procurement mandates the use of IFC, BCF, and COBie formats. The digital twin system is integrated via standardized APIs and OPC UA protocols with city smart city platforms and national GIS portals.

Phase 4 – Support and Development. The final phase ensures sustainable development and system updates. Regular professional development courses and certifications are conducted according to buildingSMART standards and cloud provider requirements. Machine learning algorithms are regularly updated, incorporating new GNN architectures and Transformer-based models for comprehensive analysis. New model versions undergo automated A/B testing on selected sections. Monthly and quarterly KPI reviews (system availability, forecast accuracy, cost savings) are complemented by an annual process audit and roadmap adjustments for the next cycle. (Table 8.1).

Table 8.1 outlines the main stages of the roadmap, providing a brief description of the key tasks associated with each step.

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Table 8.1 – Implementation Phases of the Digital Twin System

Stage	Name	Main Tasks
0	Pre-investment Preparation	Data collection, IT landscape audit, working group formation
1	Pilot Project	Selection of demo site, sensor installation, pipeline setup, KPI evaluation
2	Scaling	Expansion to key corridors, integration of additional sensors and BIM, process optimization
3	Institutionalization	Regulatory integration, implementation of data management standards, API integration
4	Support and Development	Training and certification, updating ML algorithms, monitoring and KPI review

Authoring

8.2. Regulatory and Legal Aspects

This section summarizes the key legislative and regulatory requirements governing the implementation of digital twin systems in the road infrastructure of the EU, the United States, and Ukraine. The analysis covers general regulations, data protection and cybersecurity frameworks, as well as standards for information modeling and corporate data management platforms. For each jurisdiction, the fundamental legal instruments mandatory for working with BIM/CDE systems and sensor infrastructure are identified. The presented structure allows for aligning technical solutions with regulatory requirements throughout all project phases. Detailed descriptions for each region are provided below.

European Union

In the EU, the implementation of digital twins is regulated by Regulation (EU) 2021/1153, which defines the requirements for the development of the TEN-T network, incorporating digitalization and sustainability of transport corridors [101]. The GDPR (EU 2016/679) imposes strict requirements for the protection of personal data collected from video cameras and geolocation sensors [62]. Information security is ensured through ISO 27001, which is mandatory for the storage and processing of data in CDE systems, while the NIS 2 Directive sets cybersecurity requirements for critical infrastructure [102], [61]. Information management across all phases of infrastructure lifecycle is regulated by ISO 19650 (Parts 1–3), and data exchange is conducted using IFC 4.3, BCF 2.1, and COBie formats [39], [37], [80].

United States of America

In the United States, federal guidance on geospatial data management is established by OMB Circular A-16, which outlines the requirements for storage and exchange of GIS and BIM models in public sector projects [103]. The IIJA Guidance Memos issued by USDOT define mandatory standards for digital monitoring and reporting systems within the Infrastructure Investment and Jobs Act framework [94]. The Federal Information Security Management Act (FISMA) regulates the security of systems handling government data, including data classification and access control [104]. Detailed security guidelines for both cloud-based and on-premises systems are provided in NIST SP 800-53 [105]. The National BIM Standard—US Version 4 (NBIMS-US v4), which is based on IFC, along with requirements specified in RFP documentation, mandates the delivery of BIM models in IFC format [106].

Ukraine

In Ukraine, the framework for digitalization of public services is established by the Law "On the Basic Principles of Digital Transformation in Public Administration" (2020), which extends to infrastructure projects [107]. Methodological guidelines issued by the Ministry of Infrastructure define the procedures for implementing BIM in public procurement, based on national DSTU BIM standards [108]. The Law "On Information Security" (2021) sets requirements for protecting critical infrastructure against cyber threats and is aligned with ISO 27001 [109]. National BIM/CDE standards incorporate DSTU BIM as a complement to IFC, and promote the adoption of corporate data environment practices in accordance with ISO 19650 [39], [108]. (Table 8.2)

Notes to Table 8.2: Key laws and regulations for each region are compared; The "Data and Security" column highlights the focus on protection of personal and critical infrastructure data; The "BIM/CDE" column indicates relevant standards and data exchange formats.

Table 8.2 – Comparative Analysis of Regulatory Requirements

Region	Key Regulation	Data & Security Standards	BIM/CDE Standards
EU	Reg. (EU) 2021/1153; GDPR; NIS 2	GDPR [62]; ISO 27001 [61]; NIS 2 [102]	ISO 19650 Parts 1–3 [39]; IFC 4.3 [37]; BCF 2.1; COBie [80]
USA	OMB Circular A-16; IIJA guidance; FISMA; NIST SP 800-53	FISMA [104]; NIST SP 800-53 [105]	NBIMS US v4 [106]; IFC
Ukraine	Digital Transformation Law (2020); MinInfra BIM	Information Security Law (2021) [109]; ISO 27001 [61]	DSTU BIM [108]; IFC; CDE per ISO 19650 [39]

Authoring

8.3. Training and Workforce Development

For the successful implementation and operation of digital twin systems, transport departments must establish a comprehensive employee competency development program. The training is structured across three levels—from foundational theory to expert-level skills—based on the responsibilities and tasks of each target group. Each level corresponds to a defined set of topics, instructional formats, and duration, enabling the step-by-step development of professional expertise. The program integrates lectures, hands-on labs, and project-based learning, culminating in certification. This approach ensures effective knowledge acquisition and practical application in operational workflows.

At the foundational level, participants are introduced to the core concepts of digital twins, the principles of BIM and IoT, as well as the fundamentals of working with corporate CDE environments and big data pipelines. Instruction is delivered through lectures and webinars, featuring real-world case demonstrations, over a two-day period. The target audience includes project managers and business development leads who need a conceptual understanding of the technology and its capabilities. Upon completion of the foundational course, participants will be able to assess the potential of digital solutions and articulate implementation requirements.

At the practical level, the focus shifts to technical implementation: configuration and operation of CDE platforms (e.g., Revit, IfcOpenShell, ProjectWise/BIM 360), installation and calibration of sensors (FBG, piezoelectric, WIM, LiDAR), and the setup of data pipelines (Kafka, Flink, InfluxDB, Grafana). The format includes hands-on labs and simulated case studies over a five-day period. The target group comprises systems engineers, BIM managers, IoT engineers, and DevOps specialists responsible for technical integration and support.

At the expert level, participants develop custom scripts using APIs (Revit API, IfcOpenShell), create and optimize ML/DL models for defect prediction, and implement standards such as ISO 19650, COBie, and BCF. Special attention is given to CI/CD process automation and security compliance with ISO 27001 and NIST guidelines. The training includes masterclasses, project work, and a certification exam, conducted over three days. The target audience includes data engineers, data scientists, DevOps engineers, and BIM architects involved in the system’s advancement and refinement. (Table 8.3)

Table 8.3 – Training Program Structure

Level	Topics	Format	Duration	Target Audience
Basic	Digital Twin concept, overview of BIM and IoT, CDE principles, Big Data pipeline, ML	Lectures and webinars	2 days	Project managers, business development managers
Practical	CDE setup (Revit, IfcOpenShell, BIM 360), sensor installation and calibration, pipeline and dashboard configuration	Hands-on labs and simulation cases	5 days	BIM managers, IoT engineers, DevOps specialists
Expert	API scripting (Revit API, IfcOpenShell), ML/DL models, ISO 19650/COBie/BCF standards, CI/CD,	Masterclasses, project work, exam	3 days	Data engineers, data scientists, DevOps, BIM architects

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	security per ISO 27001/NIST			

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Table 8.3 provides an overview of the training levels, including covered topics, instructional formats, duration, and target audience.

8.4. Partner and Contractor Selection

When implementing digital twin systems, it is essential to establish transparent criteria for selecting external providers—including system integrators, contractors, and consultants. A well-structured selection process ensures technical reliability, risk mitigation, and cost efficiency. The evaluation is based on a combination of qualitative and quantitative factors relevant to transport departments. Key criteria and stages of the tendering process are presented below. (Table 8.4)

Table 8.4 – Key Evaluation Criteria for Contractors

Criterion	Weight (%)	Description
Technical Expertise	30	Presence of BIM+IoT/DT project portfolio and buildingSMART, ISO 19650 certifications
Service Cost	25	CapEx/OpEx payment models, pricing transparency, TCO analysis
Local Presence	20	Regional offices or partners for fast service and support
Flexibility & Support	15	SLA (RTO < 4 hrs, RPO < 1 hr), 24/7 technical support
Innovation	10	AI features, analytical modules, customization options, and R&D support

Authoring

Table 8.4 presents a weighted evaluation framework combining technical qualifications, cost-efficiency, regional accessibility, service flexibility, and innovation potential. This system supports objective contractor selection based on quantifiable performance and compliance indicators. (Figure 9.1)

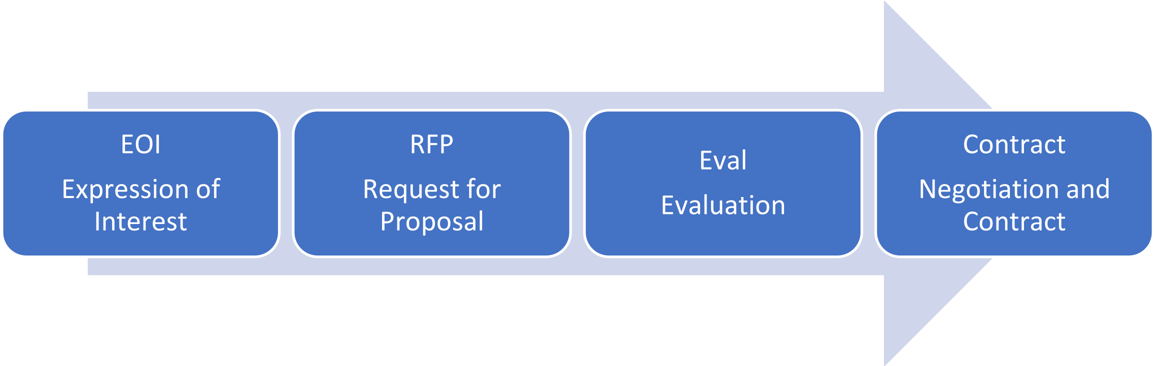

Figure 9.1 - Tender Process Flow

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8.5. Change Management and Communication

The successful implementation of digital twin systems requires the establishment of a structured change management process and effective communication across transport departments, IT teams, contractors, and consultants. The objective is to identify key stakeholders, define communication channels, and establish a reporting structure to ensure transparency and alignment. This approach facilitates timely risk identification, enables adaptive responses to changes, and keeps all project participants informed.

Change Management Plan: The initial phase involves stakeholder analysis, including DOT leadership, IT departments, BIM/IoT engineers, contractors, and subject-matter experts. Each stakeholder group is assigned a priority level and an appropriate communication format. Communication channels include email (for official notifications), the corporate CDE platform (for documentation and training sessions), and regular meetings (weekly for working groups, monthly for executive reviews). On a quarterly basis, the Steering Committee reviews and adjusts the roadmap and assesses project risks. (Table 8.5)

Table 8.5 structures the change management elements, communication channels, and frequency to ensure transparency and alignment throughout the project.

The RACI matrix is employed to clearly define roles and responsibilities among digital twin project participants: DOT, IT departments, contractors, and consultants. It

Table 8.5 – Change Management and Communication Plan

Element	Description	Frequency	Channel
Stakeholders	DOT management, IT departments, BIM/IoT engineers, contractors, consultants	Analysis at project start	Meetings, surveys
Official Notifications	KPI reports, regulatory changes, key decisions	As needed	Email newsletters
Documentation & Knowledge	Guides, technical instructions, seminar recordings	Continuous	Corporate CDE portal
Operational Meetings	Discussion of current tasks, issues, and support requests	Weekly (working groups); monthly (management)	Video conferences, office meetings
Strategic Sessions	KPI performance analysis, priority review, and roadmap update	Quarterly	Steering Committee
Weekly Reports	Status digests with progress, main risks, and requests	Weekly	Email newsletters
Monthly Reports	KPI summary (availability, latency, forecast accuracy), financial performance	Monthly	Email newsletters, CDE dashboard
Quarterly Strategies	Goal achievement review, risk assessment, roadmap adjustment	Quarterly	Steering Committee, video conferences

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helps prevent function overlap, enhances process transparency, and improves coordination of actions. Each participant is assigned one of the following roles:

Responsible (executes), Accountable (owns), Consulted (advises), and Informed (notified). This framework facilitates prompt response to changes and task monitoring.

The matrix outlines five key stages: pilot launch, CDE creation, training, scaling, and field validations. For each task, participant roles are specified, assisting

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management and IT teams in effectively tracking status and managing communication. This structured approach improves project controllability and fosters shared understanding of responsibilities among all parties. (Table 8.6)

Table 8.6 – RACI Matrix for Key Tasks

Task	DOT	IT	Contractor	Consultant
Pilot Launch	A	R	C	I
CDE Development	R	A	C	I
Staff Training	C	C	A	I
Project Scaling	A	R	C	I
Field Model Validation	C	R	A	I

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Legend:

- R (Responsible): Responsible for performing the task
- A (Accountable): Ultimately accountable and makes decisions
- C (Consulted): Consulted for advice and approvals
- I (Informed): Informed about progress and outcomes

8.6. Monitoring and Continuous Improvement

To ensure the reliability of the digital twin system and enable effective predictive maintenance, it is essential to implement continuous monitoring of key performance indicators (KPIs) and establish a process of ongoing improvement. The monitoring system should collect data on operational performance, forecast accuracy, and economic outcomes, while promptly detecting deviations beyond established thresholds. Based on the analysis of these data and user feedback, corrective actions are formulated, algorithms are updated, and processes are optimized. Regular reviews and automated notifications provide transparency and timely incident response. This approach achieves a balance between operational stability and adaptability to changing requirements and operating conditions.

KPIs and Metrics: Five key indicators have been identified to assess system performance, each with clearly defined thresholds and designated responsible personnel. System availability must be at least 99%, measured as total uninterrupted uptime of the CDE and data pipeline; this KPI is managed by the DevOps engineer. Data update latency should not exceed 2 seconds from data acquisition to display in the user interface; this is monitored by the Data Engineer. Defect model prediction accuracy (Precision/Recall) is set to a minimum of 85%, overseen by the Data Scientist. Economic efficiency is defined by thresholds of BCR ≥ 1.2 and IRR ≥ 10%, evaluated by the DOT financial analyst. Incident response time (RTO) must be less than 4 hours, for which the DevOps/IT team is responsible. Regular collection and analysis of these metrics form the basis for management decision-making and planning improvements. (Table 8.7)

Table 8.7 – Dashboard Metrics

Metric	**Threshold**	**Reporting Frequency**	**Responsible**
System Availability	≥ 99%	Monthly	DevOps Engineer
Data Update Latency	≤ 2 s	Weekly	Data Engineer
Forecast Accuracy	≥ 85%	Quarterly	Data Scientist
BCR (Benefit-Cost Ratio)	≥ 1.2	Annually	Financial Analyst
IRR (Internal Rate of Return)	≥ 10%	Annually	Financial Analyst
Incident Response Time (RTO)	< 4 hrs	On incidents	DevOps/IT Team

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Table 8.7 shows the key system metrics, their target thresholds, monitoring frequency, and responsible persons for operational control and quality management.

Cadence of Reviews and Audits. The review and audit procedure is based on three levels of control cycles. Monthly reports include summaries of operational KPIs—system availability and latency—as well as detailed analyses of incidents and corrective actions taken. Quarterly strategies focus on business metrics such as cost savings, BCR, and IRR values, along with evaluation of predictive model accuracy, followed by algorithm revisions and adjustments to the roadmap and budget. The annual audit encompasses a comprehensive review of the technical, economic, and organizational impacts of the digital twin implementation. External experts are involved to verify compliance with regulatory requirements including ISO 19650, GDPR, and FISMA. The final results of the annual audit serve as the foundation for updating development and scaling strategies for the next cycle.

8.7. Conclusion of Section 8

This section presents a comprehensive roadmap for the implementation of digital twins tailored for transport departments in the EU, the USA, and Ukraine—from pre-investment preparation through support and further development of solutions. Key regulatory and legal requirements specific to each jurisdiction have been considered, ensuring alignment of technical processes with regional regulations. A multi-level training program has been proposed to develop personnel competencies, alongside substantiated criteria and tendering methodologies for partner and contractor selection. Change management and communication mechanisms are established, supported by a clearly defined RACI matrix. A KPI system with continuous monitoring and cyclical reviews—including monthly, quarterly, and annual audits—has been defined. This model enables DOTs to effectively plan, implement, and evolve digital twins for road infrastructure, ensuring long-term economic benefits and operational reliability.

KAPITEL 9 / *CHAPTER 9*
CONCLUSION AND FUTURE PERSPECTIVES

9.1. Key Findings

Digital twins, integrating BIM and IoT technologies, have demonstrated high relevance and effectiveness in managing road and bridge infrastructure. Through continuous acquisition and analysis of sensor data, these systems enable timely identification of potentially hazardous sections and planning of preventive maintenance with minimal traffic disruptions. The integration of cloud-based CDE platforms and Big Data pipelines ensures centralized data collection, low latency, and prompt decision-making. Predictive models enhance defect forecast accuracy to a level sufficient for reducing unplanned repairs. This approach not only improves road safety but also optimizes operational and maintenance costs of infrastructure.

Within the framework of comparative economic analysis, key financial metrics were calculated for three initiatives: TEN-T (EU) with an NPV of approximately €5.2 billion, an IRR of 12%, and a BCR of 1.5; IIJA (USA) with an NPV of approximately $9.8 billion, an IRR of 11%, and a BCR of 1.3; and the “Velike Vidrodzhennya” program (Ukraine) with an NPV of approximately ₴28 billion, an IRR of 14%, and a BCR of 1.4. Positive NPV values and BCR > 1 in all cases indicate the economic feasibility of investing in digital twins and predictive maintenance. Differences in IRR reflect the specifics of regional budgetary and operational conditions, which must be considered in financing planning. The projected savings from emergency repairs and logistics delays ensure sustainable returns on investment in each case. These results confirm the validity of the CBA methodology proposed in this monograph.

Key achievements of the study include the development of a unified multilayer digital twin architecture that integrates both functional and non-functional components with corporate CDE environments and Big Data pipelines. The selection and integration of sensor technologies—FBG sensors, piezoelectric elements, WIM devices, and LiDAR—were substantiated for comprehensive monitoring of transport structures. A seamless data processing pipeline was constructed (Edge → Kafka →

Flink → TSDB → visualization), alongside the development of ML/DL algorithms for predictive maintenance, including Random Forest (RF), XGBoost, LSTM, CNN, and GNN models. A comparative economic analysis was conducted, demonstrating high IRR and BCR values, confirming the effectiveness and soundness of the proposed solutions. This monograph lays the groundwork for further research and practical implementations across various jurisdictions.

Practical recommendations include a phased roadmap for implementation targeted at transport departments—from pilot projects through scaling and institutionalization to long-term support and development. A three-tier training program tailored for managers, engineers, and experts is presented, alongside substantiated partner and contractor selection criteria utilizing a RACI matrix and a tendering process. A framework for continuous KPI monitoring and cyclical reviews (monthly, quarterly, and annual) is proposed to ensure timely strategy and model adjustments. These recommendations enable DOTs to effectively plan, execute, and advance digital twin systems, achieving sustained economic and operational efficiency.

9.2. Research Limitations

This section addresses the key limitations of the proposed methodology for the creation and implementation of digital twins in road infrastructure. Identifying these limitations helps to delineate the applicability boundaries of the results and to define directions for future improvements. Most of the identified limitations relate to data availability, the scale of pilot testing, and the need to adapt models to varying conditions. Awareness of these factors is crucial for the accurate interpretation of financial and technical indicators obtained. A systematic overview of the main limitations and their justification is provided below. (Table 9.1)

Notes to Table 9.1: The listed limitations highlight key areas where additional data and research are needed to enhance the reliability and universality of the methodology. In particular, expanding sensor networks and conducting pilot projects across diverse regions will allow refinement of initial model parameters and

Table 9.1 – Research Limitations

Limitation	Justification
Availability of real data	Sensor networks are not yet fully deployed at many sites, reducing completeness and representativeness of the sample.
Scale of pilot cases	Economic analysis is based on a limited number of demonstration projects, which may not capture practice variability.
Accuracy of ML/DL models	Developed algorithms require fine-tuning and adaptation to different climate zones and structural features.
Regional regulatory differences	The methodology needs adaptation to legal and technical standards of countries beyond the EU, USA, and Ukraine.

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improvement of economic calculations. Enhanced calibration of ML/DL algorithms to local conditions will enable more accurate defect prediction and achieve a stable level of precision. Adapting the methodology to varying regulatory requirements will broaden the applicability of the solution to other jurisdictions. Addressing these limitations will be a priority in subsequent phases of scientific and practical work.

9.3. Directions for Future Research

To deepen and expand the proposed methodology, it is advisable to identify priority research directions that will help increase the efficiency and versatility of digital twins in road infrastructure. First, new types of sensor devices and data collection platforms suitable for complex conditions need to be covered. Second, advanced machine learning methods that take regional specificities into account should be developed. Third, integration of digital twins into broader “smart city” ecosystems and national data processing platforms is crucial. Furthermore, the development of unified standards and enhancement of system resilience against external threats will create a foundation for widespread technology adoption. Below are six key areas for further scientific investigation.

Expansion of the Standard Sensor Suite. A priority is the implementation of wireless energy-harvesting sensors capable of autonomous operation powered by vibration or solar energy. This will enable coverage of remote or poorly electrified areas without the costs associated with cable installation. Additionally, the use of drones and mobile platforms for rapid aerial photography and LiDAR scanning of hard-to-reach zones is promising. Combining stationary and mobile sensors will create a more comprehensive picture of infrastructure condition and reduce data update latency. Research should focus on integrating such sensor networks into a unified CDE architecture and ensuring reliable data transmission.

Deep Transfer Learning for Predictive Models. The development of transfer learning methods will enable the adaptation of pre-trained ML/DL models across regions, accounting for climatic, geometric, and operational differences. This approach will reduce the time required to train new models and decrease the dependence on large volumes of local data. Research should focus on architectures optimized for adaptive calibration on new datasets while maintaining high prediction accuracy. An important aspect will be the automation of hyperparameter tuning and quality control during model transfer. Such solutions will accelerate the deployment of predictive algorithms across different jurisdictions and operational conditions.

Integration of Digital Twins with Smart City Ecosystems. The next step involves integrating digital twins of the road network with other urban management systems related to transportation, energy, and environmental monitoring. This includes data exchange with intelligent traffic lights and mobile transport applications to optimize routes and reduce congestion. Simultaneously, the impact of road works on air quality and energy consumption should be considered by incorporating environmental indicators into digital twin models. This will enable the formulation of balanced solutions that minimize negative effects on the environment and urban residents. Research efforts should focus on developing standardized APIs and protocols to synchronize all smart city components.

Creation of a Unified Data Hub. The concept of an industry-wide Data Hub implies a centralized platform with a unified KPI monitoring dashboard, combining Big Data pipelines and analytical services. This system will store sensor telemetry, BIM model versions, and ML analysis results accessible to all regional departments and contractors. Such centralization will reduce duplicated efforts, accelerate innovation integration, and enhance data transparency. It is essential to investigate storage architectures and metadata management, ensuring scalability and high availability. Establishing a Data Hub will facilitate collaborative research and cross-regional projects based on a shared data foundation.

Development of National and International DT Standards. The unification of APIs, semantic ontologies, and cybersecurity protocols across countries and organizations is a key direction for ensuring solution interoperability. Collaboration with buildingSMART, ISO/IEC, and industry regulators is necessary to incorporate digital twin requirements into DOT standards and national regulations. This will simplify tendering procedures and reduce barriers to large-scale deployment. Research should focus on standardizing data exchange formats and security requirements. As a result, globally recognized guidelines for the design and operation of digital twins in road infrastructure will emerge.

Research on Resilience to Cyber and Physical Attacks. An integral part of enhancing the reliability of digital twin systems is modeling attack vectors targeting IoT devices, data transmission networks, and the corporate CDE environment. Mechanisms for anomaly detection must be developed not only for physical parameters but also for network and application behavior, including machine learning methods for cybersecurity. It is important to investigate redundancy and isolation schemes for critical components, as well as protocols for incident response. Furthermore, the resilience of sensor networks to physical impacts should be assessed, and fault tolerance testing conducted. These studies will form the basis for developing comprehensive protection measures for digital twins in real operational environments.

9.4 Practical Pilots and Test Zones

This subsection identifies specific pilot projects and test zones for validating the proposed digital twin methodology and assessing its effectiveness based on key technical and economic indicators. Representative sites with diverse climatic and infrastructural characteristics have been selected for each jurisdiction — the EU, the

USA, and Ukraine. The objective is to verify the reliability of the Big Data pipeline, the accuracy of predictive models, and the implementation impact on real roadways. Special attention is given to comprehensive data collection, real-time processing, and comparison with historical benchmarks. Pilot results will enable refinement of the methodology, algorithm adjustments, and ROI evaluation during the initial years of operation. Below are details of demonstration cases and a baseline set of metrics to assess pilot success.

Development of Demonstration Cases. In the EU, the pilot expands to five additional Core Corridors, including North-South and West-East routes across Austria, Poland, Germany, and France. The plan is to test the Big Data pipeline’s resilience under varying road configurations, evaluate repair cost savings, and reduce logistics delays on each corridor. In the USA, one federal highway is selected in California, Texas, and New York to test data acquisition via NB-IoT and 5G networks and validate ML models under hot and humid climates. In Ukraine, the pilot scales to secondary roads and bridges in Kyiv, Poltava, and Odesa regions, assessing reductions in unplanned repairs in rural and suburban areas, as well as winter operation experience. All three cases will be equipped with a unified sensor set and operational ML algorithms for result comparability. This approach will identify best practices and specific challenges in deploying digital twins across different regions.

Pilot Metrics and Objectives. For objective evaluation of pilot sites, five metrics with target thresholds and brief notes have been selected. Reduction in unplanned repairs is measured against historical levels and should be at least 25%. System availability is calculated considering extreme weather conditions and must exceed 99.9%. Defect prediction accuracy (Precision/Recall) is set at no less than 90% when validated on a holdout sample. End-to-end latency from data acquisition to visualization should not exceed 1.5 seconds. ROI during the first two pilot years is targeted at ≥ 1.2, accounting for savings in emergency costs. These metrics are formulated based on industry standards and will provide a comprehensive assessment of both technical and economic success of the demonstration cases. (Table 9.2)

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Table 9.2 – Pilot Metrics and Target Values

Metric	Target Value	Note
Reduction in Unplanned Repairs	≥ 25%	Compared to historical data
System Availability	≥ 99.9%	Considering extreme weather conditions
Defect Forecast Accuracy	≥ 90%	Precision/Recall on hold-out dataset
Full Cycle Latency	≤ 1.5 s	From sensor to dashboard visualization
ROI in First 2 Years of Pilot	≥ 1.2	Accounting for reduced accident costs

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Table 9.2 - presents metrics selected based on industry goals and enables objective assessment of benefits and technical performance of pilot sites.

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Verweise / References

1. World Economic Forum (2023) Global Risks Report 2023 [online]. Available at: https://www.weforum.org/reports/global-risks-report-2023 (Accessed: 17 June 2025).
2. Directorate General for Mobility and Transport (European Commission) (2024) Transport in the European Union: Current Trends and Issues [online]. Available at: https://transport.ec.europa.eu (Accessed: 17 June 2025).
3. European Investment Bank (2023) Infrastructure Report 2023 [online]. Available at: https://www.eib.org/en/publications-research/economics/research/index (Accessed: 17 June 2025).
4. European Court of Auditors (2023) Special Report: Managing EU Transport Infrastructure [online]. Available at: https://www.eca.europa.eu/en/search-publications (Accessed: 17 June 2025).
5. Eurostat (2024) Transport Infrastructure Statistics [online]. Available at: https://ec.europa.eu/eurostat/web/main/publications (Accessed: 17 June 2025).
6. American Society of Civil Engineers (2023) 2023 Infrastructure Report Card [online]. Available at: https://infrastructurereportcard.org (Accessed: 17 June 2025).
7. U.S. Department of Transportation (2024) Economic Impacts of Poor Road Conditions [online]. Available at: https://www.transportation.gov/ (Accessed: 17 June 2025).
8. U.S. Congress (2021) Infrastructure Investment and Jobs Act (Public Law No. 117-58) [online]. Available at: https://www.congress.gov/ (Accessed: 17 June 2025).
9. Ministry for Communities and Territories Development of Ukraine (2024) Report on the Condition of Roads and Bridges [online]. Available at: https://mindev.gov.ua/npasearch?&tags=budivnictvo (Accessed: 17 June 2025).
10. State Statistics Service of Ukraine (2024) Infrastructure in Figures [online]. Available at: https://ukrstat.gov.ua/ (Accessed: 17 June 2025).
11. Transportation Today News (2024) Economic impacts of poor road conditions

 ISBN 978-3-98924-099-5

[online]. Available at: https://transportationtodaynews.com/news/26014-trip-report-finds-40-percent-of-nations-roads-in-poor-or-mediocre-condition/ (Accessed: 17 June 2025).

12. American Transportation Research Institute (2024) Cost of Congestion to the Trucking Industry [online]. Available at: https://truckingresearch.org/2024/12/truckings-annual-congestion-costs-rise-to-108-8-billion/ (Accessed: 17 June 2025).
13. Eurostat (2023) Transport Accident Costs in the EU [online]. Available at: https://ec.europa.eu/eurostat/statistics-explained/index.php (Accessed: 17 June 2025).
14. Slovoidilo UA & MinInfra UA (2025) Program "Velyke Vidnovlennia" Funding [online]. Available at: https://minfin.com.ua/2025/03/31/148106518/ (Accessed: 17 June 2025).
15. World Health Organization (2023) Global status report on road safety [online]. Available at: https://www.who.int/news/item/13-12-2023-despite-notable-progress-road-safety-remains-urgent-global-issue (Accessed: 17 June 2025).
16. European Commission (2024) Road Safety Statistics 2023 [online]. Available at: https://transport.ec.europa.eu/news-events/news/20400-lives-lost-eu-road-crashes-last-year-2024-10-10_en (Accessed: 17 June 2025).
17. Reuters (2024) US traffic fatalities 2023 [online]. Available at: https://www.reuters.com/world/us/us-traffic-deaths-down-36-2023-above-pre-pandemic-levels-2024-04-01/ (Accessed: 17 June 2025).
18. Ouhbi, S., Ait El Cadi, A., Abouqal, R. and Idoumghar, L. (2022) 'Internet of Things (IoT) for Structural Health Monitoring', Buildings, 12(10), p. 1503. doi: 10.3390/buildings12101503.
19. Rehman, M.H.U., Hussain, F., Khan, A., et al. (2023) 'Big Data Analytics for Infrastructure: Techniques, Challenges, and Future Directions', Data Science and Engineering. doi: 10.1007/s41019-023-00236-5.
20. European Commission CORDIS (2024) iDriving Project [online]. Available at: https://cordis.europa.eu/project/id/101147004 (Accessed: 17 June 2025).

21. Local Infrastructure (2024) Chattanooga SMART C-V2X Pilot [online]. Available at: https://localinfrastructure.org/resources/funding-technology-driven-innovations-in-transportation-safety-through-the-bil-in-chattanooga/ (Accessed: 17 June 2025).
22. Federal Highway Administration (2024) ATTAIN Grants Overview [online]. Available at: https://ops.fhwa.dot.gov/infrastructure-investment-and-jobs-act/ATTAIN/fy2023-2024/awards/ (Accessed: 17 June 2025).
23. Interfax Ukraine (2025) Kyiv LoRaWAN Network [online]. Available at: https://en.interfax.com.ua/news/general/795974.html (Accessed: 17 June 2025).
24. BIMBOSS (2024) Digital twins vs. building information modeling [online]. Available at: https://bimboss.com/digital-twins-vs-building-information-modeling (Accessed: 17 June 2025).
25. Autodesk University (2023) ISO 19650, CDE and DT Architectures [online]. Available at: https://www.autodesk.com/autodesk-university/article/ISO-19650-Common-Data-Environment-and-Autodesk-Construction-Cloud (Accessed: 17 June 2025).
26. Rehman, M.H.U., Faisal, M., Jan, M.A., et al. (2023) 'Key Sensor Technologies for Road Monitoring Applications: A Review', Sensors, 23(9), p. 4469. doi: 10.3390/s23094469.
27. Pan, Y., Chen, B., Wu, J., et al. (2023) 'A Predictive Maintenance Model Based on Deep Learning for Road Pavement', Applied Sciences, 13(10), p. 5765. doi: 10.3390/app13105765.
28. Ding, Y., Dai, H., Zhang, Y., et al. (2024) Scan to BIM for As-Built Roads: Automatic Road Digital Twinning from Semantically Labeled Point Cloud Data [online]. Available at: https://arxiv.org/abs/2406.12404 (Accessed: 17 June 2025).
29. Cherniavska, T. and Cherniavskyi, B. (2025) 'Digital Reconstructor: Integration of Digital Twins for the Reconstruction and Remediation of War-Affected Territories in Ukraine', in UKLO Annual International Scientific Conference 2024 – A Multidisciplinary Approach to Sustainable Development Goals (Bitola,

June 2025). doi: 10.20544/AISC.1.1.25.P13.

30. Habrat, W., Sala, D. and Klimek, R. (2024) 'Evolution of Digital Twin Frameworks in Bridge Management', Remote Sensing, 16(11), p. 1887. doi: 10.3390/rs16111887.
31. Xu, J. and Zhang, Y. (2025) 'AI-Powered Digital Twin Technology for Highway System Slope Stability Risk Monitoring', Geotechnics, 5(1), p. 19. doi: 10.3390/geotechnics5010019.
32. Grieves, M. (2002) Product Lifecycle Management for a Global Enterprise. White Paper [online]. Available at: http://www.grievesandvickers.com/wp-content/uploads/2016/12/Grieves_2002_Digital_Twin_White_Paper-1.pdf (Accessed: 17 June 2025).
33. Glaessgen, E. and Stargel, D. (2012) The Digital Twin Paradigm for Future NASA and U.S. Air Force Vehicles, NASA/TM 2012-217680 [online]. Available at: https://ntrs.nasa.gov (Accessed: 17 June 2025).
34. ISO/DIS 23247 (2024) Industrial Digital Twin—Reference Architecture [online]. International Organization for Standardization. Available at: https://www.iso.org/standard/84626.html (Accessed: 17 June 2025).
35. UK BIM Framework (2021) UK BIM Framework Guidance Documents [online]. Available at: https://www.ukbimframework.org (Accessed: 17 June 2025).
36. International Organization for Standardization (ISO) (2021–2024) Organization and digitization of information about buildings and civil engineering works using BIM (ISO 19650-1/2/3/5) [online]. Available at: https://www.iso.org/ (Accessed: 17 June 2025).
37. buildingSMART (2023) Industry Foundation Classes (IFC) Overview [online]. Available at: https://technical.buildingsmart.org/standards/ifc/ (Accessed: 17 June 2025).
38. UK BIM Framework (2022) BIM Levels Explained [online]. Available at: https://imiframework.org/ (Accessed: 17 June 2025).
39. ISO 19650-2:2018 (2018) Organization and digitization of information about buildings and civil engineering works, including building information modelling

(BIM) — Part 2: Delivery phase of the assets [online]. International Organization for Standardization. Available at: https://www.iso.org/standard/68078.html (Accessed: 17 June 2025).

40. ISO 19650-3:2020 (2020) Organization and digitization of information about buildings and civil engineering works, including building information modelling (BIM) — Part 3: Operational phase of the assets [online]. International Organization for Standardization. Available at: https://www.iso.org/standard/73150.html (Accessed: 17 June 2025).
41. Open Geospatial Consortium (2016) OGC® SensorThings API Standard [online]. Available at: https://www.ogc.org/standards/sensorthings (Accessed: 17 June 2025).
42. OASIS (2013) MQTT Version 3.1.1. OASIS Standard [online]. Available at: https://docs.oasis-open.org/mqtt/mqtt/v3.1.1/mqtt-v3.1.1.html (Accessed: 17 June 2025).
43. LoRa Alliance (2018) LoRaWAN™ Specification v1.0.2 [online]. Available at: https://lora-alliance.org/resource_hub/lorawan-specification-v1-0-2/ (Accessed: 17 June 2025).
44. OPC Foundation (2017) OPC Unified Architecture [online]. Available at: https://opcfoundation.org/about/opc-technologies/opc-ua/ (Accessed: 17 June 2025).
45. 3GPP (2016) NB-IoT (Release 13). 3GPP Technical Specification [online]. Available at: https://www.3gpp.org/specifications (Accessed: 17 June 2025).
46. 3GPP (2018) 5G – New Radio (Release 15). 3GPP Technical Specification [online]. Available at: https://www.3gpp.org/specifications (Accessed: 17 June 2025).
47. OASIS (2019) MQTT Version 5.0 [online]. Available at: https://docs.oasis-open.org/mqtt/mqtt/v5.0/mqtt-v5.0.html (Accessed: 17 June 2025).
48. LoRa Alliance (2020) LoRaWAN® Specification v1.0.4 [online]. Available at: https://lora-alliance.org/ (Accessed: 17 June 2025).
49. Open Geospatial Consortium (2012) CityGML 2.0.0 – OGC® Standard [online].

 ISBN 978-3-98924-099-5

Available at: https://www.ogc.org/standards/citygml (Accessed: 17 June 2025).
50. ISO (2018) ISO 37120: Sustainable development of communities — Indicators for city services and quality of life [online]. International Organization for Standardization. Available at: https://www.iso.org/standard/62436.html (Accessed: 17 June 2025).
51. ISO (2019) ISO 37122: Smart community infrastructures [online]. International Organization for Standardization. Available at: https://www.iso.org/standard/75019.html (Accessed: 17 June 2025).
52. NIST (2022) NIST Digital Twin Framework, NIST SP 1270 [online]. Available at: https://doi.org/10.6028/NIST.SP.1270 (Accessed: 17 June 2025).
53. European Commission (2021) Digital Twin for Cities and Regions: Horizon Europe Concepts [online]. Available at: https://digital-strategy.ec.europa.eu/en/library (Accessed: 17 June 2025).
54. ISO/IEC JTC 1/SC 41 (2023) Reference Architecture for Digital Twins [online]. International Organization for Standardization. Available at: https://www.iso.org/standard/84545.html (Accessed: 17 June 2025).
55. Google (n.d.) UX Guidelines for Dashboards [online]. Available at: https://developers.google.com (Accessed: 17 June 2025).
56. Amazon Web Services (n.d.) Recovery Time Objective (RTO) & Recovery Point Objective (RPO) [online]. Available at: https://docs.aws.amazon.com/ (Accessed: 17 June 2025).
57. Kubernetes (n.d.) Multi Zone Rescheduling Strategies [online]. Available at: https://kubernetes.io/docs/home/ (Accessed: 17 June 2025).
58. Prometheus/Grafana Monitoring (n.d.) Overview [online]. Available at: https://prometheus.io/docs/introduction/overview/ (Accessed: 17 June 2025).
59. IETF (n.d.) RFC 8446: The Transport Layer Security (TLS) Protocol Version 1.3 [online]. Available at: https://tools.ietf.org/html/rfc8446 (Accessed: 17 June 2025).
60. IETF (n.d.) RFC 6749: The OAuth 2.0 Authorization Framework [online]. Available at: https://tools.ietf.org/html/rfc6749 (Accessed: 17 June 2025).

61. International Organization for Standardization (n.d.) ISO 27001: Information Security Management [online]. Available at: https://www.iso.org/standard/54534.html (Accessed: 17 June 2025).
62. European Union (2016) Regulation (EU) 2016/679 (General Data Protection Regulation) [online]. Available at: https://eur-lex.europa.eu/eli/reg/2016/679/oj (Accessed: 17 June 2025).
63. Kubernetes (n.d.) Horizontal Pod Autoscaling (HPA) [online]. Available at: https://kubernetes.io/docs/tasks/run-application/horizontal-pod-autoscale/ (Accessed: 17 June 2025).
64. Timescale (n.d.) TimescaleDB Hypertables & Sharding [online]. Available at: https://docs.tigerdata.com/ (Accessed: 17 June 2025).
65. Kim, G., Humble, J., Debois, P. and Willis, J. (2016) The DevOps Handbook: How to Create World Class Agility, Reliability, and Security in Technology Organizations [online]. Available at: https://itrevolution.com/book/the-devops-handbook/ (Accessed: 17 June 2025).
66. OpenTelemetry Community (n.d.) OpenTelemetry: Observability Framework for Cloud Native Software [online]. Available at: https://opentelemetry.io/ (Accessed: 17 June 2025).
67. International Organization for Standardization (n.d.) IEC 60068: Environmental Testing [online]. Available at: https://www.iso.org/standard/29571.html (Accessed: 17 June 2025).
68. Apache Software Foundation (n.d.) Apache Kafka Streams [online]. Available at: https://kafka.apache.org/documentation/streams/ (Accessed: 17 June 2025).
69. Delta Lake Community (n.d.) Delta Lake: Open Format Storage Layer [online]. Available at: https://delta.io/ (Accessed: 17 June 2025).
70. Apache Software Foundation (n.d.) Apache Spark MLlib: Machine Learning Library [online]. Available at: https://spark.apache.org/mllib/ (Accessed: 17 June 2025).
71. Cesium (n.d.) CesiumJS: Virtual Globe and Map Engine [online]. Available at: https://cesium.com/platform/cesiumjs/ (Accessed: 17 June 2025).

72. buildingSMART (n.d.) BCF API Specification (BCF 2.1) [online]. Available at: https://github.com/buildingSMART/BCF-API/ (Accessed: 17 June 2025).
73. International Organization for Standardization (n.d.) ISO 8601: Data Elements and Interchange Formats – Information Interchange – Representation of Dates and Times [online]. Available at: https://www.iso.org/iso-8601-date-and-time-format.html (Accessed: 17 June 2025).
74. OpenAPI Initiative (n.d.) OpenAPI Specification 3.0 [online]. Available at: https://swagger.io/specification/ (Accessed: 17 June 2025).
75. Mozilla Developer Network (n.d.) WebSocket API [online]. Available at: https://developer.mozilla.org/docs/Web/API/WebSockets_API (Accessed: 17 June 2025).
76. González-Vila, Á., Ortega-González, F., Roldán-García, C. and Cruz-García, L. (2024) ‘Fiber Bragg Grating Sensors: Design, applications, and comparison’, Sensors, 25(7), p. 2289. https://doi.org/10.3390/s25072289
77. Qiao, P., Tang, X., Xu, B. and Zhang, W. (2020) ‘Detection of moving load on pavement using piezoelectric sensors’, Sensors, 20(8), p. 2366. https://doi.org/10.3390/s20082366
78. Liu, X., Yang, Z. and Shi, B. (2025) ‘Weigh in Motion method based on modular sensor system and neural network axle recognition’, Applied Sciences, 13(2), p. 614. https://doi.org/10.3390/app15020614
79. buildingSMART (n.d.) BCF 2.1 specification [online]. Available at: https://technical.buildingsmart.org/standards/bcf/ (Accessed: 17 June 2025).
80. buildingSMART (n.d.) COBie data exchange guide [online]. Available at: https://technical.buildingsmart.org/standards/ (Accessed: 17 June 2025).
81. Autodesk (n.d.) Revit API Developer Guide — FamilyInstance.NewFamilyInstance [online]. Available at: https://help.autodesk.com/view/RVT/2025/ENU/?guid=Revit_API_Revit_API_Developers_Guide_Revit_Geometric_Elements_Family_Instances_FamilyInstances_html (Accessed: 17 June 2025).
82. Autodesk (n.d.) Revit API — LookupParameter method [online]. Available at:

https://help.autodesk.com/view/RVT/2025/ENU/?guid=Revit_API_Revit_API_Developers_Guide_Basic_Interaction_with_Revit_Elements_Parameters_html (Accessed: 17 June 2025).

83. IfcOpenShell (n.d.) IfcOpenShell [online]. Available at: https://github.com/IfcOpenShell/IfcOpenShell (Accessed: 17 June 2025).
84. Amazon Web Services (n.d.) IoT Core protocols and protocol services [online]. Available at: https://docs.aws.amazon.com/iot/latest/developerguide/protocols.html (Accessed: 17 June 2025).
85. OASIS (n.d.) AMQP 1.0 core protocol overview [online]. Available at: https://docs.oasis-open.org/amqp/core/v1.0/amqp-core-overview-v1.0.html (Accessed: 17 June 2025).
86. Apache Software Foundation (n.d.) Apache Kafka: Protocol guide [online]. Available at: https://kafka.apache.org/protocol (Accessed: 17 June 2025).
87. Internet Engineering Task Force (2014) RFC 7231: Hypertext Transfer Protocol (HTTP/1.1): Semantics and content [online]. Available at: https://tools.ietf.org/html/rfc7231 (Accessed: 17 June 2025).
88. Internet Engineering Task Force (2011) RFC 6455: The WebSocket Protocol [online]. Available at: https://tools.ietf.org/html/rfc6455 (Accessed: 17 June 2025).
89. EUROCONTROL (n.d.) Standard inputs for cost–benefit analysis [online]. Available at: https://ansperformance.eu/economics/cba/standard-inputs/latest/chapters/discount_rate.html (Accessed: 17 June 2025).
90. The White House (2023) OMB Circular A-94, Appendix D [online]. Available at: https://www.whitehouse.gov/wp-content/uploads/2023/11/CircularA-94AppendixD.pdf (Accessed: 17 June 2025).
91. Ministry of Infrastructure of Ukraine (n.d.) Methodological Guidelines – Economic Assessment of "The Great Recovery" [online]. Available at: https://mtu.gov.ua/ (Accessed: 17 June 2025).
92. European Commission (n.d.) Multiannual Financial Framework 2024–2029

[online]. Available at: https://commission.europa.eu/priorities-2024-2029_en (Accessed: 17 June 2025).

93. U.S. Department of Transportation (n.d.) USDOT reports on IIJA implementation [online]. Available at: https://www.transportation.gov/sites/dot.gov/files/docs/OMB%20Circular%20A-94.pdf (Accessed: 17 June 2025).
94. U.S. Department of Transportation (n.d.) Infrastructure Investment and Jobs Act (IIJA) [online]. Available at: https://www.transportation.gov/infrastructure-investment-and-jobs-act (Accessed: 17 June 2025).
95. European Court of Auditors (2025) Special Report 13/2025: Support from the Recovery and Resilience Facility for the digital transition in EU member states [online]. Available at: https://www.eca.europa.eu/en/publications/sr-2025-13 (Accessed: 17 June 2025).
96. FHWA Office of Policy (2023) Predictive maintenance report [online]. Available at: https://www.fhwa.dot.gov/policy/publications.cfm (Accessed: 17 June 2025).
97. Ministry of Infrastructure of Ukraine (n.d.) The Great Recovery [online]. Available at: https://data.gov.ua (Accessed: 17 June 2025).
98. Eurostat (2023) Transport statistics explained [online]. Available at: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Articles_by_theme#Transport (Accessed: 17 June 2025).
99. USDOT Bureau of Transportation Statistics (2023) Statistical products [online]. Available at: https://www.transportation.gov/dot-strategic-plan (Accessed: 17 June 2025).
100. State Statistics Service of Ukraine (2023) Section “Transport” [online]. Available at: https://ukrstat.gov.ua/ (Accessed: 17 June 2025).
101. European Union (2021) Regulation (EU) 2021/1153 of the European Parliament and of the Council of 24 June 2021 establishing the Connecting Europe Facility [online]. Available at: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32021R1153 (Accessed: 17 June 2025).

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102. European Union (2022) Directive (EU) 2022/2555 on measures for a high common level of cybersecurity across the Union (NIS 2) [online]. Available at: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32022L2555 (Accessed: 17 June 2025).
103. Office of Management and Budget (2017) OMB Circular A–16: Coordination of Geographic Information and Related Spatial Data Activities [online]. Available at: https://www.fgdc.gov/policyandplanning/a-16/circular-a-16 (Accessed: 17 June 2025).
104. United States Congress (2020) Federal Information Security Modernization Act of 2014 (H.R. 1676 – 116th Congress) [online]. Available at: https://www.congress.gov/bill/116th-congress/house-bill/1676 (Accessed: 17 June 2025).
105. National Institute of Standards and Technology (2020) NIST Special Publication 800-53 Revision 5: Security and Privacy Controls for Information Systems and Organizations [online]. Available at: https://nvlpubs.nist.gov/nistpubs/SpecialPublications/NIST.SP.800-53r5.pdf (Accessed: 17 June 2025).
106. National Institute of Building Sciences (n.d.) NBIMS-US V4 BEP Template [online]. Available at: https://nibs.org/nbims/v4/resources/ (Accessed: 17 June 2025).
107. Cabinet of Ministers of Ukraine (2021) Strategy of digital development, digital transformations and digitalization of public finance management system until 2030 [online]. Available at: https://zakon.rada.gov.ua/go/1467-2021-p (Accessed: 17 June 2025).
108. Cabinet of Ministers of Ukraine (2024) Approval of the Strategy for Digital Development of Innovation Activities of Ukraine until 2030 and the Operational Plan for its Implementation in 2025–2027 [online]. Available at: https://zakon.rada.gov.ua/go/1351-2024-p (Accessed: 17 June 2025).
109. Verkhovna Rada of Ukraine (2021) Law of Ukraine No. 2163-IX "On Information Security" [online]. Available at: https://zakon.rada.gov.ua/laws/show/2163-IX
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(Accessed: 17 June 2025).

110. Protopopova, Z.V. (2025) 'AI-driven quality assurance in SME construction: An IoT-based cost optimization case study', SWorldJournal, Issue 31 (Part 1), pp. 156–165. doi: 10.30888/2663-5712.2025-31-01-079.
111. Ye, Z., Wei, Y., Yang, S., Li, P., Yang, F., Yang, B. and Wang, L. (2024) 'IoT-enhanced smart road infrastructure systems for comprehensive real-time monitoring', Internet of Things and Cyber-Physical Systems, 4, pp. 235–249. doi: 10.1016/j.iotcps.2024.01.002.
112. Mousavi, V., Rashidi, M., Mohammadi, M. and Samali, B. (2024) 'Evolution of digital twin frameworks in bridge management: review and future directions', Remote Sensing, 16(11), p. 1887. doi: 10.3390/rs16111887.
113. European Parliament (2014) EU road surfaces: economic and safety impact of the lack of regular road maintenance [online]. Available at: https://www.europarl.europa.eu/RegData/etudes/STUD/2014/529059/IPOL_STU%282014%29529059_EN.pdf (Accessed: 17 June 2025).
114. Ultralytics (2024) Advanced data visualization: Heatmaps using Ultralytics YOLO11 [online]. Available at: https://docs.ultralytics.com/guides/heatmaps/#real-world-applications (Accessed: 17 June 2025).

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About the Author

Digital Transformation in Modern Construction: From BIM to Intelligent Ecosystems

This monograph serves as a comprehensive guide to implementing cutting-edge digital technologies within the real-world constraints of modern construction. Its core is the synergy between Building Information Modeling (BIM). Artificial Intelligence (AI), and the Internet of Infrastructure (Digital Twin/IoT).

While the research focuses specifically on roadway infrastructure and bridge engineering, the principles of Digital Twin management presented here are universal and applicable to civil engineering projects at large. The author advocates for a transition from theoretical modeling to the creation of intelligent ecosystems that ensure structural durability and safety throughout the entire lifecycle.

Zinaida Kornilova is a researcher and expert in Civil Engineering, specializing in Digital Twin technology, AI, and BIM for **infrastructure and complex engineering structures.** She is dedicated to implementing intelligent solutions that enhance the safety, durability, and efficiency of modern construction and transportation networks.

This book is an essential resource for:

- Design Engineers & Builders seeking to integrate BIM and AI to optimize current project **workflows**.
- Infrastructure Operators interested in data-driven predictive maintenance.
- Industry Leaders & Policy Makers responsible for Smart City development and digital transformation.
- Researchers & Students in Civil Engineering and Infrastructure Management.

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