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Digital Twins in Civil Engineering Creating Digital Replicas of Physical Structures to Predict Maintenance Needs, Optimize Performance, And Reduce Costs

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Abstract- The construction industry faces challenges such as low productivity, lack of expertise, weak innovation, and poor predictability. Digital Twin (DT) technology is transforming civil engineering by creating virtual replicas of physical assets that enable real-time data collection, simulation, and predictive analysis. DTs enhance design, construction, operation, and maintenance by improving accuracy, efficiency, and sustainability. Key technologies such as artificial intelligence (AI), the Internet of Things (IoT), and augmented reality (AR) support DT applications, optimizing performance and reducing costs. However, challenges like poor data quality, integration issues, and data security concerns hinder widespread adoption. Further research is needed to address these challenges and accelerate the development of DTs in construction. Despite these hurdles, DTs offer significant potential to revolutionize infrastructure management, enabling predictive maintenance and intelligent decision-making for a smarter and more efficient built environment.

Keywords: Digital Twin, Civil Engineering, Predictive Maintenance, IoT, Artificial Intelligence etc.

I. INTRODUCTION

The concept of the digital twin has gained significant attention in recent years, particularly within engineering and construction, as advancements in technology and the economy have driven innovation in the fields of the Internet of Things (IoT) and the metaverse. Digital twins serve as virtual representations of physical assets, systems, or processes, created by integrating real-time feedback data with advanced technologies such as artificial intelligence (AI), machine learning (ML), and software analytics. This enables digital twins to simulate, monitor, and adapt to changes in the physical world with remarkable accuracy and efficiency.

A digital twin operates on the principle of bidirectional communication between physical and virtual environments. Sensors embedded in the physical entity collect real-time data, which is analyzed and used to update the digital model. This dynamic interaction allows the digital twin to reflect the current state of its physical counterpart and predict future performance, offering valuable insights for optimization and decision-making. When combined with AI and ML, digital twins can learn from historical and real-time data, enhancing their ability to simulate scenarios, detect anomalies, and provide predictive analytics.

In the construction and engineering domains, digital twins are redefining how projects are designed, executed, and maintained throughout their lifecycle. During the design phase, digital twins enable accurate modeling and simulation, reducing errors and improving efficiency. During construction, they facilitate real-time monitoring and optimization, ensuring adherence to project schedules and budgets. In the operation and maintenance phases, digital twins support predictive maintenance, energy efficiency, and sustainability by continuously analyzing performance data and identifying potential issues before they occur.

Despite their transformative potential, the adoption of digital twins in construction faces challenges. These include data quality issues, difficulties in integrating diverse systems, and concerns over data security and privacy. Furthermore, the industry must address the need for skilled technical manpower and robust methodologies to harmonize disparate data sources.

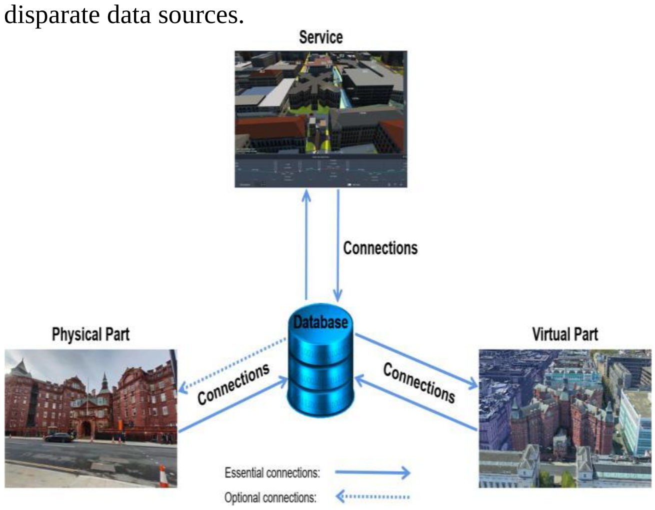

Figure 1.Predictive digital twin structures

As digital twin technology continues to evolve, its applications are expanding beyond traditional uses to include structural health monitoring, energy management, seismic evaluation, and heritage building preservation. The integration of digital twins with IoT, augmented reality, and cyber-physical systems is driving the construction industry toward greater efficiency, sustainability, and innovation. Overcoming existing challenges will unlock the full potential of digital twins, transforming the future of engineering and construction.

This project analyses the use of digital twins in smart construction through a case study approach, thus illustrating the role of digital twins in smart construction. The application of the digital twin in smart construction will facilitate the transformation and upgrading of the construction industry at home and abroad and will be beneficial for practitioners in the construction industry to efficiently and comprehensively simulate and control the whole life cycle of a building, from design and construction to use.

II. PROBLEM IDENTIFICATION

- Project Management Issues: Traditional methods struggle with modern infrastructure demands, causing delays, cost overruns, and inefficiencies.
- Lack of Real-Time Monitoring: Absence of accurate forecasting leads to reactive decision-making rather than proactive planning.
- Data Management Challenges: Poor data quality, fragmented systems, and lack of integration hinder optimization and risk mitigation.
- Technical Expertise Gap: Limited knowledge of advanced technologies like digital twins slows adoption and implementation.
- Data Security Concerns: Fear of breaches and privacy issues prevent widespread use of digital solutions.
- Sustainability Challenges: Inadequate tools to track energy efficiency and optimize resource use.
- Aging Infrastructure Maintenance: Difficulty in monitoring and ensuring the longevity of aging and heritage structures.
- Need for Digital Twin Technology: A transformative approach that enables real-time insights, improves decision-making, and optimizes operations to meet modern construction challenges.

III. METHODOLOGY

A) *Digital Twin Architecture*

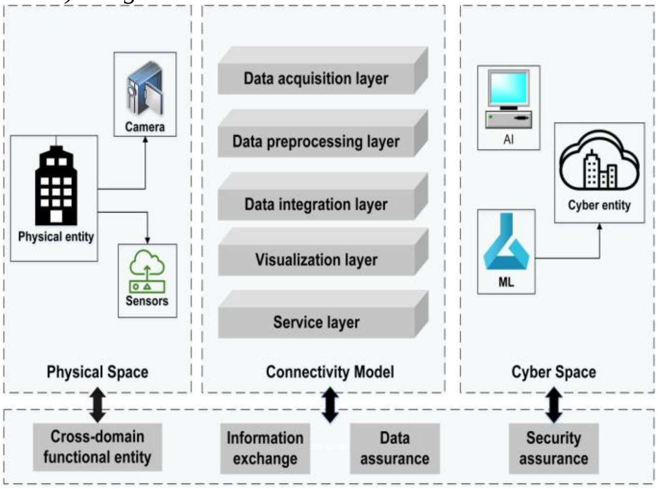

Figure 2. Digital twin architecture schematic.

Digital twin architecture is a sophisticated system that integrates various technologies to create a virtual replica of a physical entity. The development of a digital twin involves four key stages. The first step is gathering detailed data about a building's geometry, materials, and equipment characteristics. Next, real-time measurements are collected using IoT sensors to provide up-to-date information about the building's performance. This is followed by the creation of a digital model that accurately reflects real-world conditions. Lastly, a software platform is developed to integrate and manage the data, enabling seamless interactions between the physical and digital environments.

A core aspect of digital twin architecture is its ability to establish a continuous exchange of data between the physical and virtual models. This bi-directional flow of information allows for real-time adjustments, ensuring that digital representations remain accurate reflections of the actual environment. The system is based on concepts that enable the digital model to evolve dynamically as it receives real-time data from the physical entity.

At its foundation, digital twin architecture is built upon five primary layers of development. The first layer focuses on collecting essential data about the structure, including its materials, dimensions, and real-time measurements from IoT sensors. The second layer deals with data transfer, utilizing various communication protocols and mechanisms to ensure seamless connectivity between the physical and digital worlds. The third layer involves digital modeling, which entails developing virtual representations that replicate the physical properties and behaviors of real-world entities with precision. These models are not static; instead, they continuously update as new data is gathered and analyzed.

The fourth layer is responsible for data visualization, which allows users to monitor and interact with the digital twin. Various formats, such as web-based interfaces and immersive reality applications, including virtual and augmented reality (VR and AR), enable users to visualize and interact with the digital twin system. This feature enhances user engagement and decision-making capabilities.

Finally, the fifth layer of the digital twin architecture focuses on services, including real-time data analytics, simulation engines, and machine learning algorithms. These technologies analyze incoming data, predict potential outcomes, and enable informed decision-making. The bi-directional data flow between the physical and digital realms ensures that the digital twin remains an accurate, real-time representation of its physical counterpart. This real-time updating capability enhances operational efficiency, predictive maintenance, and process optimization.

Furthermore, the digital twin architecture incorporates advanced connectivity solutions to facilitate seamless information sharing. This connectivity enables constant communication between the physical and virtual models, allowing data-driven adjustments and insights. Moreover, the use of artificial intelligence, machine learning, and simulation technologies helps in the continuous optimization of the system.

With the emergence of immersive technologies like Virtual Reality (VR) and Augmented Reality (AR), digital twins can be presented in interactive formats. Web-based interfaces and immersive digital environments enable users to engage with and analyze the model in innovative ways. This ensures that real-time data analysis and decision-making processes are well-informed, enhancing operational efficiency and risk management in the construction sector.

B) Digital Twin Components

Different digital twin architectures incorporate various technologies to enhance their functionality and efficiency. Seven key digital technologies form the foundation of digital twin systems, each playing a crucial role in their development and operation. The first is Artificial Intelligence (AI), which enables automated decision-making and predictive analytics. Machine Learning (ML) follows as the second technology, allowing systems to learn from data patterns and improve performance over time. Cyber-Physical Systems (CPS) represent the third essential component, integrating digital and physical processes for seamless interaction.

The Internet of Things (IoT) serves as the fourth pillar, ensuring continuous real-time data collection from physical entities. Data Mining (DM), the fifth technology, processes vast amounts of data to extract meaningful insights that enhance decision-making. Virtual Reality (VR), the sixth component, enables immersive digital representations for better visualization and interaction. Augmented Reality (AR), the seventh key technology, overlays digital information onto physical environments to create interactive experiences.

While these seven technologies form the core of digital twin architectures, other emerging technologies act as complementary enhancements. Blockchain technology strengthens data security and ensures transparency within digital twin ecosystems. Cloud computing provides scalable storage solutions and enhances remote accessibility. Big data analytics facilitates the processing of vast datasets, improving the accuracy and efficiency of digital twin models. Simulation and emulation techniques further refine virtual models by replicating real-world scenarios with high precision.

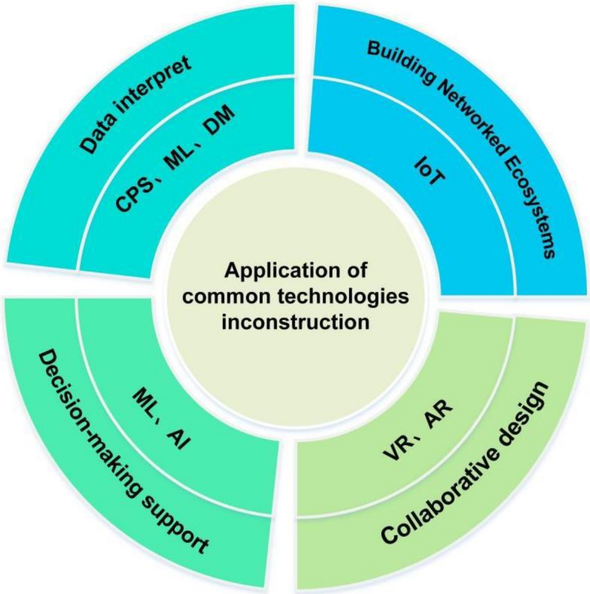

Figure 3. Application of digital twin in construction project lifecycle.

In the construction industry, these technologies revolutionize project management, structural analysis, and maintenance planning. Each technology offers unique advantages, such as real-time monitoring, predictive maintenance, and improved decision-making. However, their implementation also comes with certain limitations, including high costs, data privacy concerns, and the need for skilled professionals. Understanding the applications and constraints of these technologies is essential for optimizing their use in digital twin systems.

C) Digital Twin Framework

Effectively managing deteriorating structural systems is a significant challenge in modern engineering, as poor maintenance strategies can lead to severe safety, economic, and social consequences. Ensuring the longevity and reliability of critical civil structures requires a shift from conventional time-based maintenance to more efficient condition-based or predictive maintenance approaches.

The concept of a Digital Twin (DT) offers a transformative solution by providing a continuously updated digital representation of a physical structure, facilitating real-time monitoring, predictive analysis, and optimized maintenance planning. By creating a synchronized virtual counterpart, engineers can enhance the entire lifecycle of a structure, from construction to operation and long-term maintenance.

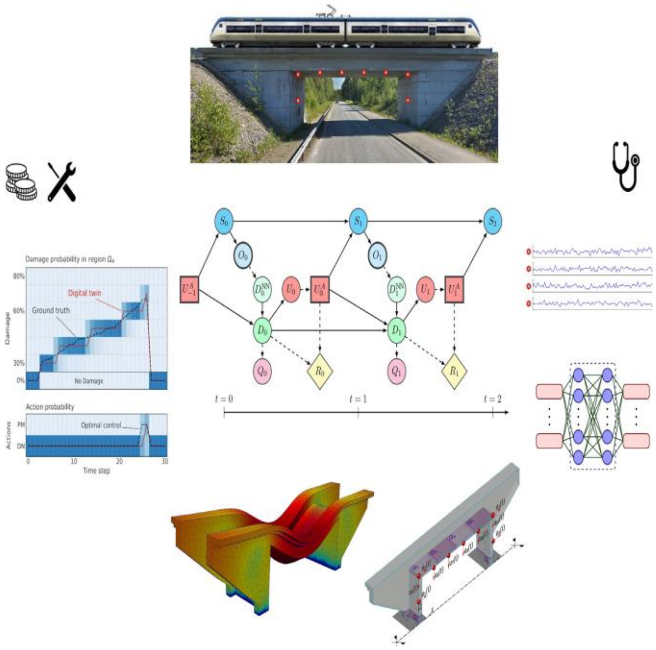

Figure 1. Predictive digital twin framework for civil engineering structures: graphical abstraction of the end-to-end information flow enabled by the probabilistic graphical model.

Digital Twin technology has been widely implemented across various fields, including structural health monitoring (SHM), predictive maintenance, smart city development, railway infrastructure management, additive manufacturing, and urban sustainability. This approach allows for a tailored computational representation of a physical asset, which evolves over time through continuous data assimilation from real-world conditions.

Within a civil engineering SHM framework, the effectiveness of a DT depends on the integration of real-time structural data into computational models. This involves collecting sensor data—such as acceleration and displacement readings—and employing data-driven techniques to assess structural health conditions. Advanced deep learning models play a crucial role in this process by automating the extraction of meaningful features and detecting damage locations and severities in structural components.

The proposed DT framework is built upon a probabilistic graphical model (PGM) that enables data assimilation, state estimation, predictive modeling, and strategic decision-making. This model is structured as a dynamic Bayesian network with additional decision nodes, forming a dynamic decision network that facilitates bidirectional information flow. The DT system operates in two primary phases:

- Physical-to-Digital Transition: Structural response data from sensors are processed using deep learning models, which estimate the current condition of the structure. Vibration-based SHM techniques analyze time-history data, helping to identify the presence, location, and severity of any damage. These insights are then used to update the digital representation, ensuring an accurate reflection of the evolving structural health state.
- Digital-to-Physical Transition: The refined digital model is used to forecast future structural behavior and associated uncertainties, supporting predictive decision-making for maintenance and management. This allows engineers to plan interventions proactively rather than reacting to failures, improving efficiency and cost-effectiveness.

Additionally, the framework incorporates an offline learning phase where deep learning models are pre-trained using simulated structural damage scenarios. Supervised training methodologies leverage physics-based numerical simulations to create labeled datasets that represent various operational and damage conditions.

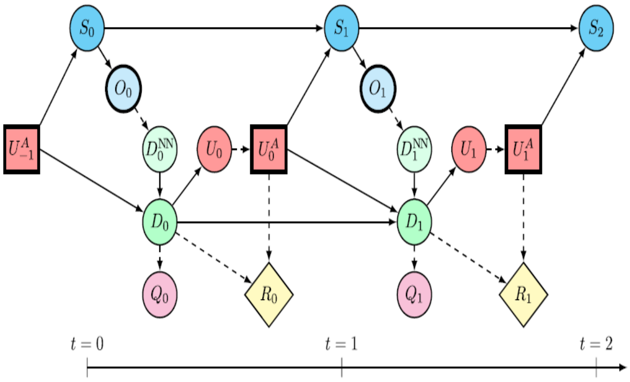

Figure 2. Dynamic decision network encoding the asset-twin coupled dynamical system

Circle nodes denote random variables, square nodes denote actions, and diamond nodes denote the objective function. Bold outlines denote observed quantities, while thin outlines denote estimated quantities. Directed solid edges represent the variables' dependencies encoded via conditional probability distributions, while directed dashed edges represent the variables' dependencies encoded via deterministic functions.

One of the unique contributions of this research is the adaptation of the PGM-based Digital Twin approach specifically for civil infrastructure maintenance and monitoring. By leveraging high-dimensional multivariate time-series data from structural sensors, the system can track uncertainties and refine its predictions continuously. Furthermore, the computational framework supporting this DT methodology is made publicly available, allowing researchers and engineers to implement and expand upon the dynamic decision network model for structural health monitoring applications.

IV. APPLICATIONS OF DIGITAL TWINS IN THE DESIGN PHASE

- Integration with BIM: Digital twins use Building Information Modeling (BIM) for virtual project representation, improving visualization, data management, and decision-making.
- Enhanced Collaboration: BIM enables a unified digital workspace for seamless coordination among designers and engineers.
- Lifecycle Management: Digital twins combined with BIM help minimize discrepancies between as-designed and as-built structures.
- Cost and Time Efficiency: Reduces operational costs and trial operation time by integrating digital technologies.

- Process Optimization: BIM-driven Construction Digital Twins (CDTs) improve process understanding through synchronized cyber-physical data flows.
- AI and Automation: AI-powered BIM automates design, drafting, and construction tasks, minimizing errors.
- Real-time Monitoring: Mixed reality and deep learning enhance real-time construction monitoring and warning systems.
- Waste Reduction: Automated modeling minimizes material wastage and prevents unnecessary rework.

V. RESULT AND DISCUSSION

A. Case study

Railway bridge :

This case study focuses on a railway bridge located along the Bothnia Line near Horneros, Sweden. This structure is an integral concrete portal frame bridge with a span of 15.7 meters, a clearance height of 4.7 meters, and a width of 5.9 meters, excluding the edge beams. The deck has a thickness of 0.5 meters, while the frame walls and wing walls are 0.7 meters and 0.8 meters thick, respectively. The bridge is supported by two foundation plates connected by stay beams and reinforced by groups of piles.

Constructed using C35/45 grade concrete, the bridge has material properties defined by a modulus of elasticity (E) of 34 GPa, Poisson's ratio (ν) of 0.2, and a density (ρ) of 2500 kg/m³. The railway superstructure consists of a single track laid on a ballast layer that is 0.6 meters deep and 4.3 meters wide, with a ballast density of 1800 kg/m³. Sleepers are spaced 0.65 meters apart, distributing the train loads to the bridge deck. The structural and mechanical modeling parameters used for this study are based on previous research on soil-structure interaction.

The bridge is designed to withstand the dynamic loads of Grona Target trains, which travel at speeds ranging between 160 km/h and 215 km/h. Each train is composed of two wagons, with a total of eight axles, where each axle supports a load varying between 16 and 22 tons. According to Eurocode 1, the train load is modeled as 25 equivalent distributed forces, which are transmitted from the sleepers to the bridge deck through the ballast layer at a slope of 4:1.

Figure 6. Horneros railway bridge.

Dataset assembly :

Synthetic displacement time histories, denoted as **U**, are obtained from 10 sensors strategically placed as shown in Fig. 6. Each sensor records data over a time span of 1.5 seconds with a sampling frequency of 400 Hz. This setup ensures the accurate capture of train movements, even at the lowest operational speed of 160 km/h, while effectively monitoring the structural response at the maximum speed of 215 km/h. The recorded data includes additive Gaussian noise, resulting in a signal-to-noise ratio (SNR) of 120.

To analyze structural integrity, the study considers both an undamaged state and various damaged conditions. Damage is simulated by applying localized stiffness reductions within six predefined subdomains (Ωj, where j = 1,…,6). In each of these regions, stiffness reductions range between 30% and 80%, and remain constant while the train passes over the bridge.

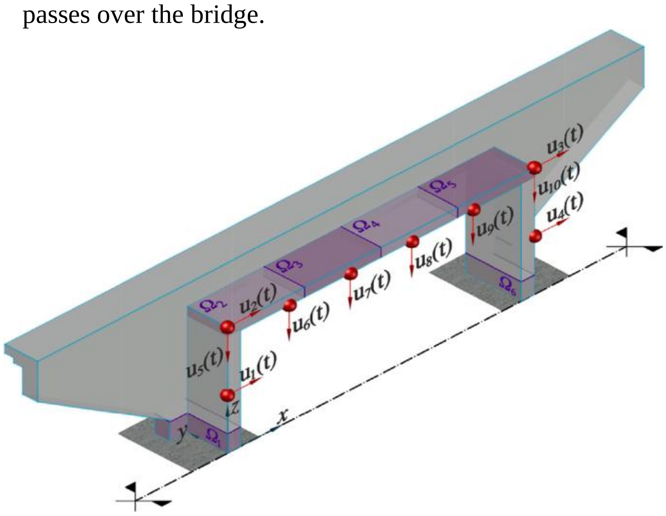

Figure 7. Railway bridge
: details of synthetic recordings related to displacements $u1(t)$,…, $u10(t)$, and predefined damage regions $\Omega1$,…,$\Omega6$.

The Full-Order Model (FOM) consists of 17,292 finite elements (NFE), representing the railway bridge's structural behavior. To ensure smooth transmission of the moving train loads, the deck's thickness has been adjusted to 0.5 meters for most of its structure, except for the deck surface, where it is reduced to 0.7 meters. The influence of the ballast layer is considered by increasing the density of the bridge deck. Additionally, the interaction between the bridge and the embankment is modeled using an applied ground-facing surface stiffness of 10^8 N/m³ in the form of a Rayleigh damping matrix.

To improve computational efficiency, a Reduced-Order Model (ROM) is generated from 400 evaluations of the FOM using different input parameters, including train speed (υ), axle load (ψ), transverse train position (y), and stiffness reduction magnitude (δ). A total of 133 Proper Orthogonal Decomposition (POD) modes are required for an accurate representation of the bridge's response.

To train the digital twin (DT) system, a training dataset ($\mathcal{D}$) of 10,000 instances is generated using the ROM. During operation, the evolving structural condition of the bridge is continuously assessed by assimilating one noisy observation (Nobs = 1) at each time step. This enables the Digital Twin (DT) to update and adapt based on real-time data, ensuring accurate monitoring of the bridge's structural health.

B. *Digital twin framework*

Just like in the previous case, the digital twin monitors two key structural health parameters: the damage location (y) and the damage severity (δ). These two values form a digital state, and there are 37 possible digital states in total, arranged by damage location first and then by severity level.

To assess the condition of the bridge, a confusion matrix (a tool for evaluating classification accuracy) is used. The overall accuracy of the digital twin in identifying the correct structural state is 91.39%. However, most mistakes happen when the model confuses damage locations that are close to each other.

As part of the bridge maintenance strategy, one possible action is the "Do Nothing" (DN) approach. This means that no repairs or maintenance work is performed, and the bridge's condition continues to degrade over time due to natural wear and tear. This deterioration follows a random pattern influenced by environmental conditions and the frequency of train passages.

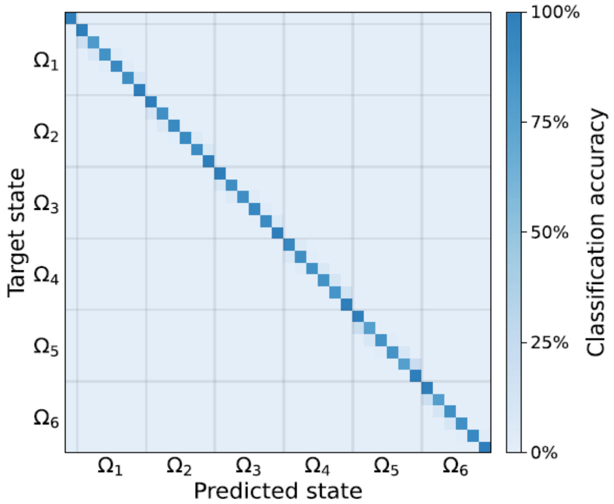

Figure 8. Railway bridge - Confusion matrix measuring the offline performance

The DL models in correctly categorizing the digital state. Results are reported in terms of classification accuracy, measuring how observational data are classified with respect to the ground truth digital state. Digital states are ordered first for damage location and then for damage level.

In addition there are two other maintenance strategies for the bridge:

1. **Perfect Maintenance (PM) Action:**
- This action involves fully restoring the bridge to its original, undamaged state.
- Any existing damage is completely repaired, bringing the structure back to perfect condition.

2. **Restrict Operational Conditions (RE) Action:**
- In this approach, only lightweight trains (weighing less than 18 tons per axle) are allowed to use the bridge.
- This helps slow down the deterioration process but also results in lower revenue, as heavier trains cannot pass.

How the Bridge Deteriorates Over Time :

If no maintenance is done (DN) or if only lightweight trains are used (RE):

- The bridge gradually deteriorates over time.
- If there are no restrictions, there is a 50% chance that new damage will appear in a random location.
- The damage level starts between 30% and 35% and then increases over time at an average rate of 1.5% per step (with a standard deviation of 1%).
- If only lightweight trains are allowed (RE action), the chance of new damage drops to 25%, and the damage spreads more slowly (around 0.95% per step with a standard deviation of 0.5%).

If maintenance is done (PM):

- The bridge is immediately repaired to its original, undamaged state, no matter how bad the damage was.
- Transition Model (How the Bridge's Condition Changes)

For the "Do Nothing" (DN) action:

- There is a 10% chance that new damage will appear in any of the 6 predefined damage zones.
- Once damage appears, there is also a 10% chance that it will increase to the next level.

For the "Restrict Operational Conditions" (RE) action:

- The chance of new damage appearing drops to 3%, and the rate of damage growth is also slower.

For the "Perfect Maintenance" (PM) action:

- The bridge is fully repaired, resetting all damage to zero regardless of its previous condition.

These transition models are represented using triangular probability matrices:

- The DN and RE actions use lower-left triangular matrices, meaning damage can only stay the same or get worse.
- The PM action uses an upper-right triangular matrix, meaning damage is fully reset to zero.

This system simulates the real-life aging of the bridge, capturing both gradual wear and sudden damage events.

$$R_t^{\text{control}}(u_t^A) = \begin{cases} +30, & \text{if } u_t^A = \text{DN}, \\ -250, & \text{if } u_t^A = \text{PM}, \\ +27, & \text{if } u_t^A = \text{RE}, \end{cases} \quad R_t^{\text{health}}(d_t) = \begin{cases} +0, & \text{if } y = 0, \\ -\exp(5\delta) + 4, & \text{if } y \neq 0, \\ -250, & \text{if } \delta \geq 79\%, \end{cases} \tag{1}$$

where the last contribution in R health t penalizes excessively compromised structural states with a significantly negative reward.

C. *Results and Discussion*

During the planning phase, we create a strategy to manage the bridge's condition.

- We assume a discount factor of 0.90, meaning future costs and benefits are considered but slightly less important than immediate ones.
- We also set a weighting factor of 1, giving equal importance to different factors in decision-making.

The Recommended Strategy:

1. Normal Operation: The bridge can operate without restrictions as long as the damage level (δ) is between 30% and 35%.
2. Restricted Operation: Once damage goes above 35%, only lightweight trains should be allowed to slow down further deterioration.
3. Repair: If the damage reaches 65% or more, the bridge must be repaired to prevent failure.

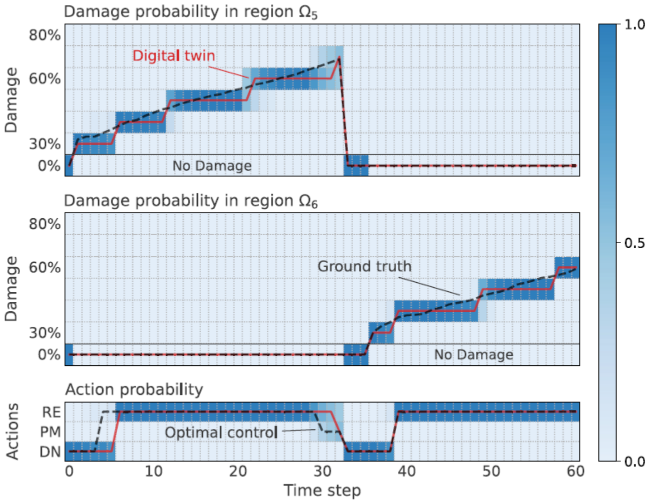

Figure 9. Railway bridge - Online phase of the digital twin framework

with three possible actions: DN (do nothing), PM (perfect maintenance), and RE (restrict operational conditions). Probabilistic and best point estimates of: (top) digital state evolution against the ground truth digital state; (bottom).

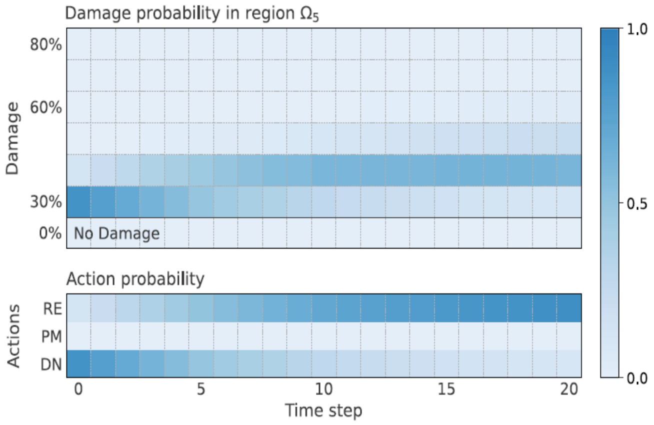

Figure 10. Railway bridge - Digital twin future predictions with three possible actions

DN (do nothing), PM (perfect maintenance), and RE (restrict operational conditions). The starting time is $t_c = 5$. In the top panel the probability $p(D_t|D_{t-1},U_{t-1})$ relates to the amount of damage in $\Omega 5$. In the bottom panel it corresponds

to $p(U_t|D_t)$.

Figure 9 shows the results of a digital model (DT) tracking the bridge's condition over 60 time steps. The DT successfully follows the changes in the bridge's condition with low uncertainty. Here's what happens over time:

- Damage starts in area Ω5.
- The DT monitors the damage and updates its previous estimate based on new data.
- When the damage level reaches between 35% and 65%, the DT recommends restricting bridge usage (RE action) to slow down further damage.
- If damage reaches 65% or more, the DT suggests immediate repair to restore the bridge.
- A similar process is observed for another part of the bridge, Ω6, when damage occurs there.

Fig. 10 shows a predicted vs. actual damage comparison. The DT successfully tracks damage but lags slightly behind real-time changes by about 2 time steps. It also tends to underestimate how quickly the damage worsens, which means the prediction model could be improved for better accuracy.

VI. CONCLUSION

This study proposed a predictive Digital Twin (DT) framework for health monitoring, maintenance, and management planning of civil structures. By leveraging a probabilistic graphical model, the DT captures the asset-twin coupled dynamics, tracking the structure's condition over time with quantified uncertainty. The approach integrates deep learning models, particularly convolutional layers, to extract damage-sensitive features from raw vibration data. These extracted parameters are sequentially updated using Bayesian inference, ensuring accurate tracking of structural health.

A two-phase computational procedure was adopted, comprising an offline phase for training deep learning models using physics-based simulations and a real-time online phase for decision-making. The DT framework was validated through simulated monitoring of an L-shaped cantilever beam and a railway bridge. The results demonstrated that the DT accurately tracks the digital state evolution and suggests appropriate maintenance actions with minimal delay—typically within two time steps of actual structural health demands. This capability allows for proactive maintenance planning, reducing unexpected failures and optimizing repair interventions.

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