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Decision making framework through digital twin for lifecycle management of tunnel in Karst

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Abstract

Aging karst tunnels face escalating risks from environmental and structural degradation. Through a systematic review of the state-of-the-art literature, this study proposes a conceptual methodology that leverages Digital Twin capabilities through the integration of physics-based and data-driven approaches for the monitoring and maintenance of karst tunnels throughout their lifecycle. The proposed framework aims to enhance predictive maintenance, improve resilience assessment, optimize stakeholder decision-making, and support sustainable lifecycle asset management.

Key words: digital twin, decision optimization, structural health monitoring, Karst tunnel, lifecycle management

Okvir za donošenje odluka primjenom digitalnog blizanca za upravljanje životnim ciklusom tunela u kršu

Sažetak

Postojeći tuneli u kršu suočavaju se sa sve većim rizicima uslijed okolišne i strukturne degradacije. Kroz sustavni pregled literature, ova studija predlaže konceptualnu metodologiju koja koristi mogućnosti digitalnih blizanaca (Digital Twin) putem integracije fizikalno utemeljenih i podatkovno vođenih pristupa za praćenje stanja i održavanje krških tunela tijekom njihovog životnog vijeka. Predloženi okvir ima za cilj unaprijediti prediktivno održavanje, poboljšati procjenu otpornosti, optimizirati donošenje odluka dionika te podržati održivo upravljanje imovinom tijekom cijelog životnog ciklusa.

Ključne riječi: digitalni blizanac, optimizacija odluka, praćenje stanja konstrukcije, Krški tunel, upravljanje životnim ciklusom

1 Introduction

Modern society relies heavily on road and rail networks for the seamless movement of goods and people. Within these networks, underground infrastructure serves as critical nodes, particularly in mountainous regions, where they are indispensable for connectivity. However, these assets are under escalating pressure from the combined effects of structural aging, climate change, and intensified operational demands [1]. While aging necessitates more frequent interventions, extreme weather and natural disasters introduce heightened systemic risks. Effective maintenance and periodic monitoring, comprising both physical repairs and strategic management, is therefore essential to preserve asset functionality. Neglecting these maintenance requirements risks not only functional degradation and economic inefficiency but also catastrophic loss of life. Such consequences were illustrated by the 2012 Sasago Tunnel collapse in Japan and the 2006 Fort Point Channel Tunnel collapse in the United States, which resulted not only in prolonged transportation disruptions and costly repair operations, but also in nine and one fatalities, respectively, due to inadequate monitoring and delayed maintenance interventions [2, 3].

Among underground infrastructure systems, tunnels represent particularly complex and critical assets due to their structural, environmental, and operational characteristics. Consequently, their effective monitoring and maintenance increasingly rely on the adoption of advanced and emerging technologies. However, the inherent heterogeneity, sparsity, and multi-source nature of monitoring data present significant challenges for interpretation and utilization. This highlights the need for a comprehensive decision-making framework capable of integrating diverse data streams and fully leveraging modern technological capabilities.

In this study, existing state-of-the-art approaches for monitoring and digital twin-based frameworks for life cycle management of tunnels are reviewed, and a methodological framework is proposed to support decision making for tunnel infrastructure. Figure 1 investigates the recent key technologies for infrastructure asset management through their lifecycle.

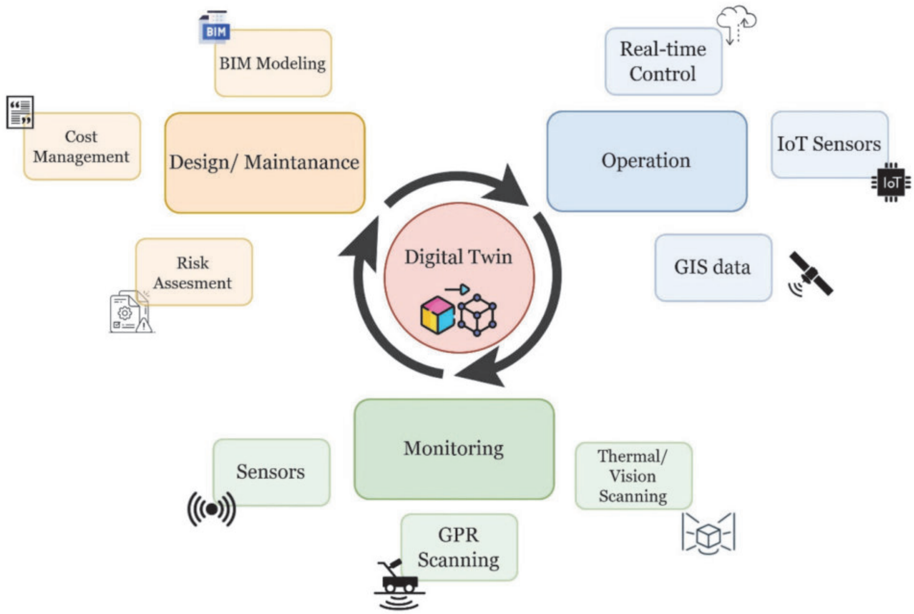

Figure 1. Digital Twin of infrastructure-level from circular view with key technologies identified

2 State-of-the-art

In recent years, the Architecture, Engineering, and Construction (AEC) industry has undergone a significant digital transformation, aligned with the European Commission's vision of Industry 5.0, which emphasizes sustainability, resilience, and human-centric development throughout the infrastructure lifecycle [4, 5]. This transformation is characterized by the integration of sensing technologies, advanced data analytics, and digital modeling, which are reshaping monitoring and maintenance strategies across the infrastructure sector, including underground assets [6].
Tunnel infrastructure, in particular, has experienced increasing adoption of innovative monitoring approaches aimed at capturing continuous deformation behavior over the asset lifecycle and enabling more proactive assessment of structural health. Broadly, these approaches can be categorized into two main groups: continuous deformation monitoring and visual inspection techniques [7]. Continuous deformation monitoring can be further divided into local and distributed methods. Local monitoring typically involves instruments such as linear variable differential transformers (LVDTs), micrometer measurement, and strain gauges [8], whereas distributed monitoring relies on technologies such as distributed optical fiber sensors (DOFS) and fiber Bragg grating (FBG) sensors [9, 10]. In ad-

dition, tilt sensors and automated surveying techniques, including periodic laser scanning, are increasingly utilized [11]. The second category, visual inspection methods concerning surface defect detection, commonly employs thermal imaging [12] and high-resolution imaging techniques [13, 14]. Furthermore, ground-penetrating radar (GPR) has shown strong potential for subsurface inspection and is increasingly being adopted in tunnel monitoring applications [15, 16].
Integrating heterogeneous monitoring data to support asset management remains a significant challenge for stakeholders and decision-makers. In this context, Digital Twin (DT) approaches are increasingly adopted in tunnel asset management to address data fusion and integration needs, enabling more informed and optimized decision-making processes. Recent research has advanced the development of predictive and prescriptive DT platforms that leverage monitoring data and analytical tools to anticipate future asset conditions and support maintenance planning [17]. A predictive DT focuses on forecasting future states by integrating statistical, physics-based, and knowledge-driven models. Its performance is continuously refined through real-time data feedback, with the primary objective of predicting infrastructure behavior and identifying potential failure scenarios [18, 19]. Extending this concept, a prescriptive DT extends these capabilities by addressing decision-making processes, providing actionable recommendations on appropriate interventions. By combining predictive insights with optimization techniques, it supports real-time decision-making and facilitates the effective management of construction and operational processes. Through the use of monitoring data and advanced analytics, prescriptive twins enable targeted intervention strategies triggered by predefined thresholds or performance indicators [20, 21, 22]. However, important limitations persist, particularly in achieving comprehensive lifecycle coverage for tunnel systems [23]. Accordingly, there is a growing need for a holistic DT-based decision-making framework that supports tunnel assets throughout their entire lifecycle. Such a framework would enable stakeholders to make informed decisions based on the integration and combined interpretation of diverse monitoring technologies.

3 Digital twin framework for Karst tunnel lifecycle management

3.1 Challenges and Outlook

Underground infrastructure, especially karst tunnels, is highly vulnerable to a wide range of natural and anthropogenic hazards, with deterioration driven by both internal and external mechanisms. Internal factors, including design deficiencies, substandard materials, and poor construction practices, can significantly reduce structural capacity and increase susceptibility to premature failure.

External influences, such as geotechnical conditions, groundwater, and heavy traffic loading, impose additional stress on tunnel systems, often interacting to accelerate degradation processes. For instance, concrete spalling may result from the combined effects of inadequate construction, reinforcement corrosion, thermal variations, and mechanical impacts [24]. Geological and groundwater conditions are particularly critical, as the surrounding ground governs structural deformation, cracking, and corrosion behavior. Groundwater further worsens deterioration through mechanisms such as erosion and freeze–thaw cycles, posing persistent risks during both construction and operation. In karst tunnels, these challenges are further intensified by significant long-term structural deformation throughout the asset lifecycle, which may ultimately lead to cavity collapse [8, 25]. Addressing these interacting factors is essential to enhance the resiliency, safety, and long-term performance of infrastructure.
As discussed in Section 2, existing implementations of Digital Twin (DT) technologies primarily focus on individual lifecycle stages and periodic maintenance activities. While these approaches have significantly advanced tunnel asset management within specific phases, comprehensive analyses encompassing the entire lifecycle remain limited. This gap underscores the need for a holistic DT framework capable of integrating and extending data and models across all lifecycle stages to fully realize the potential of this technology. Such an approach calls for more proactive and adaptive infrastructure management strategies, where the DT paradigm enables continuous digital interaction through interconnected functional modules, including sensing, data fusion, learning, prediction, and actuation. This evolution represents a shift from static and fragmented management practices toward more agile, intelligent, and data-driven infrastructure systems.
Moving forward, the integration of heterogeneous data sources is fundamental to the effective implementation of DT models. Data serves as the core component for predicting deterioration processes and enabling adaptive maintenance strategies. However, a major challenge lies in the limited availability of datasets with sufficient volume and diversity, as well as in the efficient transformation of raw data into actionable information and knowledge for decision support. In this context, the integration of hybrid physics-informed and data-driven approaches, such as Physics-Informed Neural Networks (PINNs) [26] combined with deep learning (DL) models, with real-time and periodic monitoring data offers significant potential to overcome data scarcity, improve model generalization, and enhance interoperability within DT systems. Nevertheless, this area still requires further development to achieve robust and scalable DT implementations. Advancements in this area will enhance decision-making processes by enabling the systematic incorporation of uncertainty and reliability considerations throughout the entire lifecycle of tunnel assets.

3.2 Methodology overview

This study proposes a conceptual DT-based framework for tunnel risk assessment through its lifecycle, structured around the integration of multi-source data, hybrid modeling approaches, and decision support mechanisms. An overview of the proposed framework is shown in Figure 2. At its core, the framework combines real-time monitoring data with a Building Information Modeling (BIM) environment to establish a dynamic and continuously updated digital representation of the tunnel asset. Data fusion processes enable the integration of heterogeneous inputs, including sensor measurements and synthetic data generated from numerical simulations, to address data sparsity and enhance model robustness. These enriched datasets are then utilized within a centralized analytical layer, where various neural network approaches are employed to extract patterns, estimate structural states, and predict degradation trends. The framework is designed to support bidirectional information flow, ensuring continuous feedback between physical assets and their digital counterparts.

Within the analytical layer, the methodology envisions the integration of advanced physics-based and machine learning techniques, including proposing PINN and DL architectures for long-term deformation prediction in karst tunnels with data derived from various sources discussed in Section 2. These approaches enable the simultaneous incorporation of physical laws and data-driven insights, improving predictive reliability under limited or uncertain data conditions. The outputs of these models feed into higher-level modules for risk analysis and asset management, where condition assessments are translated into actionable indicators for operation and maintenance (O&M) decision-making. The framework is intentionally designed at a conceptual level to allow flexibility for future development, including the refinement of model architectures, expansion of data sources, and incorporation of uncertainty quantification. Ultimately, it provides a scalable structure for evolving toward a fully integrated, predictive, and prescriptive DT system for tunnel infrastructure.

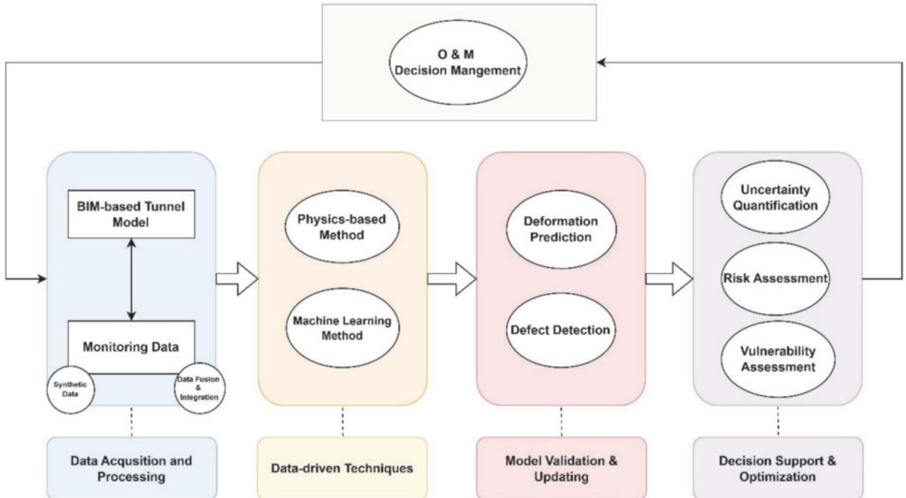

Figure 2. A conceptual digital twin-based framework for tunnel lifecycle assessment, integrating multi-source monitoring data, BIM-based digital representation, hybrid physics-informed and data-driven modeling, and risk-informed decision-making for operation and maintenance.

4 Conclusion

This paper has highlighted the growing challenges associated with the management of tunnel infrastructure, driven by aging systems, increasing internal and external stressors, and the complexity of monitoring and maintenance processes. While recent advances in sensing technologies and Digital Twin (DT) applications have significantly improved condition assessment at individual lifecycle stages, a comprehensive and integrated approach spanning the entire lifecycle remains limited. This gap underscores the need for a unified framework capable of systematically combining heterogeneous data sources, advanced modeling techniques, and decision-support tools.

In response, this paper has proposed a conceptual digital twin–based framework that integrates real-time monitoring, digital modeling, data fusion, and intelligent analytics within a unified structure for tunnel lifecycle management. By incorporating both physics-informed and data-driven approaches, the framework demonstrates the potential to enhance predictive capabilities and support more informed, risk-based decision-making. Although the proposed methodology remains at a conceptual stage, it establishes a foundation for future research aimed at developing fully operational DT systems. Further work will focus on the implementation and validation of the framework through case studies, refinement of analytical models, and the incorporation of uncertainty quantification to improve reliability and robustness. Ultimately, this approach contributes toward the transition to more proactive, adaptive, and resilient infrastructure management systems.

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