

Development of an Operational Digital Twin Framework for Bridge Infrastructure Using GNSS-Based Monitoring and Physical Verification

(GNSS 観測と物理検証に基づく橋梁インフラのための
運用型デジタルツインフレームワークの構築)



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Development of an Operational Digital Twin Framework for Bridge Infrastructure Using GNSS-Based Monitoring and Physical Verification

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Dedicated to

My Late Father Moises Tita & My Late Mother Theresia Abuk

My wife Natercia

My son Loro Tita

My Brother Caetano & Sisters Laura and Hermina

ABSTRACT

Bridges and transportation infrastructure are critical components of modern societies, yet they are increasingly threatened by aging, intensified traffic demands, environmental exposure, and limited maintenance resources. Conventional bridge management practices, largely based on periodic visual inspections and reactive maintenance, provide only fragmented and static assessments of structural condition, often failing to detect early-stage damage or predict future performance degradation. These limitations highlight the urgent need for a paradigm shift toward integrated, data-driven, and predictive infrastructure management strategies. In response, this dissertation proposes and validates a **Digital Twin (DT)–based framework** for long-term bridge structural health monitoring (SHM) and transportation system analysis, integrating **Building Information Modeling (BIM)**, **Global Navigation Satellite System (GNSS) displacement monitoring**, **data assimilation and machine learning techniques**, and **finite element analysis (FEA)**.

The proposed framework conceptualizes the digital twin as a dynamic virtual representation of a physical bridge, continuously synchronized with real-world monitoring data and physics-based simulations. Unlike conventional monitoring systems that merely observe structural responses, the Digital Twin enables interpretation, numerical validation, prediction, and decision support across the entire infrastructure lifecycle. BIM serves as the geometric and semantic backbone of the Digital Twin, ensuring interoperability across design, construction, operation, and maintenance phases. High-precision GNSS monitoring is adopted to capture three-dimensional bridge displacements under operational loads, environmental effects, and abnormal events, offering unique advantages for long-span and complex bridge systems.

A core challenge addressed in this research is the transformation of noisy and environmentally influenced GNSS measurements into reliable structural displacement information. To overcome this challenge, the study integrates **data assimilation techniques**, specifically the **Ensemble Kalman Filter (EnKF)**, with **machine learning–based estimation using Random Forest (RF)** models. These methods enhance displacement estimation accuracy, reduce noise and thermal bias, and provide uncertainty quantification, thereby improving the reliability of Digital Twin–based SHM. The estimated displacements are further validated through **physics-based finite element models**, including **soil–structure interaction effects**, ensuring that observed behaviors are structurally consistent and physically interpretable.

The Digital Twin framework is demonstrated through multiple case studies at both the asset and system levels. At the asset level, BIM-based Digital Twins are developed for bridges to support structural performance evaluation, maintenance planning, and post-accident assessment. GNSS-based monitoring is applied to detect long-term deformation trends and sudden changes resulting from abnormal events such as vessel collisions, illustrating the framework’s effectiveness in supporting rapid and objective decision-making. At the system level, the framework is extended to urban transportation analysis using Digital Twin–BIM–based traffic simulation. A case study in Dili, Timor-Leste, demonstrates how traffic congestion, operational efficiency, and environmental impacts can be evaluated within an integrated digital environment, supporting evidence-based urban planning and infrastructure policy.

The results demonstrate that the proposed Digital Twin framework significantly enhances displacement estimation accuracy, enables early anomaly detection through synchronized sensing–simulation comparison, and supports holistic decision-making by linking structural performance with transportation system behavior. Compared to conventional inspection-based approaches, the framework provides richer lifecycle

insights, improved reliability, and greater scalability. This dissertation contributes a validated, multi-layer Digital Twin methodology for bridges and transportation infrastructure, offering practical guidance for implementation in both developed and developing contexts. Ultimately, the research supports the transition from reactive infrastructure management toward proactive, predictive, and resilient digital infrastructure systems.

Consequently, the summary of each chapter is as follows:

1. Chapter 2. Conceptual Foundations and Related Work for Operational Digital Twins of Bridge Infrastructure

This chapter reviews the theoretical foundations of Digital Twin technology within the context of Industry 4.0 and digital transformation in civil infrastructure. It examines key enabling technologies, including IoT, GNSS, AI, cloud computing, and BIM, and reviews state-of-the-art structural health monitoring (SHM) technologies for bridges. The chapter also discusses advanced data analytics, sensor fusion, and finite element analysis as essential components of Digital Twin systems. Research gaps related to interoperability, scalability, and integration of sensing and simulation are identified, establishing the foundation for the proposed framework.

2. Chapter 3. Integrated Digital Twin Framework for transportation Infrastructure Management

Chapter 3 presents the overall Digital Twin framework developed in this dissertation. It defines the system architecture integrating BIM-based modeling, GNSS displacement monitoring, data assimilation and machine learning techniques, finite element validation, and traffic management modules. The chapter explains how real-time data flows enable closed-loop interaction between physical assets and their digital counterparts, supporting both asset-level SHM and system-level transportation analysis.

3. Chapter 4. DT–BIM-Based Digital Representation and Physics-Based Validation for Bridge Infrastructure

This chapter focuses on the development of a BIM-based Digital Twin for bridge management using a prestressed concrete box-girder bridge as a case study. It demonstrates BIM–FEA interoperability for structural performance evaluation, including displacement, stress distribution, and shear-lag effects. The chapter illustrates how the Digital Twin supports maintenance planning and structural assessment throughout the bridge lifecycle.

4. Chapter 5. System Level Traffic Management Using Digital Twin–BIM Technology: A Case Study in Dili, Timor Leste

Chapter 5 extends the Digital Twin concept to urban transportation systems. A Digital Twin–BIM workflow is developed for traffic simulation and management in Dili, Timor-Leste, addressing challenges of rapid urbanization, congestion, and environmental impact. Traffic demand modeling, simulation, and environmental assessment are conducted, demonstrating the applicability of Digital Twins for system-level infrastructure planning in developing contexts.

5. Chapter 6. Operational Digital Twin Application under Abnormal and Emergency Conditions

This chapter presents a Digital Twin–based approach for post-accident bridge assessment using GNSS monitoring integrated with BIM. A real-world vessel collision case study illustrates how GNSS displacement measurements and FEA validation enable rapid, objective evaluation of structural condition, highlighting the advantages of Digital Twin–based monitoring over traditional inspection methods.

6. Chapter 7. Data Assimilation and Machine Learning for Bridge Displacement Estimation Using RTK-GNSS: A Perspective on Robust Prediction and Uncertainty Quantification

Chapter 7 investigates advanced data-driven techniques to improve GNSS displacement estimation. Ensemble Kalman Filtering and Random Forest regression are applied to real monitoring data to reduce noise, capture thermal effects, and quantify uncertainty. Comparative analysis demonstrates improved accuracy and robustness relative to conventional processing approaches.

7. Chapter 8. Digital Twin for bridge anomaly detection and validation based on GNSS and FEA

This chapter integrates GNSS monitoring, BIM, and finite element analysis for Digital Twin–based anomaly detection. Observed bridge deformations are validated against FEA simulations, including soil–structure interaction effects, demonstrating the ability of the Digital Twin to identify abnormal structural behavior and validate monitoring data through physics-based models.

8. Chapter 9. Discussions and Conclusions

The final chapter synthesizes the research findings, discusses contributions to knowledge, and evaluates limitations. It highlights the effectiveness of the proposed Digital Twin framework in enhancing SHM accuracy, decision-making, and system-level analysis, and outlines future research directions, including non-linear modeling, automation, and large-scale deployment.

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1. Introduction

1.1. Research Motivation and Practical Challenges in Bridge Infrastructure Management

Bridges are critical components of transportation infrastructure, supporting social activities, economic development, and regional connectivity [1]. In many countries, including Japan, a large proportion of existing bridges were constructed during periods of rapid economic growth and are now approaching or exceeding their intended service life [2]. As a result, bridge owners and administrators are facing increasing demands for inspection, maintenance, and risk management under constrained financial and human resources [3].

In response to these challenges, digital technologies have been actively introduced into infrastructure management [4]. Among them, the concept of the digital twin (DT) has attracted significant attention as a promising approach for integrating geometric models, sensor data, and analytical tools within a unified virtual environment [5]. In the context of bridge engineering, digital twins are expected to enhance situational awareness, support maintenance planning, and improve responses to abnormal events such as accidents or natural hazards [6].

However, despite these expectations, the practical implementation of digital twins in real bridge management remains limited [7]. Many existing digital twin applications in the architecture, engineering, and construction (AEC) domain focus primarily on visualization, information sharing, or static model representation [8]. While such applications improve communication among stakeholders, they often fall short of supporting engineering-level decision-making for operational bridges [9].

A major obstacle to the operational use of digital twins lies in the nature of structural monitoring data [10]. Continuous monitoring systems, including Global Navigation Satellite System (GNSS)-based displacement measurements, provide valuable information on bridge behavior under traffic loads and environmental influences [11]. At the same time, these data are inherently affected by measurement noise, environmental disturbances, and non-stationary structural responses [12]. As a result, raw monitoring data cannot be directly interpreted as reliable indicators of structural condition or performance [13].

Consequently, bridge administrators are confronted with a critical gap between the availability of large volumes of monitoring data and their effective use for maintenance and management decisions [14]. Without appropriate mechanisms to interpret uncertain observations and relate them to physical structural behavior, digital twins remain descriptive rather than functional [15]. This situation motivates the need for a new approach in which digital twins are explicitly designed to operate under uncertainty and to support engineering decision-making in real bridge infrastructure management as demonstrated in **Figure 1.1**.

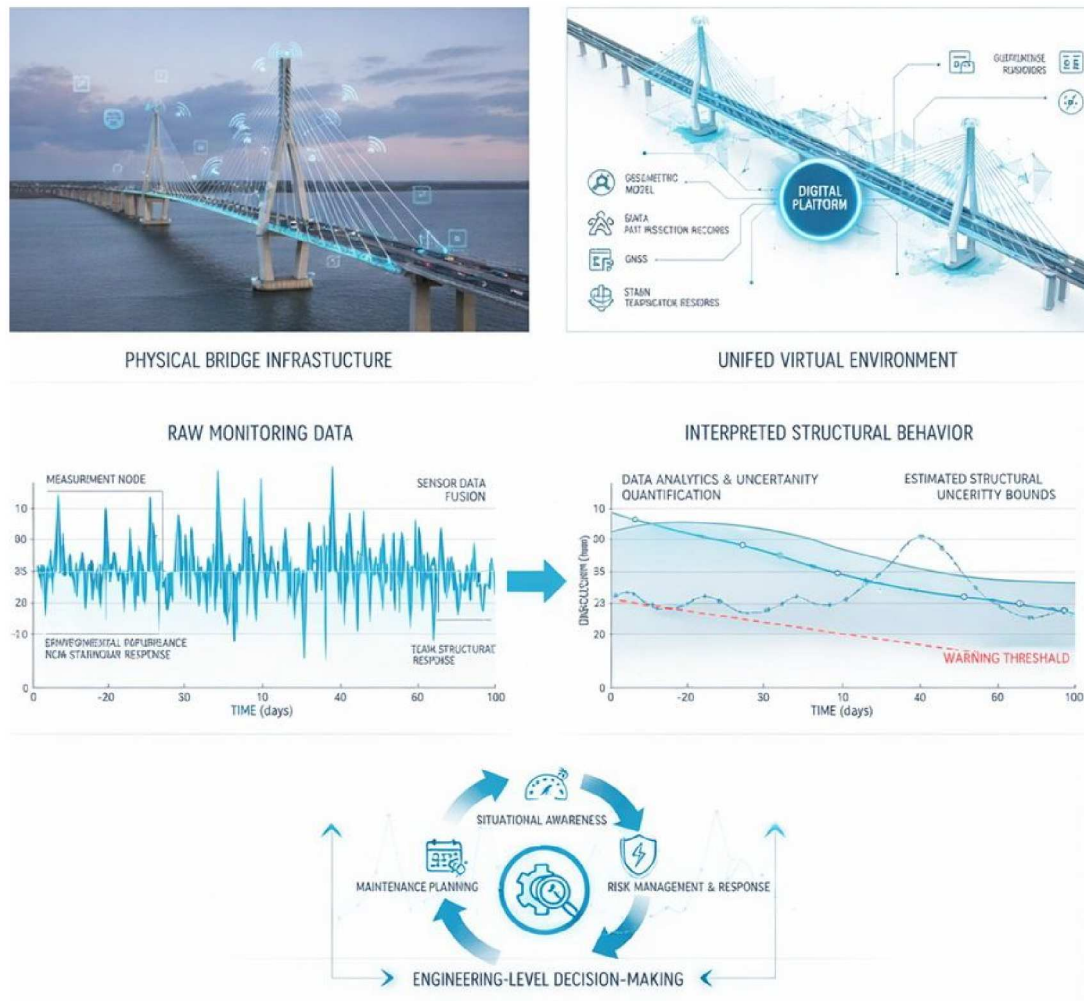


Figure 1. 1 Digital Twin approaches for Bridge management

1.2. Limitations of Existing Digital Twin Approaches under Uncertain Monitoring Environments

Despite the growing interest in digital twin technologies for bridge infrastructure, a fundamental problem remains unresolved: existing digital twins cannot reliably function as operational tools under uncertain monitoring environments[7, 8]. In many current implementations, digital twins are constructed as static or semi-static representations that rely on pre-defined models and descriptive monitoring data, limiting their ability to support engineering-level decision making[6].

Structural monitoring systems, such as GNSS-based displacement measurements, have been increasingly introduced to capture the real-time behavior of bridges [11]. These systems provide valuable insights into structural responses to traffic loads, temperature variations, and environmental effects. However, such monitoring data are inherently uncertain. Measurement noise, signal interruptions, environmental

disturbances, and non-stationary structural behavior introduce significant variability, making it difficult to interpret observed data as reliable indicators of structural condition directly [10, 13].

As a result, most existing digital twin frameworks treat monitoring data as supplementary information rather than as a core component for system operation [8]. The digital twin is often updated in a descriptive manner, without explicitly accounting for uncertainty or estimating the underlying structural state [15]. Consequently, the digital twin remains disconnected from physical interpretation and cannot provide robust support for maintenance planning, anomaly detection, or accident response.

This leads to a critical gap between data availability and practical usability [14]. While large volumes of monitoring data are collected continuously, bridge administrators lack systematic mechanisms to translate uncertain observations into actionable engineering knowledge. Without reliable state estimation and physical consistency checks, digital twins are unable to transition from visualization-oriented platforms to functional cyber-physical systems [5, 6].

Therefore, the central problem addressed in this dissertation is the absence of a digital twin framework that can robustly operate under uncertain and noisy structural monitoring environments, enabling reliable interpretation of monitoring data and supporting engineering decision-making for real bridge infrastructure. Addressing this problem requires rethinking the role of digital twins from static information models to systems that explicitly integrate uncertainty, estimation, and physical validation.

1.3. Research Objective and Dissertation Positioning

Based on the problem identified in the preceding section, this dissertation defines its research objective and clarifies its academic and practical positioning within the field of bridge infrastructure management.

This doctoral dissertation aims to establish a practical and engineering-oriented framework for digital twins of bridge infrastructure, capable of functioning under uncertain and noisy observation environments.

While the concept of digital twins has been widely discussed in the context of visualization and information integration, their practical deployment in real bridge management remains limited by the reliability of sensor observations, model uncertainty, and the lack of systematic decision-support mechanisms. In particular, continuous structural monitoring data obtained from GNSS are inherently affected by noise, environmental disturbances, and non-stationary behavior, which hinder their direct use for infrastructure management.

To address this challenge, this dissertation positions the digital twin not as a static information model, but as a dynamic state-estimation and decision-support system. An integrated framework is proposed in which GNSS-based displacement monitoring is combined with probabilistic data assimilation and machine learning techniques to robustly estimate bridge behavior under uncertainty. Finite element analysis is further incorporated to verify the physical consistency of the estimated states, thereby enhancing the reliability of the digital twin as demonstrated in **Figure 1.2**.

Furthermore, this research extends the application of the proposed digital twin framework beyond structural response evaluation to bridge management and transportation system analysis, demonstrating its potential for supporting infrastructure maintenance, accident response, and evidence-based policy making. Through multiple real-world case studies, this dissertation demonstrates how a digital twin can evolve from a visualization-oriented model into an operational cyber–physical system that supports informed decision-making throughout the lifecycle of bridge infrastructure.

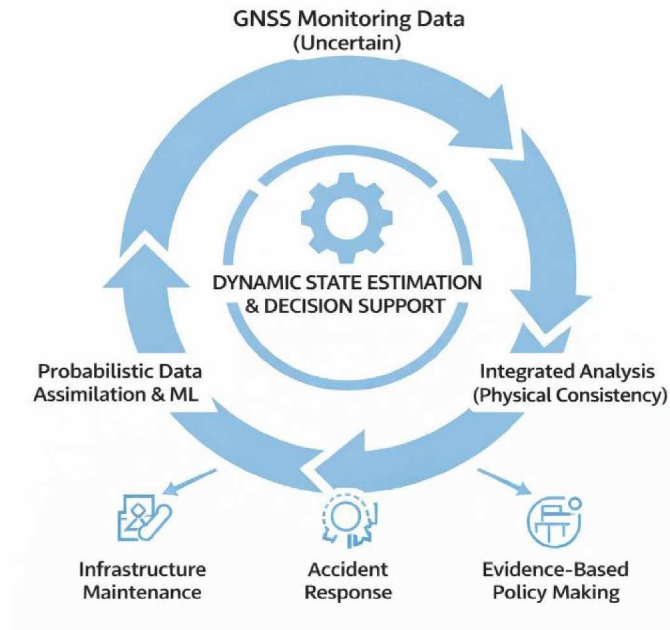


Figure 1.2 Digital Twin Framework for Infrastructure Management

1.4. Concept of an Operational Digital Twin for Bridge Infrastructure

In this dissertation, the term operational digital twin is used to describe a digital twin that actively supports engineering interpretation and decision making for real bridge infrastructure, rather than serving solely as a static information model or visualization platform [6, 16]. This concept emphasizes functionality under real-world conditions, where monitoring data is uncertain and structural behavior is influenced by complex environmental and operational factors[17].

An operational digital twin is characterized by its ability to continuously interpret monitoring data in relation to the physical behavior of the structure[18]. In the context of bridge infrastructure, this requires more than the integration of geometric models and sensor data[7]. It necessitates a systematic mechanism to estimate the underlying structural state from noisy observations and to assess the physical plausibility of the estimated behavior. Without such mechanisms, the digital twin remains descriptive and cannot reliably support maintenance planning or abnormal event response[5, 19].

Accordingly, this dissertation defines an operational digital twin for bridge infrastructure as a cyber–physical system that integrates three essential components: (1) continuous structural monitoring, (2) robust state estimation under uncertainty, and (3) physical verification based on structural mechanics. GNSS-based displacement monitoring provides time-series observations of bridge behavior, while probabilistic data assimilation and machine learning techniques are employed to estimate the structural state from uncertain measurements. Finite element analysis is incorporated to evaluate the physical consistency of the estimated responses and to link observed behavior with structural mechanics.

This definition distinguishes the proposed digital twin framework from existing digital twin implementations that primarily focus on visualization or data aggregation. By explicitly embedding state estimation and physical validation within the digital twin architecture, the proposed approach enables the digital twin to function as an engineering system capable of supporting decision-making throughout the bridge lifecycle.

The concept of an operational digital twin presented in this dissertation serves as the theoretical foundation for the integrated framework developed in the subsequent chapters. To summarize the logical structure of this research and the role of the proposed framework, **Fig. 1.3** provides an overview of the progressive development from infrastructure challenges to integrated decision support.

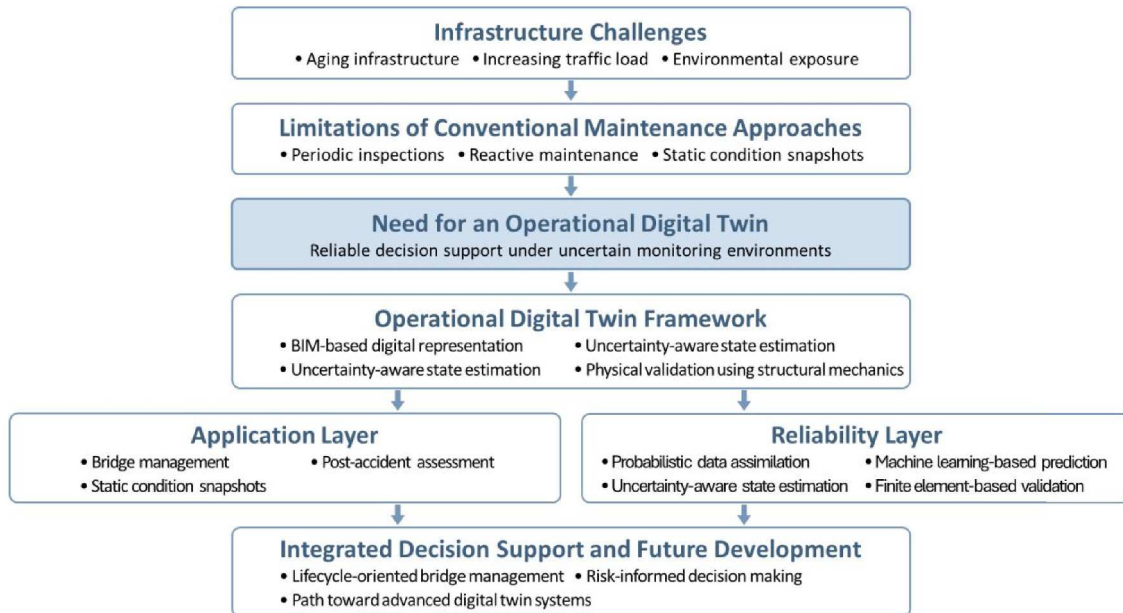


Figure 1.3 Logical structures of the proposed operational digital twin framework for bridge infrastructure under uncertain monitoring environments.

As shown in Fig. 1.3, this dissertation starts from the challenges associated with aging infrastructure and the limitations of conventional maintenance approaches, which motivate the need for an operational digital twin that can provide reliable decision support under uncertain monitoring environments. The proposed framework integrates a BIM-based digital representation with GNSS-based displacement monitoring, uncertainty-aware state estimation, and physical validation grounded in structural mechanics. Building upon this core, the application layer demonstrates practical use cases in bridge management, traffic management,

and post-accident assessment, while the reliability layer strengthens robustness through probabilistic data assimilation, machine learning, and finite element-based validation.

1.5. Scope of the Dissertation and Research Contributions

The scope of this dissertation is defined by the development, validation, and application of an operational digital twin framework for bridge infrastructure operating under uncertain monitoring environments. The research focuses primarily on bridges equipped with continuous GNSS-based displacement monitoring systems, where structural responses are affected by environmental variability, measurement noise, and non-stationary behavior. While the proposed framework is discussed in the context of bridge infrastructure, the methodological components are designed to be extensible to other civil infrastructure systems that require reliable state estimation and decision support.

Within this scope, this dissertation makes the following principal research contributions. First, it proposes a practical operational digital twin framework that explicitly integrates continuous monitoring, uncertainty-aware state estimation, and physics-based verification. By positioning the digital twin as a dynamic cyber-physical system rather than a static information model, the framework enables engineering interpretation and decision support under real-world conditions.

Second, this research advances the use of GNSS-based displacement monitoring for bridge infrastructure by addressing its inherent uncertainty through probabilistic data assimilation and machine learning techniques. The proposed approach enables robust estimation of structural states from noisy and incomplete observations, thereby improving the reliability of monitoring-based assessments.

Third, the dissertation demonstrates a systematic method for linking estimated structural responses with physical models using finite element analysis. This physical verification process provides a mechanism to assess the plausibility of estimated behaviors and strengthens the credibility of the digital twin as an engineering tool.

Finally, the proposed operational digital twin framework is applied to multiple real-world case studies, including bridge management, traffic-related response evaluation, and post-accident assessment. These applications illustrate how the digital twin can support maintenance planning, abnormal event response, and evidence-based decision making, and demonstrate its potential role in lifecycle-oriented infrastructure management.

1.6. Structure of the Dissertation

This dissertation is organized into nine chapters, each contributing to the development and validation of an operational digital twin framework for bridge infrastructure under uncertain monitoring environments. Chapter 1 introduces the research motivation, problem definition, conceptual positioning, scope, and contributions of the study. Chapter 2 reviews related studies on digital twins, bridge structural health monitoring, GNSS-based displacement monitoring, and state estimation methods, and clarifies the research gaps addressed in this dissertation. Chapter 3 presents the overall architecture of the proposed operational digital

twin framework. Chapters 4 through 8 describe the methodological development, physical verification, and practical applications of the framework, including BIM-based digital representation, state estimation, physical validation, and real-world case studies. Finally, Chapter 9 summarizes the main findings and discusses conclusions and future research directions.

1.7. Reference

1. Frangopol, D. M., Dong, Y., & Sabatino, S. (2017). Bridge life-cycle performance and cost: analysis, prediction, optimisation and decision-making. *Structure and Infrastructure Engineering*, 13(10), 1239–1257. <https://doi.org/10.1080/15732479.2016.1267772>
2. Ministry of Land, Infrastructure, Transport and Tourism (MLIT). (2019). *Road Maintenance and Management in Japan*.
3. Liu, M., & Frangopol, D. M. (2005). Mult objective maintenance planning optimization for deteriorating bridges considering condition, safety, and life-cycle cost. *Journal of Structural Engineering*, 131(5), 833–842. [https://doi.org/10.1061/\(ASCE\)0733-9444](https://doi.org/10.1061/(ASCE)0733-9444)
4. Borrmann, A., König, M., Koch, C., & Beetz, J. (Eds.). (2018). *Building information modeling: Technology foundations and industry practice*. Springer Cham. <https://doi.org/10.1007/978-3-319-92862-3>
5. Grieves, M., Vickers, J. (2017). Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems. In: Kahlen, J., Flumerfelt, S., Alves, A. (eds) *Transdisciplinary Perspectives on Complex Systems*. Springer, Cham. https://doi.org/10.1007/978-3-319-38756-7_4
6. Boje, C., Guerriero, A., Kubicki, S., & Rezgui, Y. (2020). Towards a semantic Construction Digital Twin: Directions for future research. *Automation in Construction*, 114, 103179. <https://doi.org/10.1016/j.autcon.2020.103179>
7. Sacks, R., Girolami, M., & Brilakis, I. (2020). Building information modelling, artificial intelligence and construction tech. *Developments in the Built Environment*, 4, 100011. <https://doi.org/10.1016/j.dibe.2020.100011>
8. Lu, Q., Xie, X., Heaton, J., Parlikad, A. K., & Schooling, J. (2020). From BIM towards digital twin: Strategy and future development for smart asset management. In T. Borangiu, D. Trentesaux, P. Leitão, A. Giret Boggino, & V. Botti (Eds.), *Service oriented, holonic and multi-agent manufacturing systems for industry of the future* (Vol. 853, pp. 392–404). Springer, Cham. https://doi.org/10.1007/978-3-030-27477-1_30
9. Li, T., Rui, Y., Zhu, H., Lu, L., & Li, X. (2024). Comprehensive digital twin for infrastructure: A novel ontology and graph-based modelling paradigm. *Advanced Engineering Informatics*, 62(Part B), 102747. <https://doi.org/10.1016/j.aei.2024.102747>
10. Farrar, C. R., & Worden, K. (2013). *Structural health monitoring: A machine learning perspective*. John Wiley & Sons. <https://doi.org/10.1002/9781118443118>
11. Roberts, G. W., Meng, X., & Dodson, A. H. (2004). Integrating a global positioning system and accelerometers to monitor the deflection of bridges. *Journal of Surveying Engineering*, 130(2), 65–72. [https://doi.org/10.1061/\(ASCE\)0733-9453\(2004\)130:2\(65](https://doi.org/10.1061/(ASCE)0733-9453(2004)130:2(65)
12. Brownjohn, J. M. W. (2007). Structural health monitoring of civil infrastructure. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 365(1851), 589–622. <https://doi.org/10.1098/rsta.2006.1925>

13. Sohn, H, Farrar, C R, Hemez, F M, & Czarnecki, J J (2001). A Review of Structural Health Review of Structural Health Monitoring Literature 1996-2001
14. Catbas, F. N., Susoy, M., & Frangopol, D. M. (2008). Structural health monitoring and reliability estimation: Long span truss bridge application with environmental monitoring data. *Engineering Structures*, 30(9), 2347–2359. <https://doi.org/10.1016/j.engstruct.2008.01.013>
15. Kapteyn, M.G., Pretorius, J.V.R. & Willcox, K.E. A probabilistic graphical model foundation for enabling predictive digital twins at scale. *Nat Comput Sci* 1, 337–347 (2021). <https://doi.org/10.1038/s43588-021-00069-0>
16. Sun, Z., Jayasinghe, S., Sidiq, A., Shahrivar, F., Mahmoodian, M., & Setunge, S. (2025). Approach Towards the Development of Digital Twin for Structural Health Monitoring of Civil Infrastructure: A Comprehensive Review. *Sensors*, 25(1), 59. <https://doi.org/10.3390/s25010059>
17. Long, Y., Chu, S., Zhang, K., Zhou, P., Shi, H., & Hu, T. (2025). *Real-time structural health monitoring based on measured and simulated data*. **Nondestructive Testing and Evaluation**, 1–17. <https://doi.org/10.1080/10589759.2025.2487578>
18. Febrianto, Eky, Liam Butler, Mark Girolami, and Fehmi Cirak. 2021. *Digital twinning of self-sensing structures using the statistical finite element method*. arXiv preprint arXiv:2103.13729. <https://doi.org/10.48550/arXiv.2103.13729>
19. Liu, C., Zhang, P., & Xu, X. (2023). Literature review of digital twin technologies for civil infrastructure. *Journal of Infrastructure Intelligence and Resilience*, 2(3), 100050. <https://doi.org/10.1016/j.iintel.2023.100050>

2. Conceptual Foundations and Related Work for Operational Digital Twins of Bridge Infrastructure

2.1. Digital Twin Concepts in Civil and Infrastructure Engineering

2.1.1 Definitions and Evolution of Digital Twins

The concept of the digital twin was originally introduced in the context of product lifecycle management, where it referred to a digital representation of a physical asset that evolves alongside its real-world counterpart [1]. Early definitions emphasized the use of digital models to mirror physical systems throughout their lifecycle, enabling improved design, monitoring, and maintenance through data-driven insights[1, 2]. In this initial stage, digital twins were primarily associated with manufacturing systems, where controlled environments and repeatable processes allowed close synchronization between physical assets and their digital representations[3].

As the concept matured, distinctions emerged between **digital models**, **digital shadows**, and **digital twins**[3]. A digital model typically represents a static or periodically updated representation of a physical system, while a digital shadow incorporates unidirectional data flow from the physical asset to the digital domain. In contrast, a digital twin is characterized by bidirectional interaction, in which information flows continuously between the physical and digital systems[1, 3]. This bidirectional coupling enables not only observation but also interpretation and, in some cases, intervention based on the digital representation[2].

With the expansion of sensing, communication, and computational technologies, the scope of digital twins has extended beyond manufacturing to complex, open systems such as buildings, cities, and civil infrastructure[4, 5]. In these contexts, digital twins are increasingly expected to support real-time monitoring, predictive analysis, and decision-making under uncertain and dynamic conditions[6]. Consequently, the definition of a digital twin has evolved from a static or descriptive model toward a dynamic, data-driven representation that continuously reflects the state of the physical system[2, 7]. This explanation can be demonstrated as in **Figure 2.1**.

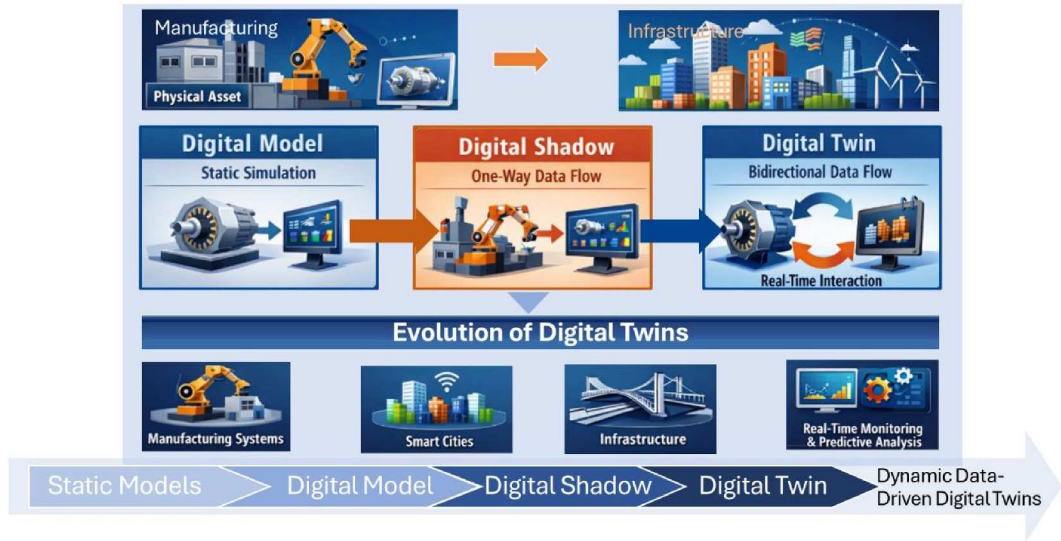


Figure 2. 1 Definition and Evolution of Digital Twins

Despite this evolution, the term “digital twin” is still used inconsistently across the literature, often referring to systems with varying levels of data integration, model fidelity, and functional capability. In many studies, digital twins remain focused on visualization or information integration, without explicitly addressing how observed data are interpreted in relation to the underlying physical behavior of the system. This diversity in usage highlights the need for a clearer conceptual distinction when applying digital twin concepts to engineering decision support, particularly in domains characterized by uncertainty and limited observability.

2.1.2 Digital Twins as Cyber–Physical Systems

Digital twins are closely related to the broader concept of cyber–physical systems (CPS), which describe systems in which physical processes are tightly integrated with computational models through sensing, communication, and control [8, 9]. In a CPS, the physical system and its cyber representation form a closed loop, where measurements from the physical domain are continuously used to update the cyber model, and the results of computation and analysis can influence physical operation or decision making. Within this framework, a digital twin can be regarded as a core cyber component that represents the evolving state of the physical system[8] as demonstrated in **Figure 2.2**.

From a CPS perspective, the defining feature of a digital twin is not merely the coexistence of physical and digital components, but the continuous coupling between them. This coupling is typically realized through sensor networks that acquire observations of the physical system, data processing mechanisms for interpretation, and models representing system behavior in the cyber domain. The effectiveness of a digital twin, therefore, depends on how reliably the cyber representation can reflect the true state of the physical system, particularly when observations are incomplete, noisy, or affected by environmental disturbances[10, 11].

In many existing CPS-oriented digital twin implementations, the emphasis is placed on data connectivity and real-time information flow [8]. While such connectivity enables timely access to monitoring data, it does not, by itself, guarantee that the cyber model accurately represents the underlying physical behavior[11]. Without explicit mechanisms for state estimation and validation, the digital twin may remain a data-driven mirror that reproduces observed signals without interpreting their physical meaning. This limitation becomes critical in engineering applications where decisions must be grounded in an understanding of structural response and system behavior.

For civil and infrastructure systems, the CPS interpretation of digital twins is further complicated by the scale, longevity, and safety-critical nature of the assets[12]. Unlike manufacturing systems, where control actions can often be directly implemented, infrastructure-oriented digital twins primarily support engineering assessment and decision making rather than direct control. As a result, the role of the digital twin within a CPS shift from real-time actuation toward continuous state interpretation and reliability assessment, highlighting the importance of robust estimation and physically consistent modeling.

These considerations indicate that, when digital twins are viewed as cyber–physical systems, their functional value depends not only on data integration but also on the ability to infer and validate the physical state of the system. This observation is particularly relevant for civil infrastructure applications, where uncertainty and limited observability are inherent. The next section, therefore, examines how digital twin concepts have been adapted to civil and infrastructure engineering, and discusses the specific challenges associated with applying CPS-based digital twins to long-lived structural systems.

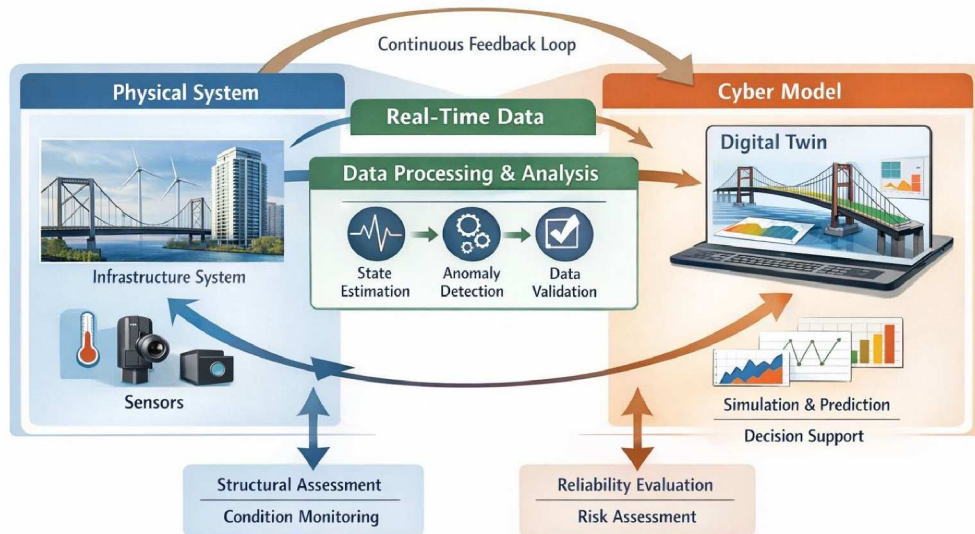


Figure 2.2 Digital Twins as Cyber-Physical Systems

2.1.3 Digital Twins in Civil and Infrastructure Engineering

The application of digital twin concepts to civil and infrastructure engineering differs fundamentally from their implementation in manufacturing systems[2, 13]. Civil infrastructure assets, such as bridges,

tunnels, and transportation networks, are typically long-lived, large-scale, and unique systems that are exposed to complex environmental and operational conditions throughout their service life[1, 14]. These characteristics impose significant constraints on how digital twins can be constructed, updated, and utilized in infrastructure contexts[5, 6].

In contrast to manufacturing environments, where digital twins often operate within controlled and repeatable processes, infrastructure-oriented digital twins must function under **uncontrolled** and uncertain conditions[2, 15]. Structural behavior is influenced by variable traffic loads, environmental effects such as temperature and wind, material aging, and occasional extreme events[14, 16]. Moreover, infrastructure systems cannot be subjected to controlled experiments or frequent physical interventions, making direct validation of digital models inherently challenging[17]. As a result, digital twins for civil infrastructure must rely on limited and noisy observations to infer system behavior over long-time horizons[5, 6].

Within civil infrastructure engineering, Building Information Modeling (BIM) commonly serves as the foundation for digital twin implementations[14, 15]. BIM provides a structured digital representation that integrates geometric, semantic, and attribute information, enabling consistent management of design, construction, and maintenance data[15, 18]. When combined with continuous monitoring systems, BIM-based digital twins can support the visualization of structural conditions, integration of inspection records, and contextual interpretation of sensor data[14, 19]. However, BIM alone does not represent the dynamic structural state, and additional analytical mechanisms are required to interpret monitoring data in terms of structural behavior[6, 17]. The clear path can be seen in **Figure 2.3**.

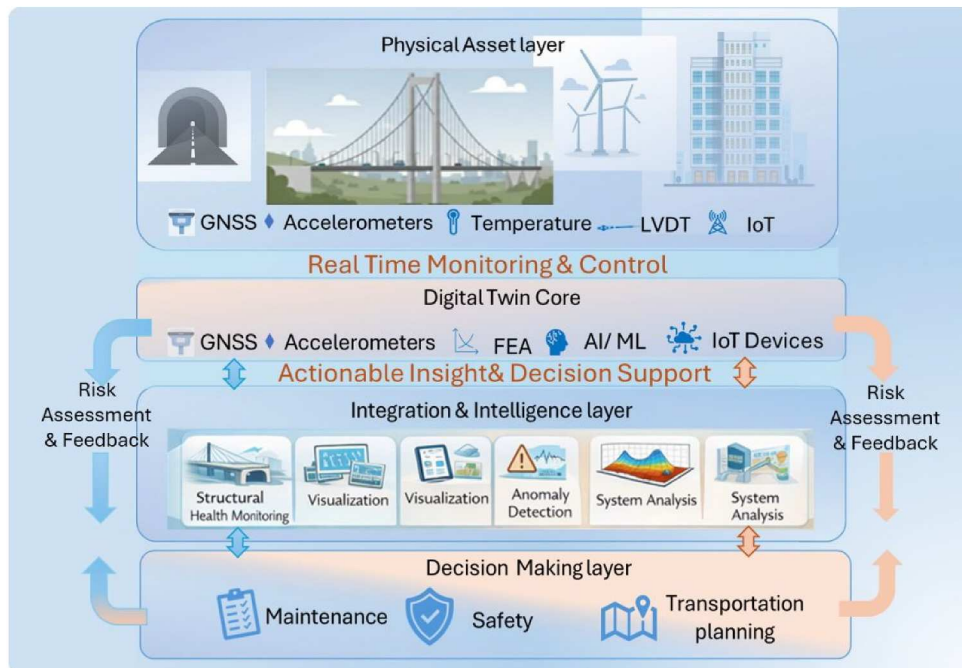


Figure 2.3 Digital Twin for Infrastructure Management.

Recent studies have explored the integration of various sensing technologies, such as GNSS, accelerometers, strain gauges, vision-based systems, and wireless sensor networks, into infrastructure-oriented digital twins[20, 21]. These sensing modalities enable the acquisition of time-series data related to displacement, vibration, and deformation, which are essential for assessing structural performance[14, 17]. Nevertheless, the presence of measurement noise, environmental disturbances, and data gaps often limits the direct use of these observations for engineering assessment. Consequently, the effectiveness of infrastructure digital twins depends on how monitoring data are processed and interpreted rather than on data availability alone.

These characteristics highlight a key distinction between digital twins in civil infrastructure and those in other domains: the primary role of the digital twin is not real-time control but engineering interpretation and decision support under uncertainty. To fulfill this role, infrastructure-oriented digital twins must go beyond visualization and data aggregation and instead incorporate mechanisms that can robustly estimate structural state and assess the physical plausibility of observed behavior. This requirement motivates a critical examination of existing infrastructure digital twin implementations, which is discussed in the following section.

2.1.4 Limitations of Existing Infrastructure-Oriented Digital Twins

Despite the growing interest in digital twin applications for civil infrastructure, many existing implementations remain limited in their ability to support reliable engineering decision-making[5, 23]. A common characteristic of current infrastructure-oriented digital twins is their emphasis on visualization, data integration, and information management, rather than on the explicit interpretation of structural behavior[14, 23]. While these functions improve data accessibility and situational awareness, they do not, by themselves, ensure that the digital representation accurately reflects the physical state of the structure[17].

One major limitation lies in the treatment of monitoring data[20, 22]. In many digital twin implementations, sensor measurements are directly mapped onto the digital model without rigorous consideration of measurement uncertainty, environmental effects, or non-stationary behavior[24, 25]. As a result, observed data are often interpreted at face value, even though they may be significantly affected by noise, temperature variations, sensor drift, or data gaps. Without systematic state estimation mechanisms, it is difficult to distinguish between true structural responses and apparent changes caused by external disturbances or measurement artifacts.

Another limitation concerns the lack of explicit physical validation[5, 17]. Although numerical models such as finite element models are sometimes incorporated into digital twin platforms, they are frequently used in an offline or illustrative manner[2, 13]. In many cases, there is no formal process to assess the consistency between estimated structural responses and the governing principles of structural mechanics[17, 26]. Consequently, the digital twin may produce representations that are visually plausible but physically questionable, undermining its credibility as an engineering tool[5].

Furthermore, existing infrastructure digital twins often lack a clear functional definition of their role within the asset management process[23, 28]. The objectives of the digital twin, whether for condition assessment, anomaly detection, maintenance planning, or emergency response, are not always explicitly

stated, leading to ambiguous system requirements and evaluation criteria. This ambiguity makes it difficult to assess the performance of digital twin implementations or to compare different approaches systematically.

These limitations indicate that, although digital twins for civil infrastructure have advanced in terms of data integration and platform development, their operational capability as engineering decision-support systems remains insufficient. In particular, the absence of robust state estimation under uncertainty and systematic physical validation prevents many existing digital twins from being reliably used in practice. Addressing these shortcomings requires a shift from visualization-oriented implementations toward an operational digital twin framework that explicitly integrates monitoring data, state estimation, and physically grounded verification.

2.1.5 Need for an Operational Digital Twin

The limitations identified in existing infrastructure-oriented digital twin implementations underscore a fundamental gap between current digital representations and the requirements of practical engineering decision making[5, 17, 22]. In the context of civil infrastructure, particularly bridge systems, decision support must be based on an accurate and physically meaningful interpretation of structural behavior under uncertain and evolving conditions[16, 26]. Visualization and data aggregation alone are therefore insufficient to meet the demands of infrastructure management throughout the asset lifecycle[14, 23].

To address this gap, there is a clear need for a digital twin that functions as an operational system, rather than as a descriptive or illustrative model. An operational digital twin must be capable of continuously interpreting monitoring data in relation to the underlying physical state of the structure. This necessitates explicit mechanisms for estimating structural state from noisy and incomplete observations, as well as methods for assessing the physical plausibility of the estimated responses based on structural mechanics.

In bridge infrastructure applications, monitoring data such as GNSS-based displacement measurements provides valuable but inherently uncertain information. Without robust state estimation frameworks, these observations cannot be directly translated into reliable indicators of structural performance or safety. Moreover, without systematic physical validation, estimated states may lack engineering credibility, limiting their usefulness for maintenance planning, anomaly assessment, and emergency response. An operational digital twin must therefore integrate monitoring, uncertainty-aware state estimation, and physically grounded verification within a unified framework.

By incorporating these elements, an operational digital twin can move beyond the passive reflection of observed data and actively support engineering interpretation and decision-making. Such a system enables the digital twin to serve as a cyber-physical interface that links real-time observations with structural mechanics, thereby enhancing the reliability and transparency of infrastructure management decisions. This perspective forms the conceptual foundation for the integrated digital twin framework proposed in this dissertation.

The following chapters build upon this need by presenting the architecture, methodologies, and practical applications of an operational digital twin framework for bridge infrastructure. Chapter 3 introduces the overall system architecture, followed by detailed discussions of state estimation, physical verification, and real-world case studies that demonstrate how the proposed framework addresses the limitations identified in existing digital twin implementations.

2.2. Bridge Structural Health Monitoring

Structural Health Monitoring (SHM) has been widely studied as a systematic approach for assessing the condition and performance of bridge structures through continuous or periodic measurements. The primary objective of SHM is to detect, localize, and evaluate structural deterioration or abnormal behavior at an early stage, thereby supporting timely maintenance and ensuring structural safety. Over the past decades, advances in sensing technologies, data acquisition systems, and communication infrastructure have significantly expanded the scope and applicability of bridge SHM [28, 29].

Bridge SHM systems typically rely on a variety of sensing modalities to capture different aspects of structural behavior. Commonly used sensors include accelerometers for vibration-based monitoring, strain gauges and fiber optic sensors for local deformation measurement, displacement sensors for global response assessment, and GNSS receivers for long-term monitoring of three-dimensional displacement. Vision-based techniques using cameras or UAVs have also been introduced to support inspection and damage detection [30-38]. These heterogeneous sensing technologies enable multi-scale observation of bridge behavior, ranging from local component responses to global structural deformation.

Despite these technological advances, bridge SHM faces inherent challenges related to data quality and interpretation. Monitoring data is often affected by measurement noise, environmental influences such as temperature and wind, sensor malfunction, and data loss. In addition, bridge responses exhibit non-stationary behavior due to varying traffic loads, seasonal effects, and long-term material degradation. As a result, raw SHM data cannot be directly interpreted as indicators of structural condition without appropriate processing and analysis.

To address these challenges, various data processing and analysis techniques have been proposed in the SHM literature. These include signal filtering, feature extraction, modal identification, and statistical pattern recognition[39, 40]. More recently, machine learning and data-driven approaches have been applied to anomaly detection and damage classification using large monitoring datasets[41, 42]. While these methods have demonstrated promising results, their performance often depends on the availability of representative training data and stable monitoring conditions, which are difficult to guarantee in real bridge environments.

Another important aspect of bridge SHM is the integration of monitoring data with structural models. Model-based SHM approaches aim to interpret observed responses in terms of underlying structural parameters or states by combining measurements with analytical or numerical models[43,44]. Such approaches provide a pathway toward physically meaningful assessment, but they also require careful treatment of model uncertainty and measurement error. In practice, many SHM implementations remain focused on data-driven indicators without explicitly linking observations to structural mechanics.

These characteristics highlight a fundamental limitation of conventional bridge SHM: while extensive data can be collected, transforming these data into reliable engineering knowledge remains challenging. For digital twin applications, this limitation becomes particularly critical, as the digital twin must continuously interpret monitoring data to represent the evolving structural state. Consequently, bridge SHM should be viewed not only as a data acquisition process, but as an integral component of a broader framework that combines monitoring with state estimation and physical interpretation. This perspective motivates the subsequent review of advanced data analysis and state estimation techniques for SHM, discussed in the following section.

2.3. Advanced Data Analytics and State Estimation for Bridge SHM

The limitations of conventional bridge SHM in transforming monitoring data into reliable engineering knowledge have motivated the development of advanced data analytics and state estimation techniques. These approaches aim to extract meaningful information from noisy, heterogeneous, and often incomplete monitoring data, and to infer the underlying structural behavior of bridges under operational conditions[45]. In recent years, researchers have actively explored both data-driven and model-based methods to enhance the interpretability and reliability of SHM outcomes.

Advanced data analytics in bridge SHM encompass a wide range of techniques, including statistical signal processing, feature extraction, and pattern recognition. Filtering methods are commonly applied to reduce measurement noise and environmental effects, while dimensionality reduction techniques are used to identify dominant response patterns from large datasets. These methods provide useful indicators of structural behavior; however, they often rely on heuristic assumptions and may not directly correspond to physically meaningful structural states[46-49].

Machine learning approaches have gained increasing attention for anomaly detection, damage classification, and performance assessment in SHM applications. Supervised and unsupervised learning algorithms have been applied to vibration signals, displacement time series, and other monitoring data to identify deviations from normal behavior[50-53]. While such approaches can effectively detect changes in data patterns, their reliance on training data and sensitivity to changing operational conditions pose challenges for long-term bridge monitoring. In particular, distinguishing between structural anomalies and variations caused by environmental or operational factors remains difficult without explicit physical interpretation.

State estimation methods provide a complementary perspective by explicitly modeling the relationship between observations and the underlying structural state. Techniques such as Kalman filtering and its extensions, including nonlinear and ensemble-based approaches, have been employed to estimate structural responses by combining monitoring data with analytical or numerical models. These methods offer a systematic framework for handling measurement uncertainty and model error, and they enable the estimation of latent variables that cannot be directly observed [54 - 67].

In bridge SHM, state estimation is particularly relevant for interpreting displacement measurements obtained from GNSS and other sensors. Such measurements are inherently affected by noise, multipath effects, and environmental disturbances, making direct interpretation unreliable. By incorporating probabilistic state estimation frameworks, it becomes possible to distinguish structural responses from measurement

artifacts and to quantify the uncertainty associated with estimated states. However, the effectiveness of state estimation depends on the adequacy of the underlying structural model and the treatment of model uncertainty.

Despite these advances, many existing SHM studies treat advanced data analytics and state estimation as isolated processes, without fully integrating them into a unified framework that supports continuous decision making. Data-driven methods may lack physical grounding, while model-based approaches may suffer from simplifications or parameter uncertainty. Bridging this gap requires an approach that combines uncertainty-aware data analytics with physically interpretable state estimation, forming a critical component of an operational digital twin for bridge infrastructure.

This observation underscores the importance of coupling advanced data analytics and state estimation with physical validation mechanisms. While data analytics and estimation can infer plausible structural states, their reliability must be assessed against the governing principles of structural mechanics. The next section, therefore, reviews the role of finite element analysis as a tool for physical verification and validation within bridge SHM and digital twin frameworks.

2.4. Physical Verification and Validation Using Finite Element Analysis

Finite Element Analysis (FEA) has long been established as a fundamental tool for evaluating the structural behavior of bridges under various loading and boundary conditions[68 -71]. In the context of bridge structural health monitoring and digital twin development, FEA provides a physically grounded framework for interpreting observed responses and assessing the plausibility of estimated structural states. By representing the governing equations of structural mechanics in a discretized numerical form, FEA enables the evaluation of stress, deformation, and dynamic characteristics that cannot be directly measured in practice[72].

In many SHM-related studies, FEA is used to support model-based interpretation of monitoring data, such as identifying damage-sensitive parameters, simulating structural response under assumed damage scenarios, or validating observed trends in displacement or vibration. When combined with monitoring data, FEA can help bridge the gap between measured responses and underlying structural behavior. However, traditional applications often treat FEA as an offline analysis tool, separate from the continuous monitoring process.

For digital twin applications, the role of FEA extends beyond conventional simulation. In an infrastructure-oriented digital twin, FEA can serve as a physical verification mechanism that evaluates whether estimated structural states are consistent with structural mechanics. This verification is particularly important when state estimation and data-driven analytics are applied to noisy and uncertain monitoring data. Without such physical validation, estimated states may appear statistically plausible while violating fundamental mechanical principles[14, 87].

Several studies have explored the integration of FEA with monitoring and state estimation frameworks, including model updating, parameter identification, and hybrid data–model approaches. These methods aim to reduce discrepancies between simulated and observed responses by adjusting model parameters or boundary conditions. While promising, such approaches face challenges related to computational cost, model

uncertainty, and the simplification of complex structural behavior. In practice, achieving a balance between model fidelity and computational efficiency remains a critical issue for operational use.

Another challenge in applying FEA for physical verification lies in the treatment of uncertainty. Structural models inevitably involve uncertainties in material properties, boundary conditions, and loading assumptions. When FEA is used to validate estimated states, these uncertainties must be explicitly considered to avoid overconfidence in model predictions. Probabilistic or ensemble-based approaches have been proposed to address this issue, but their integration into practical digital twin systems is still limited.

These observations indicate that although FEA provides a powerful physical foundation for bridge assessment, its effective use within digital twin frameworks requires careful integration with monitoring and state estimation processes. Rather than serving solely as a simulation tool, FEA should be positioned as a component of a broader verification strategy that enhances the credibility of estimated structural states. This perspective highlights the need for integrated frameworks that combine advanced data analytics, state estimation, and physically grounded verification, which is a central theme of the operational digital twin approach adopted in this dissertation.

2.5. Digital Twins for Traffic Management and System-Level Applications

Beyond structural condition assessment, digital twin concepts have increasingly been applied at the transportation system level to support traffic management, operational planning, and policy evaluation. In these applications, digital twins are used to represent dynamic interactions among infrastructure, traffic flow, and environmental factors, enabling simulation-based analysis of mobility, congestion, and network performance[74, 75]. Such system-level digital twins aim to enhance situational awareness and decision making by integrating heterogeneous data sources within a unified cyber–physical framework[76, 77].

In traffic management applications, digital twins typically combine infrastructure models with real-time or near-real-time traffic data obtained from sensors, cameras, probe vehicles, and connected vehicle systems. By continuously updating the digital representation of traffic conditions, these systems enable short-term forecasting, incident detection, and evaluation of control strategies such as signal timing adjustments or route guidance. Compared with static traffic models, digital twins provide a more adaptive and responsive approach to managing complex transportation networks.

Recent studies have also explored the integration of traffic-oriented digital twins with environmental and safety considerations. By coupling traffic simulations with emission models and exposure assessments, digital twins can support the evaluation of environmental impacts and sustainability measures. Similarly, digital twins have been applied to assess the effects of traffic incidents, road closures, or infrastructure failures on network-level performance, providing valuable insights for emergency response and resilience planning[78- 82].

Despite these advances, many traffic-focused digital twin implementations remain largely data-driven and are often loosely connected to the structural condition of infrastructure assets. Traffic dynamics are frequently modeled independently of structural performance, and the interaction between traffic loads and structural behavior is not explicitly considered. As a result, system-level digital twins may provide accurate

representations of traffic flow while overlooking the structural implications of operational decisions, such as increased loads due to congestion or rerouting during abnormal events.

For bridge infrastructure, this separation represents a critical limitation. Bridges serve as key nodes within transportation networks, where structural conditions and traffic operation are inherently coupled. An operational digital twin for bridge infrastructure should therefore not only assess structural response but also consider the broader transportation context in which the structure operates. Integrating structural digital twins with traffic-oriented digital twins offers the potential to support more comprehensive decision-making, including maintenance planning, load management, and post-incident assessment.

These observations suggest that system-level applications of digital twins highlight both the opportunities and challenges of extending digital twin concepts beyond individual structures. While traffic management digital twins demonstrate the value of real-time data integration and simulation-based decision support, their limited consideration of structural behavior underscores the need for integrated frameworks that link structural state estimation with transportation system analysis. This needs to further reinforce the motivation for an operational digital twin framework that unifies structural monitoring, physical verification, and system-level application, as discussed in the following section.

2.6. Research Gaps and Positioning of This Dissertation

This chapter has reviewed existing studies related to digital twin concepts, bridge structural health monitoring, advanced data analytics and state estimation, physical verification using finite element analysis, and system-level applications such as traffic management. While significant progress has been made in each of these research areas, the review reveals several critical gaps that limit the practical deployment of digital twins as engineering decision-support systems for bridge infrastructure.

First, many infrastructure-oriented digital twin implementations remain focused on visualization and data integration, without explicitly defining how monitoring data should be interpreted in relation to the underlying structural state. Although continuous monitoring technologies are widely available, the absence of robust state estimation mechanisms prevents reliable differentiation between true structural behavior and apparent changes caused by measurement noise, environmental effects, or operational variability.

Second, advanced data analytics and machine learning techniques have demonstrated strong potential for anomaly detection and pattern recognition in bridge SHM. However, these approaches are often applied in a data-driven manner, with limited physical grounding. As a result, detected anomalies may lack clear structural interpretation, and the reliability of the results may degrade under changing environmental or operational conditions. This highlights the need for uncertainty-aware state estimation frameworks that can bridge the gap between data patterns and physically meaningful structural states.

Third, while finite element analysis provides a well-established foundation for structural assessment, its integration into digital twin systems is frequently limited to offline simulation or illustrative validation. Systematic mechanisms for continuously verifying estimated structural states against structural mechanics, while accounting for model uncertainty, remain underdeveloped. Without such physical verification, digital twins risk producing results that are statistically plausible but mechanically inconsistent.

Fourth, existing digital twin applications at the transportation system level often treat structural performance and traffic operation as separate problems. This separation limits the ability of digital twins to support comprehensive decision-making for bridge infrastructure, where structural conditions and traffic dynamics are inherently coupled. Integrating structural digital twins with system-level applications remains a largely unexplored area.

Taken together, these gaps indicate that current digital twin research lacks an integrated framework capable of robustly supporting engineering decision-making for bridge infrastructure under uncertain monitoring environments. There is a clear need for an operational digital twin that unifies continuous monitoring, uncertainty-aware state estimation, and physically grounded verification, while also enabling practical applications in bridge management and transportation systems.

Based on this assessment, the remainder of this dissertation focuses on the development and validation of an integrated operational digital twin framework for bridge infrastructure. Chapter 3 introduces the overall system architecture, followed by detailed methodological developments and real-world case studies in the subsequent chapters, demonstrating how the proposed framework addresses the research gaps identified in this chapter.

2.7. Reference

1. Grieves, M., & Vickers, J. (2017). Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems. In J. Kahlen, S. Flumerfelt, & A. Alves (Eds.), *Transdisciplinary perspectives on complex systems*. Springer. https://doi.org/10.1007/978-3-319-38756-7_4
2. Tao, F., Zhang, H., Liu, A., & Nee, A. Y. C. (2019). Digital twin in industry: State-of-the-art. *IEEE Transactions on Industrial Informatics*, 15(4), 2405–2415. <https://doi.org/10.1109/TII.2018.2873186>
3. Kritzinger, W., Karner, M., Traar, G., Henjes, J., & Sihn, W. (2018). Digital twin in manufacturing: A categorical literature review and classification. *IFAC-PapersOnLine*, 51(11), 1016–1022. <https://doi.org/10.1016/j.ifacol.2018.08.474>
4. Batty, M. (2018). Digital twins. *Environment and Planning B: Urban Analytics and City Science*, 45(5), 817–820. <https://doi.org/10.1177/2399808318796416>
5. Boje, C., Guerriero, A., Kubicki, S., & Rezgui, Y. (2020). Towards a semantic construction digital twin: Directions for future research. *Automation in Construction*, 114, Article 103179. <https://doi.org/10.1016/j.autcon.2020.103179>
6. Lu, Q., Xie, X., Parlikad, A. K., & Schooling, J. M. (2020). Digital twin-enabled anomaly detection for built asset monitoring in operation and maintenance. *Automation in Construction*, 118, Article 103277. <https://doi.org/10.1016/j.autcon.2020.103277>
7. Fuller, A., Fan, Z., Day, C., & Barlow, C. (2020). Digital twin: Enabling technologies, challenges and open research. *IEEE Access*, 8, 108952–108971. <https://doi.org/10.1109/ACCESS.2020.2998358>
8. Parnianifard, A., Jearavongtakul, S., Sasithong, P., Sinpan, N., Poomrittigul, S., Bajpai, A., Vanichchanunt, P., & Wuttisittikulkij, L. (2022). Digital twins towards cyber-physical systems: A brief survey. *Engineering Journal*, 26(9), 47–61. <https://doi.org/10.4186/ej.2022.26.9.47>
9. Tao, F., Qi, Q., Wang, L., & Nee, A. Y. C. (2019). Digital twins and cyber-physical systems toward smart manufacturing and Industry 4.0: Correlation and comparison. *Engineering*, 5(4), 653–661. <https://doi.org/10.1016/j.eng.2019.01.014>
10. Fitzgerald, J., Larsen, P. G., Margaria, T., Woodcock, J., & Gomes, C. (2022). Engineering of digital twins for cyber-physical systems. In T. Margaria & B. Steffen (Eds.), *Leveraging applications of formal*

- methods, verification and validation. Practice (Lecture Notes in Computer Science, Vol. 13704). Springer. https://doi.org/10.1007/978-3-031-19762-8_1
11. Larsen, P. G., Fitzgerald, J., & Woodcock, J. (2023). How do we engineer trustworthy digital twins? Research Directions: Cyber-Physical Systems, 1, e3, 1–2. <https://doi.org/10.1017/cbp.2023>
 12. Naderi, H., & Shojaei, A. (2023). Digital twinning of civil infrastructures: Current state of model architectures, interoperability solutions, and future prospects. Automation in Construction, 149, Article 104785. <https://doi.org/10.1016/j.autcon.2023.104785>
 13. Lu, Q., Xie, X., Heaton, J., Parlikad, A. K., & Schooling, J. (2020). From BIM towards digital twin: Strategy and future development for smart asset management. In T. Borangiu, D. Trentesaux, P. Leitão, A. Giret Boggino, & V. Botti (Eds.), Service oriented, holonic and multi-agent manufacturing systems for industry of the future (SOHOMA 2019) (Studies in Computational Intelligence, Vol. 853, pp. 392–404). Springer. https://doi.org/10.1007/978-3-030-27477-1_30
 14. Tita, E. E., Watanabe, G., Shao, P., & Arie, K. (2023). Development and Application of Digital Twin–BIM Technology for Bridge Management. Applied Sciences, 13(13), 7435. <https://doi.org/10.3390/app13137435>
 15. Sacks, R., Eastman, C., Lee, G., & Teicholz, P. (2018). BIM handbook: A guide to building information modeling for owners, designers, engineers, contractors, and facility managers (3rd ed.). John Wiley & Sons. <https://doi.org/10.1002/9781119287568>
 16. Farrar, C. R., & Worden, K. (2013). Structural health monitoring: A machine learning perspective. John Wiley & Sons. <https://doi.org/10.1002/9781118443118>
 17. Worden, K., Cross, E. J., Barthorpe, R. J., Wagg, D. J., & Gardner, P. (2020). On digital twins, mirrors, and virtualizations: Frameworks for model verification and validation. ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part B: Mechanical Engineering, 6(3), 030902. <https://doi.org/10.1115/1.4046740>
 18. Eastman, C., Teicholz, P., Sacks, R., & Liston, K. (2008). BIM handbook: A guide to building information modeling for owners, managers, designers, engineers, and contractors. John Wiley & Sons. <https://doi.org/10.1002/9780470261309>
 19. Srivastava, V., & Narkhede, D. I. (2025). An integrated digital twin and sensor-based framework for advanced structural health monitoring of bridges. Journal of Civil Engineering and Applications, 6(1), 91–100. <https://doi.org/10.22271/27078388.2025.v6.i1a.43>
 20. Farrar, C. R., & Worden, K. (2013). Structural health monitoring: A machine learning perspective. John Wiley & Sons. <https://doi.org/10.1002/9781118443118>
 21. Sun, Z., Jayasinghe, S., Sidiq, A., Shahrivar, F., Mahmoodian, M., & Setunge, S. (2025). Approach towards the development of digital twin for structural health monitoring of civil infrastructure: A comprehensive review. Sensors, 25(1), 59. <https://doi.org/10.3390/s25010059>
 22. Lu, Q., Xie, X., Heaton, J., Parlikad, A. K., & Schooling, J. (2020). From BIM towards digital twin: Strategy and future development for smart asset management. In T. Borangiu, D. Trentesaux, P. Leitão, A. Giret Boggino, & V. Botti (Eds.), Service oriented, holonic and multi-agent manufacturing systems for industry of the future (Studies in Computational Intelligence, Vol. 853, pp. 392–404). Springer. https://doi.org/10.1007/978-3-030-27477-1_30
 23. Sacks, R., Brilakis, I., Pikas, E., Xie, H. S., & Girolami, M. (2020). Construction with digital twin information systems. Data-Centric Engineering, 1, Article e14. <https://doi.org/10.1017/dce.2020.16>

24. Cross, E. J., Koo, K. Y., Brownjohn, J. M. W., & Worden, K. (2013). Long-term monitoring and data analysis of the Tamar Bridge. *Mechanical Systems and Signal Processing*, 35(1–2), 16–34.
<https://doi.org/10.1016/j.ymssp.2012.08.026>
25. Liu, C., Zhang, P., & Xu, X. (2023). Literature review of digital twin technologies for civil infrastructure. *Journal of Infrastructure Intelligence and Resilience*, 2(3), Article 100050.
<https://doi.org/10.1016/j.iintel.2023.100050>
26. Frangopol, D. M., & Soliman, M. (2016). Life-cycle of structural systems: Recent achievements and future directions. *Structure and Infrastructure Engineering*, 12(1), 1–20.
<https://doi.org/10.1080/15732479.2014.999794>
27. Lu, Q., Xie, X., Heaton, J., Parlikad, A. K., & Schooling, J. (2020). From BIM towards digital twin: Strategy and future development for smart asset management. In T. Borangiu, D. Trentesaux, P. Leitão, A. Giret Boggino, & V. Botti (Eds.), *Service oriented, holonic and multi-agent manufacturing systems for industry of the future (Studies in Computational Intelligence, Vol. 853, pp. 392–404)*. Springer. https://doi.org/10.1007/978-3-030-27477-1_30
28. B. Glisic and D. Inaudi, *Fibre Optic Methods for Structural Health Monitoring*. Chichester, U.K.: Wiley, 2007. [Online]. Available: <https://doi.org/10.1002/9780470517819>
29. C. R. Farrar and K. Worden, "An Introduction to Structural Health Monitoring," in *New Trends in Vibration Based Structural Health Monitoring*, A. Deraemaeker and K. Worden, Eds. Vienna, Austria: Springer, 2010, CISM Courses and Lectures, vol. 520. doi: 10.1007/978-3-7091-0399-9_1.
30. J. Yu, X. Meng, B. Yan, B. Xu, Q. Fan, and Y. Xie, "Global Navigation Satellite System-based positioning technology for structural health monitoring: a review," *Structural Control and Health Monitoring*, vol. 27, no. 1, p. e2467, Oct. 2019. doi: 10.1002/stc.2467.
31. R. Xi, Q. He, and X. Meng, "Bridge monitoring using multi-GNSS observations with high cutoff elevations: A case study," *Measurement*, vol. 168, p. 108303, 2021. doi: 10.1016/j.measurement.2020.108303.
32. X. An, X. Meng, L. Hu, et al., "GNSS integrated displacement and attitude determination for structural health monitoring of long-span bridges," *Satellite Navigation*, vol. 6, p. 19, 2025. doi: 10.1186/s43020-025-00174-9.
33. S. Gonen and E. Erduran, "A Hybrid Method for Vibration-Based Bridge Damage Detection," *Remote Sensing*, vol. 14, no. 23, p. 6054, 2022. doi: 10.3390/rs14236054.
34. O. Avci, O. Abdeljaber, S. Kiranyaz, M. Hussein, M. Gabbouj, and D. J. Inman, "A review of vibration-based damage detection in civil structures: From traditional methods to Machine Learning and Deep Learning applications," *Mechanical Systems and Signal Processing*, vol. 147, p. 107077, 2021. doi: 10.1016/j.ymssp.2020.107077.
35. N. V. Golovastikov, N. L. Kazanskiy, and S. N. Khonina, "Optical Fiber-Based Structural Health Monitoring: Advancements, Applications, and Integration with Artificial Intelligence for Civil and Urban Infrastructure," *Photonics*, vol. 12, no. 6, p. 615, 2025. doi: 10.3390/photonics12060615.
36. S. Ri, J. Ye, N. Toyama, et al., "Drone-based displacement measurement of infrastructures utilizing phase information," *Nature Communications*, vol. 15, p. 395, 2024. doi: 10.1038/s41467-023-44649-2.
37. Z. Peng, J. Li, H. Hao, and Y. Zhong, "Smart structural health monitoring using computer vision and edge computing," *Engineering Structures*, vol. 319, p. 118809, 2024. doi: 10.1016/j.engstruct.2024.118809.

38. C. R. Farrar and K. Worden, "An Introduction to Structural Health Monitoring," in *New Trends in Vibration Based Structural Health Monitoring*, A. Deraemaeker and K. Worden, Eds. Vienna, Austria: Springer, 2010, CISM Courses and Lectures, vol. 520. doi: 10.1007/978-3-7091-0399-9_1.
39. H. Naderi and A. Shojaei, "Digital twinning of civil infrastructures: Current state of model architectures, interoperability solutions, and future prospects," *Automation in Construction*, vol. 149, p. 104785, 2023. doi: 10.1016/j.autcon.2023.104785.
40. V. M. Di Mucci, A. Cardellicchio, S. Ruggieri, A. Nettis, V. Renò, and G. Uva, "Artificial intelligence in structural health management of existing bridges," *Automation in Construction*, vol. 167, p. 105719, 2024. doi: 10.1016/j.autcon.2024.105719.
41. A. Jiménez Rios, V. Plevris, and M. Nogal, "Bridge management through digital twin-based anomaly detection systems: A systematic review," *Frontiers in Built Environment*, vol. 9, Art. no. 1176621, 2023. doi: 10.3389/fbuil.2023.1176621.
42. H. Naderi and A. Shojaei, "Digital twinning of civil infrastructures: Current state of model architectures, interoperability solutions, and future prospects," *Automation in Construction*, vol. 149, p. 104785, 2023. doi: 10.1016/j.autcon.2023.104785.
43. A. Jiménez Rios, V. Plevris, and M. Nogal, "Bridge management through digital twin-based anomaly detection systems: A systematic review," *Frontiers in Built Environment*, vol. 9, Art. no. 1176621, 2023. doi: 10.3389/fbuil.2023.1176621.
44. A. Entezami, H. Sarmadi, B. Behkamal, and S. Mariani, "Big Data Analytics and Structural Health Monitoring: A Statistical Pattern Recognition-Based Approach," *Sensors*, vol. 20, no. 8, p. 2328, 2020. doi: 10.3390/s20082328.
45. C. R. Farrar and K. Worden, "An Introduction to Structural Health Monitoring," in *New Trends in Vibration Based Structural Health Monitoring*, A. Deraemaeker and K. Worden, Eds. Vienna, Austria: Springer, 2010, CISM Courses and Lectures, vol. 520. doi: 10.1007/978-3-7091-0399-9_1.
46. H. Naderi and A. Shojaei, "Digital twinning of civil infrastructures: Current state of model architectures, interoperability solutions, and future prospects," *Automation in Construction*, vol. 149, p. 104785, 2023. doi: 10.1016/j.autcon.2023.104785.
47. V. M. Di Mucci, A. Cardellicchio, S. Ruggieri, A. Nettis, V. Renò, and G. Uva, "Artificial intelligence in structural health management of existing bridges," *Automation in Construction*, vol. 167, p. 105719, 2024. doi: 10.1016/j.autcon.2024.105719.
48. A. Jiménez Rios, V. Plevris, and M. Nogal, "Bridge management through digital twin-based anomaly detection systems: A systematic review," *Frontiers in Built Environment*, vol. 9, Art. no. 1176621, 2023. doi: 10.3389/fbuil.2023.1176621.
49. I. Santos-Vila, R. Soto, E. Vega, B. Crawford, and A. Peña, "Damage Detection on Real Bridges Using Machine Learning Techniques: A Systematic Review," *Applied Sciences*, vol. 15, no. 16, p. 8884, 2025, doi: 10.3390/app15168884.
50. Y.-J. Cha, R. Ali, J. Lewis, and O. Büyükoztürk, "Deep learning-based structural health monitoring," *Automation in Construction*, vol. 161, p. 105328, 2024, doi: 10.1016/j.autcon.2024.105328.
51. F. Ponsi, C. Castagnetti, E. Bassoli, F. Mancini, and L. Vincenzi, "Multi-sensor and Multi-frequency Data Fusion for Structural Health Monitoring," in *Proc. 10th Int. Operational Modal Analysis Conf. (IOMAC 2024)*, C. Rainieri, C. Gentile, and M. Aenlle López, Eds., *Lecture Notes in Civil Engineering*, vol. 515. Cham, Switzerland: Springer, 2024, pp. [online]. doi: 10.1007/978-3-031-61425-5_28.

52. O. Hakimi, H. Liu, and O. Abudayyeh, "Deep learning-driven multi-level data fusion framework for predictive maintenance and structural health monitoring of concrete bridge decks," *Automation in Construction*, vol. 175, p. 106180, 2025, doi: 10.1016/j.autcon.2025.106180.
53. X. Qu, X. Ding, Y. L. Xu, et al., "Real-time outlier detection in integrated GNSS and accelerometer structural health monitoring systems based on a robust multi-rate Kalman filter," *Journal of Geodesy*, vol. 97, no. 38, 2023. doi: 10.1007/s00190-023-01724-2.
54. P. Kähler and Y. Petryna, "Vibration monitoring of structures with indirect load identification and Kalman update," *Procedia Structural Integrity*, vol. 64, pp. 1248–1255, 2024. doi: 10.1016/j.prostr.2024.09.193.
55. X. Qu, X. Ding, Y. L. Xu, et al., "Real-time outlier detection in integrated GNSS and accelerometer structural health monitoring systems based on a robust multi-rate Kalman filter," *Journal of Geodesy*, vol. 97, no. 38, 2023. doi: 10.1007/s00190-023-01724-2.
56. P. Kähler and Y. Petryna, "Vibration monitoring of structures with indirect load identification and Kalman update," *Procedia Structural Integrity*, vol. 64, pp. 1248–1255, 2024, doi: 10.1016/j.prostr.2024.09.193.
57. M. Diaz, P.-É. Charbonnel, and L. Chamoin, "A new Kalman filter approach for structural parameter tracking: Application to the monitoring of damaging structures tested on shaking-tables," *Mechanical Systems and Signal Processing*, vol. 182, p. 109529, 2023, doi: 10.1016/j.ymssp.2022.109529.
58. V. M. Rădulescu, G. M. T. Rădulescu, S. M. Naş, A. T. Rădulescu, and C. M. Rădulescu, "Structural health monitoring of bridges under the influence of natural environmental factors and geomatic technologies: A literature review and bibliometric analysis," *Buildings*, vol. 14, p. 2811, 2024, doi: 10.3390/buildings14092811.
59. X. Li, F.-L. Zhang, W. Xiang, W.-X. Liu, and S.-J. Fu, "Structural health monitoring system based on digital twins and real-time data-driven methods," *Structures*, vol. 70, p. 107739, 2024, doi: 10.1016/j.istruc.2024.107739.
60. K. J. Lee and C. B. Yun, "Extended Kalman Filter for Identification of Nonlinear Earthquake Responses of Bridges," *IFAC Proc. Volumes*, vol. 41, no. 2, pp. 15768–15773, 2008, doi: 10.3182/20080706-5-KR-1001.02666.
61. K. Kim and H. Sohn, "Dynamic Displacement Estimation for Long-Span Bridges Using Acceleration and Heuristically Enhanced Displacement Measurements of Real-Time Kinematic Global Navigation System," *Sensors*, vol. 20, no. 18, p. 5092, 2020, doi: 10.3390/s20185092.
62. X. An, X. Meng, L. Hu, et al., "GNSS integrated displacement and attitude determination for structural health monitoring of long-span bridges," *Satellite Navigation*, vol. 6, no. 19, 2025, doi: 10.1186/s43020-025-00174-9.
63. G. Evensen, "The Ensemble Kalman Filter: theoretical formulation and practical implementation," *Ocean Dynamics*, vol. 53, pp. 343–367, 2003, doi: 10.1007/s10236-003-0036-9.
64. M. Diaz, P.-É. Charbonnel, and L. Chamoin, "A new Kalman filter approach for structural parameter tracking: Application to the monitoring of damaging structures tested on shaking-tables," *Mechanical Systems and Signal Processing*, vol. 182, p. 109529, 2023, doi: 10.1016/j.ymssp.2022.109529.
65. H. Qiu, L. Rosafalco, A. Ghisi, and S. Mariani, "Structural Health-Monitoring Strategy Based on Adaptive Kalman Filtering," *Eng. Proc.*, vol. 82, p. 76, 2024, doi: 10.3390/ecsa-11-20493.

66. M. Diaz, P.-É. Charbonnel, and L. Chamoin, "A new Kalman filter approach for structural parameter tracking: Application to the monitoring of damaging structures tested on shaking-tables," *Mech. Syst. Signal Process.*, vol. 182, p. 109529, 2023, doi: 10.1016/j.ymssp.2022.109529.
67. M. J. Turner, R. W. Clough, H. C. Martin, and L. J. Topp, "Stiffness and deflection analysis of complex structures," *Journal of Aeronautical Sciences*, vol. 23, no. 9, pp. 805–823, 1956, doi: 10.2514/8.3664.
68. R. W. Clough, "The finite element method in plane stress analysis," *Proc. 2nd ASCE Conf. Electron. Comput.*, Pittsburgh, PA, USA, 1960, pp. 345–378.
69. K.-J. Bathe, *Finite Element Procedures*. Englewood Cliffs, NJ, USA: Prentice Hall, 1995.
70. O. C. Zienkiewicz, R. L. Taylor, and J. Z. Zhu, *The Finite Element Method*. Oxford, U.K.: Elsevier, 2013.
71. C. R. Farrar and K. Worden, "An introduction to structural health monitoring," *Philos. Trans. R. Soc. A: Math., Phys. Eng. Sci.*, vol. 365, no. 1851, pp. 303–315, Jan. 2007, doi: 10.1098/rsta.2006.1928.
72. X. Li, F.-L. Zhang, W. Xiang, W.-X. Liu, and S.-J. Fu, "Structural health monitoring system based on digital twins and real-time data-driven methods," *Structures*, vol. 70, p. 107739, 2024, doi: 10.1016/j.istruc.2024.107739.
73. H. Naderi and A. Shojaei, "Digital twinning of civil infrastructures: Current state of model architectures, interoperability solutions, and future prospects," *Automation in Construction*, vol. 149, p. 104785, 2023. doi: 10.1016/j.autcon.2023.104785.
74. A. Jiménez Rios, V. Plevris, and M. Nogal, "Bridge management through digital twin-based anomaly detection systems: A systematic review," *Frontiers in Built Environment*, vol. 9, p. 1176621, 2023. doi: 10.3389/fbuil.2023.1176621.
75. X. Li, F.-L. Zhang, W. Xiang, W.-X. Liu, and S.-J. Fu, "Structural health monitoring system based on digital twins and real-time data-driven methods," *Structures*, vol. 70, p. 107739, 2024. doi: 10.1016/j.istruc.2024.107739.
76. V. M. Di Mucci, A. Cardellicchio, S. Ruggieri, A. Nettis, V. Renò, and G. Uva, "Artificial intelligence in structural health management of existing bridges," *Automation in Construction*, vol. 167, p. 105719, 2024. doi: 10.1016/j.autcon.2024.105719.
77. S. Hassani, U. Dackermann, M. Mousavi, and J. Li, "A systematic review of data fusion techniques for optimized structural health monitoring," *Information Fusion*, vol. 103, p. 102136, 2024. doi: 10.1016/j.inffus.2023.102136.
78. O. Avci, O. Abdeljaber, S. Kiranyaz, M. Hussein, M. Gabbouj, and D. J. Inman, "A review of vibration-based damage detection in civil structures: From traditional methods to machine learning and deep learning applications," *Mechanical Systems and Signal Processing*, vol. 147, p. 107077, 2021. doi: 10.1016/j.ymssp.2020.107077.
79. J. Yu, X. Meng, B. Yan, B. Xu, Q. Fan, and Y. Xie, "Global Navigation Satellite System-based positioning technology for structural health monitoring: A review," *Structural Control and Health Monitoring*, vol. 27, no. 1, p. e2467, 2019. doi: 10.1002/stc.2467.
80. P. Kähler and Y. Petryna, "Vibration monitoring of structures with indirect load identification and Kalman update," *Procedia Structural Integrity*, vol. 64, pp. 1248–1255, 2024. doi: 10.1016/j.prostr.2024.09.193.

81. A. Entezami, H. Sarmadi, B. Behkamal, and S. Mariani, "Big data analytics and structural health monitoring: A statistical pattern recognition-based approach," *Sensors*, vol. 20, no. 8, p. 2328, Apr. 2020. doi: 10.3390/s20082328.

3. Integrated Digital Twin Framework for transportation Infrastructure Management

Overview

This chapter presents the development of an operational digital twin framework for transportation infrastructure management, designed to integrate asset-level structural assessment with system-level transportation applications. Based on the conceptual foundations and research gaps identified in Chapters 1 and 2, the proposed framework emphasizes continuous interpretation of monitoring data, uncertainty-aware state estimation, and physically grounded validation.

At the asset level, the framework focuses on bridge health monitoring by integrating Building Information Modeling (BIM) for digital model development, Global Navigation Satellite System (GNSS) measurements for three-dimensional displacement monitoring, advanced data assimilation techniques using the Ensemble Kalman Filter (EnKF) and machine learning, and structural simulation and verification through Finite Element Analysis (FEA). The integration of these components enables robust evaluation of bridge structural performance and condition under uncertain monitoring environments.

At the system level, the framework extends beyond individual structures to transportation network analysis, leveraging BIM-based modeling of urban road networks for traffic simulation and management. This multi-scale integration allows structural condition assessment and traffic operation to be considered within a unified digital twin framework, supporting informed decision-making for traffic optimization, safety enhancement, and operational efficiency.

By unifying asset-level structural monitoring and system-level transportation analysis, the proposed framework represents an operational digital twin that supports data-driven, predictive, and adaptive infrastructure management. This chapter provides the overall system architecture and serves as the foundation for the detailed methodological developments and case studies presented in the subsequent chapters.

3.1. Digital Twin Framework

Figure 3.1 illustrates the overall architecture and workflow of the proposed operational digital twin framework. The framework is designed as a multi-scale system that integrates asset-level bridge health monitoring with system-level transportation management.

At the asset level, the framework focuses on bridge management and includes:

- Bridge model development based on Revit Building Information Modeling (BIM).
- Three-dimensional bridge displacement monitoring using Global Navigation Satellite Systems (GNSS)
- Data assimilation through the Ensemble Kalman Filter (EnKF) and machine learning techniques.

- Structural simulation and validation via Finite Element Analysis (FEA).

The primary aim of asset-level management is to perform structural health monitoring (SHM), thereby enabling the evaluation of bridge conditions and performance over time.

At the system level, the framework extends to traffic simulation and management, supporting the optimization of traffic flow, safety, and operational efficiency within the broader transportation network. By integrating these two levels, the proposed digital twin framework advances toward smart transportation infrastructure management.

The application of DT technology not only enhances real-time monitoring and decision-making at the asset scale but also facilitates predictive and adaptive management strategies at the system scale. Consequently, DT is positioned as a transformative technology for modern infrastructure management.

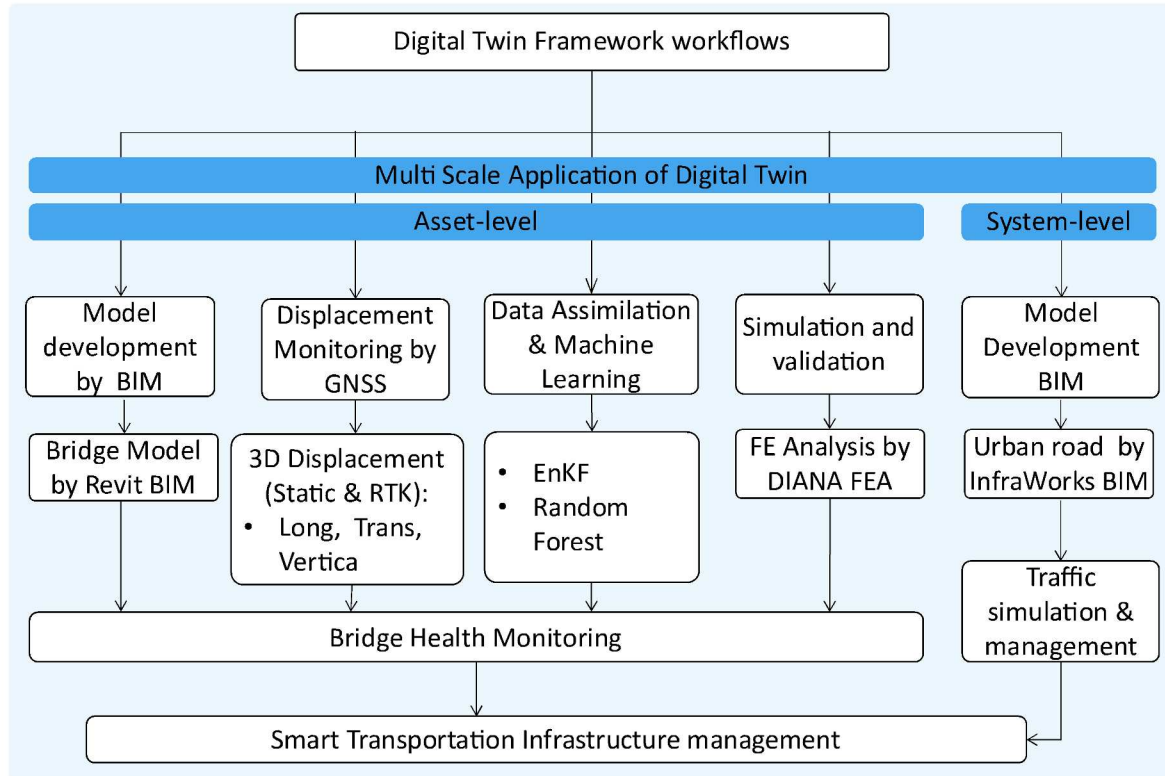


Figure 3. 1 Overall architecture and workflow of the proposed operational digital twin framework for transportation infrastructure management.

The framework integrates asset-level bridge health monitoring and system-level transportation management within a unified digital twin architecture. At the asset level, BIM-based model development, GNSS-based three-dimensional displacement monitoring, uncertainty-aware state estimation using data assimilation and machine learning, and physical validation through finite element analysis are combined to support reliable interpretation of structural behavior. At the system level, BIM-based modeling of urban road networks is coupled with traffic simulation and management. The integration of these two levels enables the

digital twin to function as an operational decision-support system for smart transportation infrastructure management

3.2. Digital Twin Model Development for Bridges

The development of digital twin models for bridges involves a systematic workflow that integrates Building Information Modeling (BIM), parametric modeling, and visualization technologies to create a dynamic and adaptive digital representation of physical bridge assets, as shown in **Figure 3.2**. The overall process is divided into the following stages:

- Data Collection and Preparation

The process begins with acquiring the design and structural data that form the foundation for model creation. Geometric characteristics, material properties, and construction details are gathered from design drawings, field surveys, and existing databases. These datasets are essential for constructing an accurate and reliable digital representation of the bridge.

- BIM Model Development in Revit

The collected data is used in Revit BIM, providing an environment for model creation and parameter management. Parametric rules are defined through Dynamo, a visual programming tool integrated into Revit, to support flexible and automated model generation. This ensures bridge components can adapt and reconfigure according to various scenarios.

- Family Creation and Parametric Modeling

In Revit, bridge elements are organized into families and function as templates for structural members. Two types of families are used:

- Generic Model: Represents standard bridge elements with fixed parameters.
- Adaptive Generic Model: Enables flexible configurations to adapt to varying shapes, curvatures, and placement conditions.

This parametric structure allows DT to accurately represent both typical and complex bridge geometries.

- Project Integration

The generic and adaptive family components are integrated at the project level to generate a complete bridge model. At this stage, all structural elements, including the superstructure, substructure, and foundations are integrated and consolidated into a single model. This ensures accurate geometric representation and consistency with real-world design specifications.

- Bridge Model Integration and Visualization

The integrated Revit model undergoes further processing for integration into a broader infrastructure environment. The model is exported to InfraWorks BIM for visualization, enabling realistic rendering,

contextual placement within the surrounding environment, and interaction with the transportation network. This step facilitates comprehensive evaluation of the bridge model within its operational context.

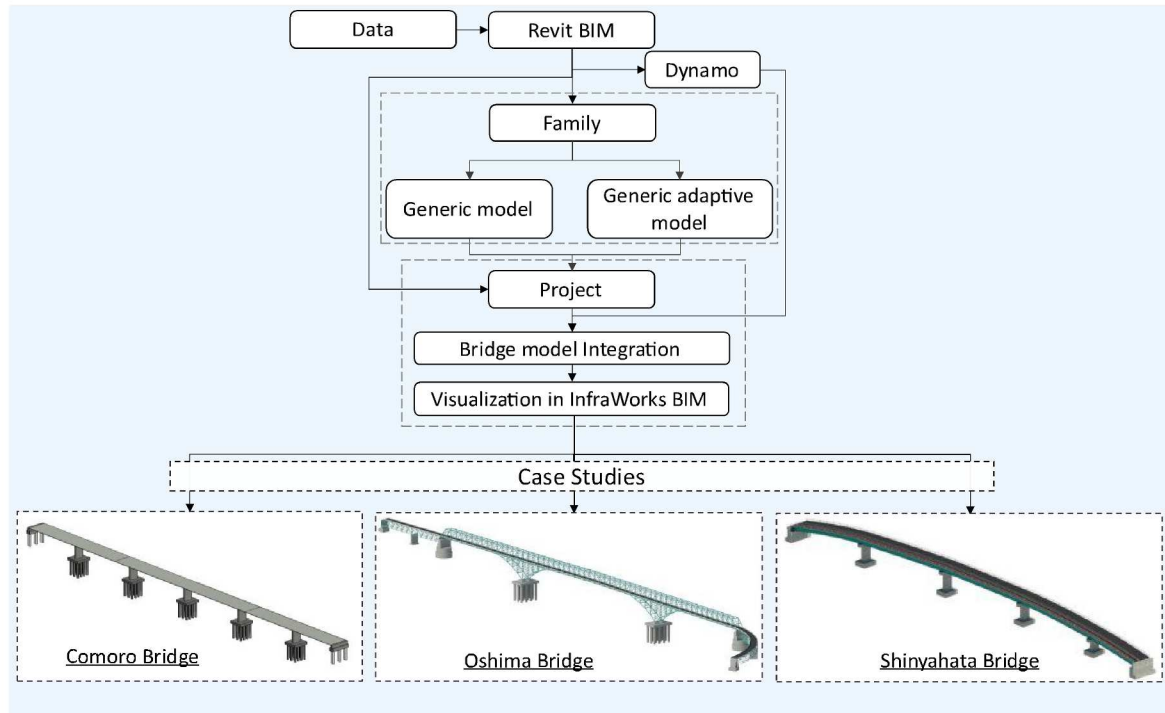


Figure 3. 2 Digital Twin Model Development for Bridges

- Case Studies Application

To demonstrate the applicability of the developed digital twin modeling workflow, this method was applied to three bridges:

- Comoro Bridge: A straight multi-span bridge exhibiting a typical configuration.
- Oshima Bridge: A large-scale structure with distinctive geometric features, emphasizing adaptive modeling.
- Shinyahata Bridge: An example of a curved alignment, demonstrating parametric adaptability.

Through these case studies, the DT modeling framework proved its versatility in representing bridges with diverse geometries and complexities, validating the workflow's effectiveness.

So, this workflow combines Revit BIM, Dynamo-based parametric modeling, and visualization through InfraWorks to establish a scalable and adaptable digital twin modeling process for bridges. The ability to generate both generic and adaptive models and integrate them into realistic infrastructure environments forms the foundation for subsequent monitoring, simulation, and decision support capabilities within the digital twin framework.

3.3. Displacement Monitoring by GNSS

The proposed GNSS-based monitoring system enables high-precision real-time measurement of bridge displacement, facilitating continuous structural health monitoring (SHM) for long and complex bridges, as shown in **Figure 3.3**. As a result, extracting meaningful displacement signals becomes more difficult, and the cost-effectiveness of GNSS deployment decreases compared with its use on medium- and long-span structures.

This system integrates satellite positioning technology, advanced data processing, and cloud-based communication to accurately and reliably monitor the performance of structures.

- Satellite and GNSS Receivers

The monitoring process begins with signals transmitted from Global Navigation Satellite Systems (GNSS) (e.g., GPS, Galileo, GLONASS). These signals are received by GNSS receivers installed at strategic observation points (R1 to R4) on the bridge superstructure and at a fixed reference station located near the site. The reference station establishes a stable coordinate system, enabling precise relative displacement measurements of the bridge structure.

- Observation Points and Sensors

GNSS antennas are installed at critical locations on bridges (mid-span, Abutments, piers, etc.) to capture longitudinal, lateral, and vertical displacements. To account for environmental effects and cross-verify GNSS data, auxiliary sensors such as displacement gauges and temperature sensors are installed. This multimodal measurement enhances monitoring reliability.

- Data Transmission and Communication

GNSS data collected at observation points is transmitted to cloud servers via 5G and fiber-optic communication systems. This ensures high-speed, low-latency data transfer to control rooms, offices, and field terminals, enabling real-time visualization and decision-making.

- Data Processing and Noise Removal

GNSS displacement data is inherently susceptible to environmental noise, multipath errors, and atmospheric disturbances. To address these challenges, this system applies an advanced noise reduction algorithm developed in Python. Techniques such as filtering, outlier detection, and signal processing enhance measurement accuracy and practicality.

- Real-Time Visualization and Analysis

Processed data is transmitted via the internet to the monitoring platform, accessible from the control room, field offices, and local stations. Real-time visualization enables operators to assess structural responses to loading, thermal effects, and environmental factors. This facilitates early detection of abnormal displacements, supporting preventive maintenance strategies.

- Limitations for Short-Span Bridges

Although the digital twin framework is adaptable to bridges of varying spans, the use of GNSS for displacement monitoring on short-span bridges (< 30 m) presents inherent challenges. Such structures typically exhibit very small deformation amplitudes that approach the noise threshold of GNSS measurements. Consequently, extracting meaningful displacement signals becomes more difficult, and the cost-effectiveness of GNSS deployment is reduced relative to medium- and long-span bridges.

- Application Example

The illustrated system is installed on a five-span continuous steel box girder curved bridge in Hiroshima, Japan, supported by reinforced concrete (RC) piers and abutments. The bridge's total length is 282.5m, width is 12.25m (7.7m roadway, 3.5m sidewalk), and the slope angle varies from 80.5° to 118.5° . The GNSS monitoring system enables detailed evaluation of displacement patterns in both horizontal and vertical directions, making it ideal for complex curved bridge geometries.

Overall, the GNSS-based displacement monitoring system provides a comprehensive, real-time, high-precision solution for bridge structural health monitoring (SHM). By combining satellite positioning, cloud-based data management, noise reduction algorithms, and multi-sensor integration, it continuously evaluates bridge performance. This system not only deepens understanding of structural behavior under operational conditions but also provides the foundation for digital twin integration, ensuring predictive maintenance and enhanced infrastructure resilience.

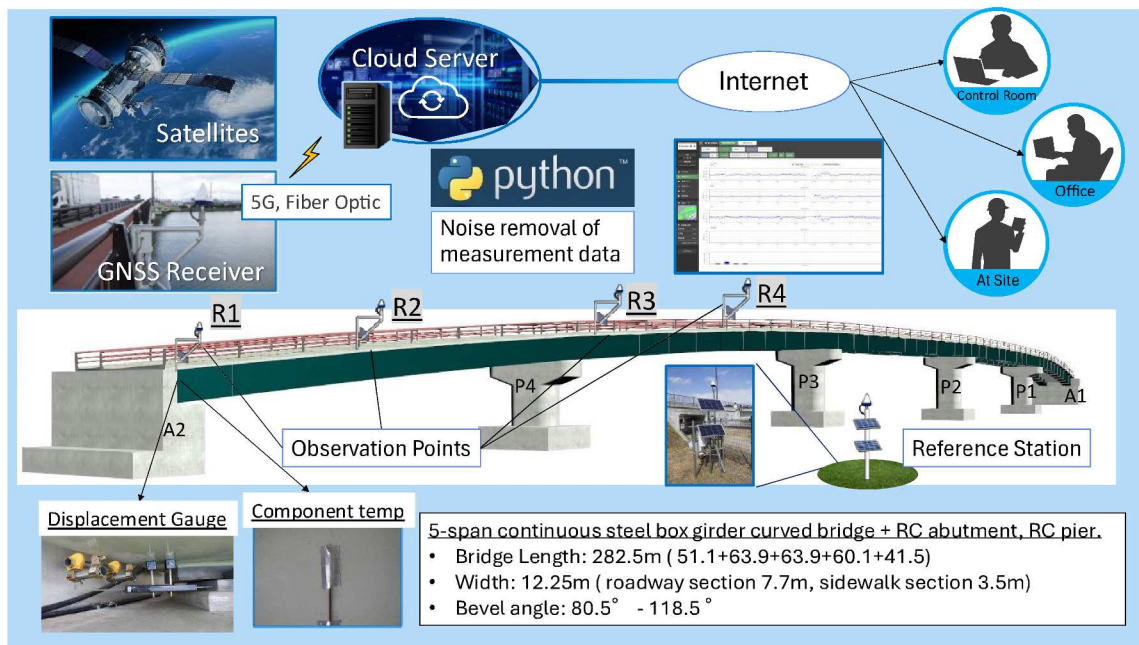


Figure 3. 3 Displacement Monitoring by GNSS

3.4. Data Assimilation and Machine Learning Approaches for GNSS-Based Bridge Monitoring

Monitoring and analyzing bridge displacement within a digital twin framework requires robust computational methods capable of assimilating real-time data whilst accounting for non-linear environmental influences. This study employs the Random Forest (RF) model not merely as a statistical black-box predictor, but as a physically interpretable learning framework capturing the primary thermo-mechanical mechanisms governing bridge displacement. Rather than providing general predictions, RF systematically identifies key deformation patterns driven by environmental variables such as thermal expansion and contraction, diurnal heating and cooling cycles, solar radiation exposure, and wind-induced thermal modulation.

The learning relationships extracted by RF align well with established principles of structural mechanics and demonstrate the ability to approximate underlying thermal-structural interactions in a physically meaningful manner. Consequently, the role of RF in this study extends beyond numerical curve fitting, providing engineering insights into how environmental factors shape the nonlinear displacement response of bridges.

To achieve a comprehensive displacement estimation strategy within the DT environment, two complementary approaches were adopted:

- The Ensemble Kalman Filter (EnKF): a model-driven sequential estimator that fuses real-time measurement data with physics-based predictions, and
- Random Forest (RF): a data-driven machine learning algorithm that captures nonlinear, environment-induced displacement patterns.

By combining these techniques, DT integrates both physical modelling and data-driven learning, enabling robust real-time displacement prediction and interpretation even under changing environmental conditions.

The workflow is shown in **Figure 3.4** in the following.

1. Data Acquisition and Preprocessing

The workflow begins with the collection of raw GNSS data. While raw data provides high-frequency displacement measurements, it is inherently susceptible to noise, multipath errors, and environmental interference. To improve data quality, a preprocessing stage is implemented, including outlier removal and noise filtering. This ensures that subsequent assimilation processing and machine learning stages operate based on reliable input data.

2. Ensemble Kalman Filter (EnKF)

EnKF functions as a model-driven data assimilation method, integrating GNSS observations with system dynamics to provide real-time displacement estimation and uncertainty quantification.

- Initialization

Each ensemble member is initialized with the observed initial displacement:

$$x_t^{(i)} = y_0, \quad i = 1, \dots, N \quad (3.1)$$

where N is the ensemble size.

- Prediction Step

The system state evolves over time with the inclusion of process noise:

$$x_t^{(i)} = x_{t-1}^{(i)} + w_t^{(i)}, w_t^{(i)} \sim N(0, W_t) \quad (3.2)$$

This step propagates structural dynamics forward while accounting for uncertainty.

- Update Step

New GNSS observations are assimilated into the model:

$$z_t^{(i)} = x_t^{(i)} + v_t^{(i)}, v_t^{(i)} \sim N(0, V_t) \quad (3.3)$$

Kalman gain K_t balance model predictions with observational accuracy:

$$K_t = P_t / \left(\frac{P_t}{V_t} \right) \quad (3.4)$$

$$x_t^{(i)} = x_t^{(i)} + K_t(y_t - z_t^{(i)}) \quad (3.5)$$

where P_t represents ensemble variance and V_t the observation noise variance.

- Estimation Step

The ensemble means that it yields the final displacement estimate:

$$\hat{x}_t = \frac{1}{N} \sum_{i=1}^N x_t^{(i)} \quad (3.6)$$

This provides both point estimates and uncertainty boundaries derived from ensemble dispersion.

3. Random Forest (RF) Methodology

In parallel, the RF algorithm is adopted as a data-driven approach to capture the complex nonlinear relationships between displacement and environmental factors such as temperature, wind, and solar radiation.

- Training Phase

For each tree m in the forest, the following steps occur:

1. A bootstrap sample of the training dataset is drawn.
2. A random subset of features is selected.
3. A decision tree $f_m(x)$ is trained on the sampled data.

- Prediction Phase

The displacement prediction is computed as the average of all decision trees:

$$\hat{y} = \frac{1}{M} \sum_{m=1}^M f_m(x) \quad (3.7)$$

where M is the number of trees in the forest.

- Confidence Interval Estimation

Uncertainty is quantified by measuring variability across tree outputs:

$$\sigma^2 = \frac{1}{M} \sum_{m=1}^M (f_m(x) - \hat{y})^2 \quad (3.8)$$

So, by integrated EnKF and RF can provide good displacement estimation of the bridge.

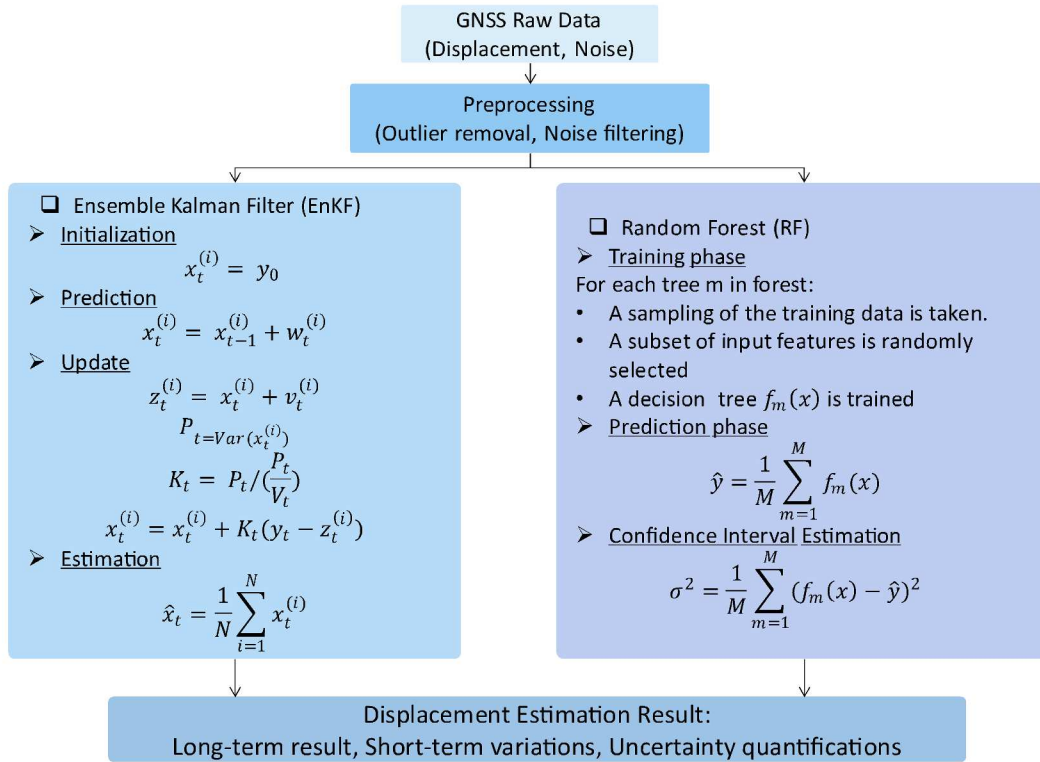


Figure 3. 4 Data Assimilation and Machine Learning approach

3.5. Physical Verification and Validation of GNSS-Based Bridge Responses Using Finite Element Analysis (FEA)

The accuracy of GNSS-based bridge displacement monitoring must be verified through numerical simulation to ensure that the observed deformations are physically realistic and structurally consistent. This study employed finite element analysis (FEA) to simulate the structural behavior of bridges under various loading and environmental conditions, including temperature effects and soil-foundation interactions.

Subsequently, FEA results were compared with GNSS displacement measurements to validate the monitoring system's effectiveness and enhance the reliability of the developed digital twin framework.

- **Simulation Framework**

The simulation and verification workflow in **Figure 3.5** consists primarily of two modeling strategies:

1. **Fixed-Based Assumption Case**

- Assume that the piers and abutments are rigidly fixed to the ground and neglect the elasticity of the ground.
- This assumption simplifies the boundary conditions and provides a basic model for analyzing the structural behavior of the superstructure independently of the foundation's influence.

2. **Soil–Foundation Interaction Case**

- This model incorporates the effects of the supporting soil and piles, enabling realistic interactions between the structure and foundation system.
- By considering soil stiffness, damping, and pile parameters, it becomes possible to more accurately represent the dynamic and thermal responses of bridges.

Both models were developed as full-scale three-dimensional finite element representations using the actual geometric and material data of the case study bridge.

- **Model Development and Parameters**

- (a) **Material Properties**

The mechanical properties of concrete and steel were defined based on design specifications and standard code values.

- *Concrete*: Elastic modulus, Poisson's ratio, and compressive strength.
- *Steel*: Yield stress, modulus of elasticity, and density.

These parameters were essential for capturing the stiffness distribution and load transfer characteristics between structural members.

- (b) **Bearing Elements**

Bridge bearings were modeled using nonlinear spring elements to represent translational stiffness and rotational stiffness in the longitudinal, transverse, and vertical directions. These bearings play a crucial role in the redistribution of loads on the bridge deck and in displacements caused by thermal expansion.

- (c) **Loads**

To capture realistic bridge behavior, multiple load conditions were applied:

- Dead load: Self-weight of structural members.
- Live load: Simulated vehicle loads and pedestrian loads acting on the bridge deck.
- Temperature effects: Applied temperature gradients derived from measurement data to evaluate thermal displacement and thermal stress.

The combined effects of mechanical and environmental loads enabled a comprehensive evaluation of displacement behavior under operational conditions.

(d) Soil and Pile Parameters

In the case of soil-foundation interaction, the soil conditions beneath the foundation were modeled using soil springs and solid elements.

- Soil Properties: Elastic modulus, Poisson's ratio, and density obtained from ground investigations.
- Pile Parameters: Length, diameter, and stiffness of the modeled pile to simulate vertical and lateral resistance.

This integration of structural and ground domains improved the model's accuracy in representing actual boundary conditions.

(e) Discretization (Mesh Generation)

The bridge structure was discretized into finite elements using solid elements, shell elements, and beam elements. To accurately capture stress concentrations and displacement gradients, the mesh was refined at critical locations such as the main span, bearings, and piers.

• Analysis Scenarios

To evaluate bridge performance and validate GNSS data, two primary analysis scenarios were conducted:

- Before-Collision Condition: Represents the bridge under normal, undamaged operational conditions.
- After-Collision Condition: Represents structural behavior after external impact or abnormal events, such as vehicle collision or damage to bearing supports.

These scenarios provided insights into how the structure's stiffness, load distribution, and displacement patterns changed after the event, as well as how effectively the GNSS system captured such changes.

• Finite Element Analysis Results

- Longitudinal and Transversal displacement were observed in the bridge superstructure.
- Deformation due to temperature changes was analyzed, clarifying the relationship between thermal fluctuations and GNSS recorded movements.
- The correlation between the ground foundation model and GNSS data improved, particularly evident in long-term vertical displacement trends.

Comparisons between FEA results and GNSS observations were conducted to confirming agreement in displacement trends and verifying measurement reliability.

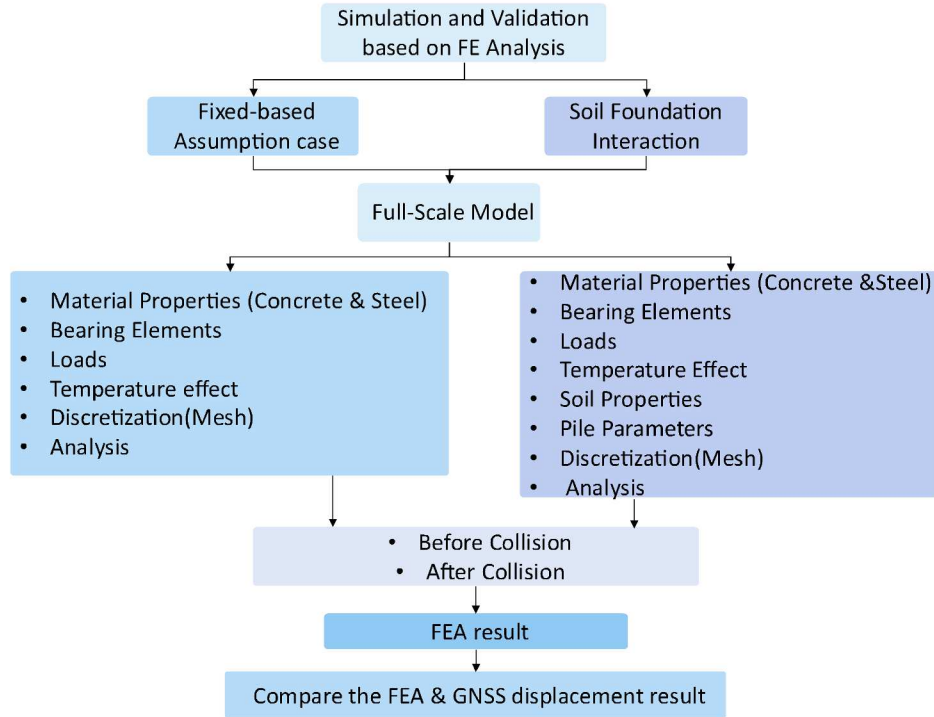


Figure 3. 5 Simulation and Validation on GNSS Observation Based on FEA

It is important to explicitly clarify that the finite element analysis (FEA) conducted in this stage of the study employs a linear elastic modeling approach. While linear analysis is suitable for examining global deformation patterns and validating the displacement trends observed from GNSS measurements, it does not capture nonlinear structural behaviors such as cracking, stiffness degradation, or progressive deterioration.

These considerations are addressed in detail in Chapter 8 and are identified as a key area for future extension of the digital twin framework to enhance predictive damage assessment capabilities.

3.6. Traffic Management as a System-Level Application of the Digital Twin Framework

The digital twin and BIM-based traffic management workflow provides a systematic approach for analyzing and improving traffic conditions in urban areas such as Dili, East Timor. This workflow integrates data collection, modeling, calibration, validation, and simulation to develop evidence-based traffic management policies (EBTMP). This section constitutes the **system-level component** of the proposed digital twin

framework, expanding the analysis from individual bridge behavior to the broader transportation network. Whereas earlier sections focus on structural responses at the asset level, the system-level digital twin integrates traffic simulation, congestion analysis, and environmental impact assessment to evaluate how infrastructure performance influences and is influenced by network-level mobility conditions. This higher-level analysis complements the bridge-level digital twin by addressing operational factors such as traffic flow, route choice behavior, and air pollution, thereby providing a holistic perspective on infrastructure resilience and transportation system performance.

As shown in **Figure 3.6**, the process begins with data collection, followed by the calculation of average daily traffic (ADT) and the construction of an origin-destination (OD) matrix. These datasets serve as key inputs for the digital twin model, which undergoes calibration and validation before being used for traffic simulation and analysis. This workflow ensures the simulation environment accurately reflects real-world traffic dynamics and environmental impacts.

- **Data Collection**

The first step involves conducting traffic volume measurements and acquiring geometric data within the target survey area.

- Traffic data includes vehicle types, traffic volumes, and time-of-day distributions collected across multiple road sections.
- Geometric data includes road widths, lane configurations, and intersection layouts.

These datasets form the foundation for constructing a realistic DT-BIM environment.

- **Average Daily Traffic (ADT) Calculation**

Average Daily Traffic represents the mean number of vehicles passing a specific point per day over the observation period. It is calculated using:

$$ADT = \frac{1}{n} \sum_{i=1}^n VOL_i \quad (3.9)$$

where VOL_i is the total daily vehicle volume on day i , and n is the number of observation days. This value helps determine peak-hour periods for simulation input

- **Origin–Destination (OD) Matrix Development**

The OD matrix quantifies vehicle movement between origins and destinations in the study area, providing a spatial distribution of traffic flow. It is formulated as:

$$P_T = \begin{bmatrix} T_{11} & T_{12} & \dots & T_{1n} \\ T_{21} & T_{22} & \dots & T_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ T_{n1} & T_{n2} & \dots & T_{nn} \end{bmatrix} \quad (3.10)$$

where T_{ij} represents the number of trips from the origin i to destination j .

The OD matrix serves as a critical input for simulating vehicle trajectories and traffic interactions.

- **Digital Twin Model Development**

The basic digital twin model is constructed using a BIM environment. It reproduces the geometric and operational characteristics of the road network, including intersections, traffic signals, and lane configurations. The DT model provides a dynamic, data-driven representation of the real-world transportation system.

- **Calibration and Validation**

Calibration aligns the DT model with actual traffic conditions by adjusting parameters such as flow rate, driver behavior, and signal timing. Validation ensures the model accurately predicts real-world observations. This step ensures the reliability of simulation results and supports evidence-based policy making.

- **Traffic Demand Input and Simulation**

After verification, traffic demand and parameters (e.g., vehicle configuration, signal timing, intersection control) are input into the DT-BIM system.

The simulation employs microscopic traffic models such as the Gipps following-vehicle model. This model represents vehicle behavior as follows:

$$v_n(t + \Delta t) = \min \left[v_n(t) + 2.5a_n\Delta t \left(1 - \frac{v_n(t)}{v_{n,desired}} \right), \sqrt{0.025 + \frac{v_n(t)}{v_{n,desired}}, b_n\Delta t + \sqrt{b_n^2(\Delta t)^2 - b_n[2(x_{n-1} - x_n - s_n) - v_n(t)]\Delta t - \frac{v_{n-1}^2(t)}{b_{n-1}}}} \right] \quad (3.11)$$

where $v_n(t)$ is the current speed of the vehicle n , a_n is the maximum acceleration, b_n is the desired deceleration, and s_n is the safe distance between vehicles.

This equation helps predict vehicle interactions and congestion patterns under various traffic conditions

- **Simulation and Analysis**

The simulation results reveal congestion levels, queue lengths, delays, and Air Pollutant Concentrations like (CO₂, NO_x, PM₁₀). So, the mass Concentration can be calculated using this equation:

$$C = \frac{M(g)}{V_{air}(m^3)} \quad (3.12)$$

where (C) mass concentration in the air is calculated by dividing the total mass emitted (M) (in grams) by the Volume of the mixing zone (V_{air}) (in cubic meters).

The analysis identifies critical congestion hotspots and major pollution contributors, providing quantitative evidence for optimizing signal control and mobility strategies

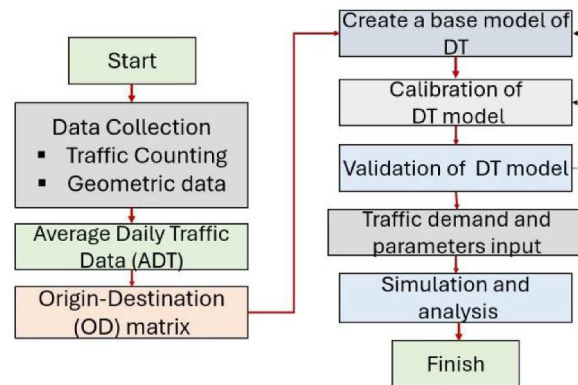


Figure 3. 6 Traffic Management Workflow-based Digital Twin

This workflow provides a comprehensive framework for managing urban transportation through the integration of digital twins and BIM. By linking real-time data, simulations, and environmental assessments, it supports data-driven decision-making. This approach aims to enhance urban mobility, alleviate congestion, and reduce emissions, forming the foundation for sustainable transportation planning.

3.7. References

1. E. E. Tita, G. Watanabe, P. Shao, and K. Ariei, "Development and Application of Digital Twin-BIM Technology for Bridge Management," *Appl. Sci.*, vol. 13, no. 13, p. 7435, 2023. doi: 10.3390/app13137435.
2. F. Tao, H. Zhang, A. Liu, and A. Y. C. Nee, "Digital Twin in Industry: State-of-the-Art," *IEEE Trans. Ind. Inform.*, vol. 15, no. 4, pp. 2405–2415, Apr. 2019.
3. C. J. Turner, J. Oyekan, L. Stergioulas, and D. Griffin, "Utilizing Industry 4.0 on the Construction Site: Challenges and Opportunities," *IEEE Trans. Ind. Inform.*, vol. 17, no. 2, pp. 746–756, Feb. 2021.
4. D. G. Broo, M. Bravo-Haro, and J. Schooling, "Design and implementation of a smart infrastructure digital twin," *Autom. Constr.*, vol. 136, p. 104171, Apr. 2022.
5. Ministry of Land, Infrastructure, Transport and Tourism (MLIT), *Infrastructure Maintenance Yearbook*, Tokyo, Japan, 2018.
6. C. R. Farrar and K. Worden, *Structural Health Monitoring: A Machine Learning Perspective*. Chichester, UK: John Wiley & Sons, 2011.
7. C. Eastman, P. Teicholz, R. Sacks, and K. Liston, *BIM Handbook: A Guide to Building Information Modeling for Owners, Managers, Designers, Engineers and Contractors*, 2nd ed. Hoboken, NJ: Wiley, 2011.
8. B. Succar, "Building information modeling framework: A research and delivery foundation for industry stakeholders," *Automation in Construction*, vol. 18, no. 3, pp. 357–375, May 2009.

9. Ma, Y., Zeng, L., Xu, M., Wang, L., and Zhang, L. (2022). Structural displacement estimation by fusing vision and acceleration using Kalman filter: dealing with no synchronization. *Automation in Construction*, 138, 104274.
10. Forootan, E., Farzaneh, S., Naderi, K., and Cederholm, J. P. (2021). Analyzing GNSS measurements to detect and predict bridge movements using the Kalman filter (KF) and neural network (NN) techniques. *Geomatics*, 1(1), pp. 65-80. doi:10.3390/geomatics1010006
11. Shen, N., Chen, L., Liu, J., Wang, L., Tao, T., Wu, D., and Chen, R. (2019). A review of Global Navigation Satellite System (GNSS) based dynamic monitoring technologies for structural health monitoring. *Remote Sensing*, 11(9), 1001. doi:10.3390/rs11091001
12. Tao, F.; Zhang, H.; Liu, A.; Nee, A.Y.C. Digital Twin in Industry: State-of-the-Art. *IEEE Trans. Ind. Inform.* 2019, 15, 2405–2415.
13. Turner, C.J.; Oyekan, J.; Stergioulas, L.; Griffin, D. Utilizing Industry 4.0 on the Construction Site: Challenges and Opportunities. *IEEE Trans. Ind. Inform.* 2021, 17, 746–756.
14. Tita, E. E., Watanabe, G., Ximenes, H. da C., & Viegas, H. M. S. (2024). Initiatives in Dili of Timor-Leste for implementing traffic management using digital twin-BIM technology. *Intelligence, Informatics and Infrastructure*, 5(1), 42–56. https://doi.org/10.11532/jsceiiai.5.1_42

4. DT-BIM-Based Digital Representation and Physics-Based Validation for Bridge Infrastructure

Overview

This chapter presents the development and application of a DT-BIM-based digital representation for bridge infrastructure, positioned as a core component of the operational digital twin framework introduced in Chapter 3. Specifically, the chapter focuses on (i) BIM-based model development for an existing bridge, and (ii) physically grounded verification and validation through finite element analysis (FEA), which together establish a reliable baseline for subsequent monitoring-based state estimation and decision support.

A prestressed concrete box-girder bridge (Comoro Bridge, Dili, Timor-Leste) is used as a case study. A detailed BIM model is developed from available design and construction information, and an interoperability workflow is implemented to link the BIM model with FEA for structural performance evaluation. In addition, potential applications of the DT-BIM model are demonstrated, including visualization, traffic-related scenario exploration, and maintenance information management. While continuous GNSS-based monitoring is planned for the target bridge, the emphasis of this chapter is to establish the digital representation and the physics-based validation foundation required for an operational digital twin under uncertain monitoring environments.

4.1. Introduction

A digital twin refers to a virtual replication of a physical object, system, or process, and has increasingly been adopted across diverse domains for purposes such as asset management, smart infrastructure, and decision support. In many DT- and cyber-physical system (CPS)-related studies, the concept is discussed in connection with Industry 4.0, which promotes tighter integration between physical assets and digital technologies to enable data-driven operation and management [1,2]. In the architecture, engineering, and construction (AEC) domain, Building Information Modeling (BIM) provides a practical foundation for such digital representations of buildings and civil infrastructures, enabling the integration of geometry, semantics, and lifecycle information in a structured manner. By supporting design coordination, quantity estimation, construction planning, and information sharing among stakeholders, BIM has been widely recognized as a key enabler of productivity improvement and cost reduction throughout the asset lifecycle [3–6].

Bridges play a critical role in modern transportation infrastructure, and ensuring their safety, reliability, and durability requires systematic management supported by inspection, structural health monitoring (SHM), and maintenance planning [7,8]. A major advantage of DT-based approaches is their potential to integrate ICT/IoT and heterogeneous data sources to monitor, visualize, and evaluate time-varying structural performance. Accordingly, numerous studies have explored DT-based SHM systems and their applications to infrastructure maintenance and management [9–20]. Our research group has also investigated structural performance evaluation and anomaly detection for long-span bridges using GNSS-based monitoring and

related technologies and has highlighted that structural analysis using DT–BIM technology is essential for physically interpreting and verifying bridge behavior in relation to monitoring observations [21,22].

In Timor-Leste, a research project on maintenance strategies supported by GNSS-based monitoring is planned for the target bridge in this study (Comoro Bridge). In this context, this chapter focuses on establishing the DT–BIM-based digital representation and its interoperability with finite element analysis (FEA) to evaluate fundamental structural performance characteristics. The developed DT–BIM model and physics-based assessment provide a necessary baseline for subsequent monitoring-based interpretation and operational decision support within the overall digital twin framework.

4.2. PC Box-Girder Bridge of Comoro

The Comoro Bridge is a prestressed concrete box-girder bridge constructed in Dili, East Timor, as shown in **Figure 4.1**, **Figure 4.2** and **Figure 4.3**. Dili is East Timor’s capital as well as its administrative and economic center. Since there was only one bridge connecting West Dili and East Dili prior to the construction of this bridge, traffic congestion was very serious during that period. From this reason, there was a strong demand for the construction of a transportation system that could address the heavy traffic, and finally, the construction of a new bridge was promoted.



Figure 4.1 Existing Comoro Bridge

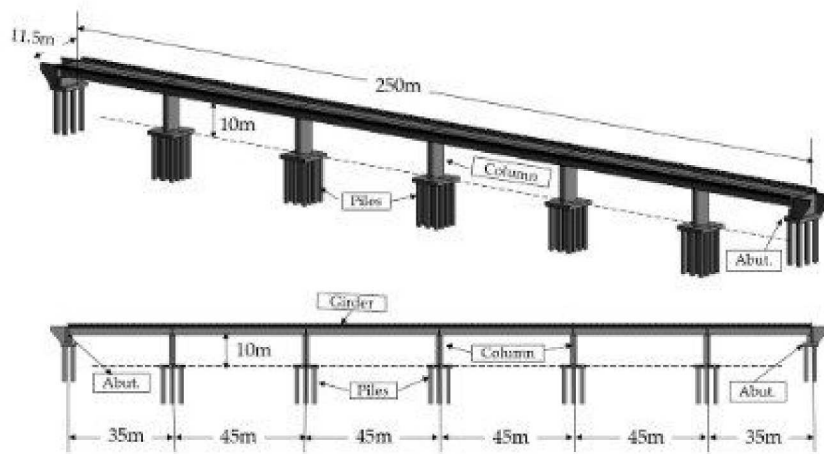


Figure 4. 2 Geometrical model of Comoro Bridge



Figure 4. 3 Location map.

The construction of the bridge began in August 2016, and the bridge was opened to the public in September 2018. It spans a total length of 250 m with a width of 11.50 m. It consists of six spans, including two abutments at both side spans and five piers (35 m + 4 at 45 m + 35 m). Positioned over the Comoro River, it connects the western and eastern parts of Dili. Since it played a significant role as a transportation facility in improving traffic services within the City of Dili, structural health monitoring was planned to be conducted. Therefore, it was chosen as a target bridge for this study.

4.3. Digital Twin and BIM Strategy

4.3.1. Digital Twin

A digital twin is a highly promising technology as it enables us to realize smart manufacturing and Industry 4.0. It is characterized by the seamless integration between cyber and physical spaces [1,2]. Moreover, digital twin technology provides a dynamic and up-to-date representation of a physical object or

system. By consolidating all data in one centralized location, the digital twin evolves in real time with inputs from sensors and other sources. It offers several benefits, including: (a) An optimized performance with actionable insights, simulations, and a holistic view of both online and offline data enabling swift and informed decision-making to optimize performance and efficiency. (b) A comprehensive data visibility: by eliminating data silos and integrating historical and real-time data, the digital twin unlocks value throughout the life cycle of a project. (c) Intelligent predictions: real-time sensor data and predictive recommendations through machine learning and artificial intelligence greatly enhance maintenance and operational capabilities. (d) Faster results: creating digital twins of complex assets, factories, and processes exponentially enhance operational value, reduces development efforts, and accelerates time to market. Therefore, in this study, we explored the use of the digital twin–BIM technology for landscape visualization, traffic flow simulation, finite element analysis, and structural maintenance.

4.3.2. Building Information Modeling (BIM)

Building information modeling (BIM) has become an invaluable tool for architects, engineers, and the construction industry. The U.S. National Building Information Model Standard Project Committee has defined BIM as a digital representation of a facility's physical and functional characteristics. BIM facilitates improved collaboration among architects, engineers, contractors, and other project participants. It provides a shared digital platform where all relevant project information can be accessed, updated, and shared in real time, fostering better communication and coordination. BIM data are utilized during the entire process of a structure's life cycle, including its design, construction, maintenance, and renovation, as depicted in **Figure 4.4**. By facilitating an improved communication and coordination among team members, BIM minimizes errors, reduces rework, and enhances efficiency in the design, construction, and operation of buildings and infrastructure projects. Consequently, BIM offers several advantages, including maximizing efficiency, reducing cost, reducing waste, improved cost estimates, enhanced project insights, effective communication and collaboration, risk mitigation, and superior outcomes.



Figure 4. 4 BIM process

4.3.3. Development of a Digital Twin–BIM Model for Bridge Management Workflows

The development of the digital twin–BIM model in this research is presented in **Figure 4.5**. This workflow is designed to accommodate bridges of any shape. Specifically, this study focuses on modeling a PC box-girder bridge in Dili City, Timor-Leste. The modeling processes are as follows: (1) Data sources: in order to accurately idealize the existing bridge, it is essential to gather bridge information and documents, such as the design report and construction drawings, from the owner or relevant institution. (2) BIM design tool (Revit): The substructure and superstructure components of the bridge are created as BIM objects (Revit families), as illustrated in **Figure 4.6**. Once the components are developed, they are loaded into the BIM template (Revit project) to facilitate model integration. Ultimately, the digital-twin bridge model is established, as shown in **Figure 4.7**. (3) Additionally, a visual programming language (Dynamo) is utilized, as depicted in **Figure 4.8**. Dynamo allows access to the Revit API, enhancing productivity for designers and modelers. (4) Upon completion of the digital twin model, it can be integrated with BIM simulation tools for landscape visualization and traffic flow simulation. Furthermore, the digital model can be linked with a finite element (FE) analysis to evaluate structural performance. Lastly, the model can be employed for structural maintenance purposes.

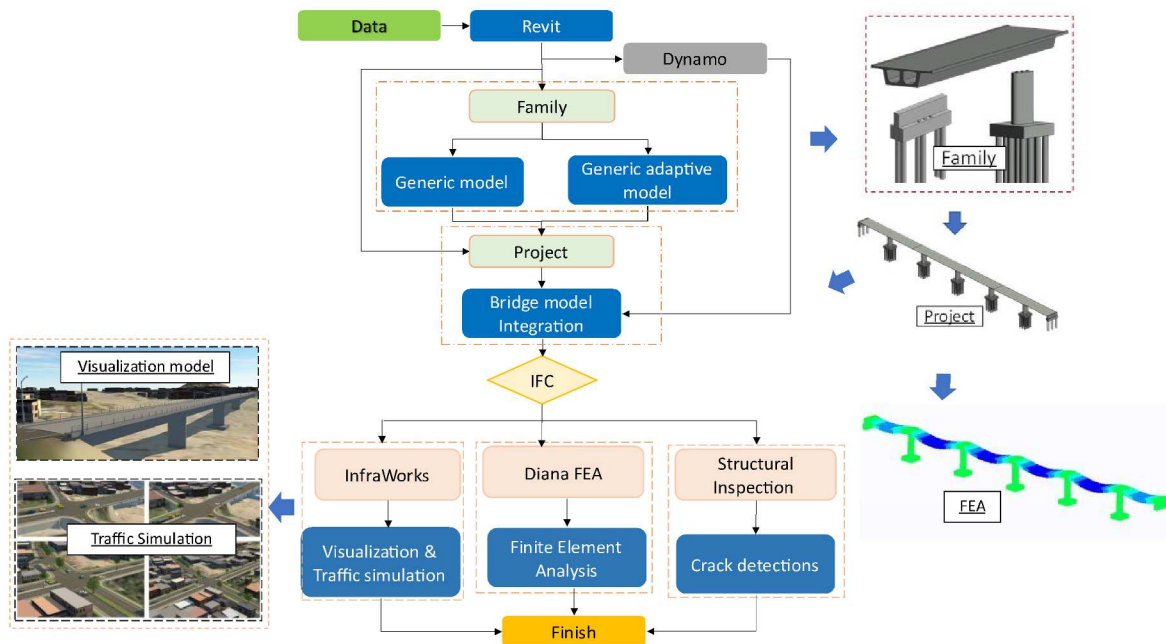


Figure 4. 5 The Development of a Digital Twin–BIM Model for Bridge Management Workflow

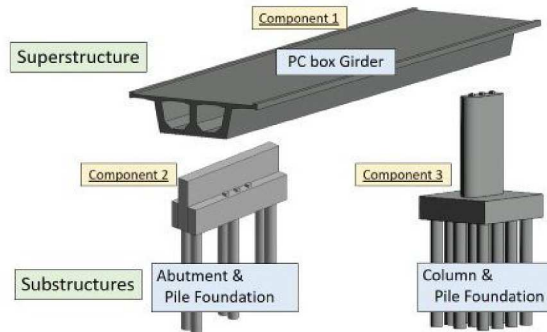


Figure 4. 6 Bridge components.

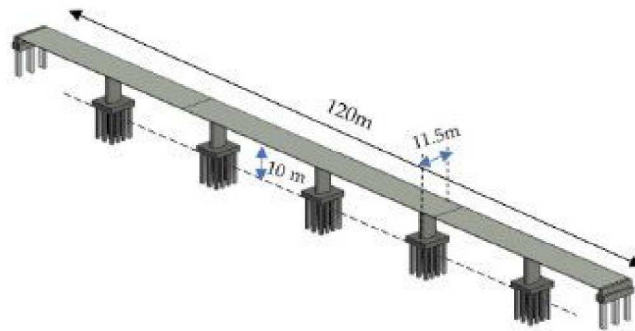


Figure 4. 7 Bridge model

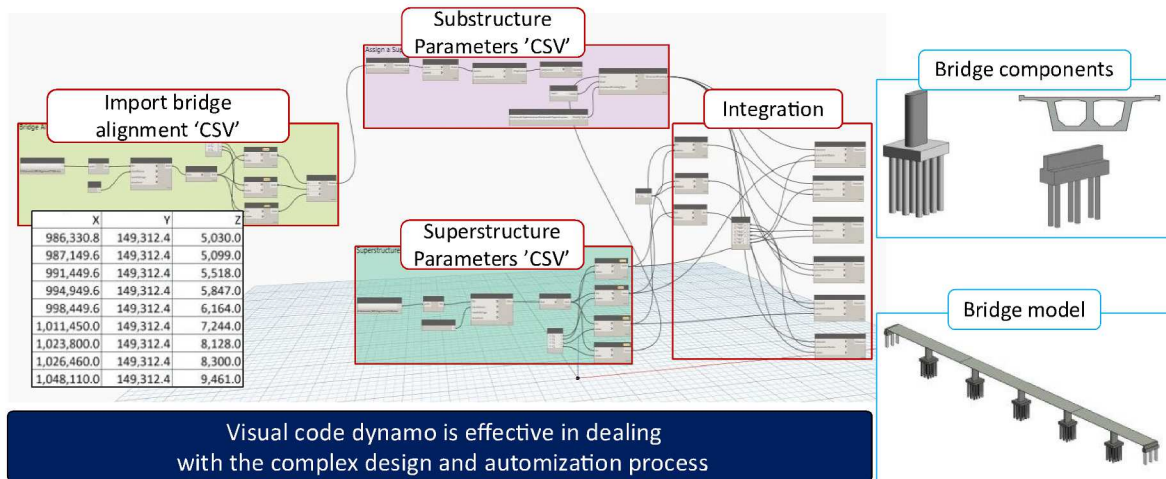


Figure 4. 8 Dynamo Visual Programming Language

4.4. Building Information Management

4.4.1. BIM Management Applications Using Digital Twin of Comoro Bridge

In this study, BIM management was implemented through the utilization of the digital twin of Comoro Bridge for landscape visualization, traffic management, structural performance evaluation, and structural maintenance, as illustrated in **Figure 4.9**.

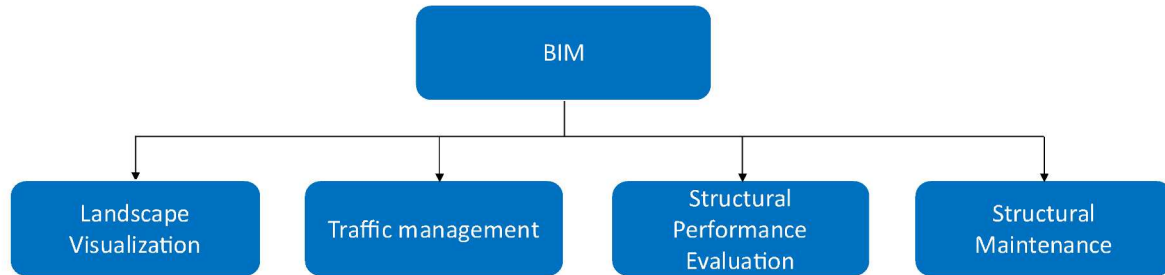


Figure 4. 9 BIM management applications

4.4.2. Digital Twin of Comoro Bridge for Landscape Visualization

By utilizing Building Information Modeling (BIM) technology, the physical model of the Comoro Bridge can be effortlessly replicated into cyberspace, as shown in **Figure 4.10** and **Figure 4.11**. This enables the digital twin model to comprehensively visualize the Comoro Bridge encompassing its actual surrounding environment.



Figure 4. 10 Real bridge model

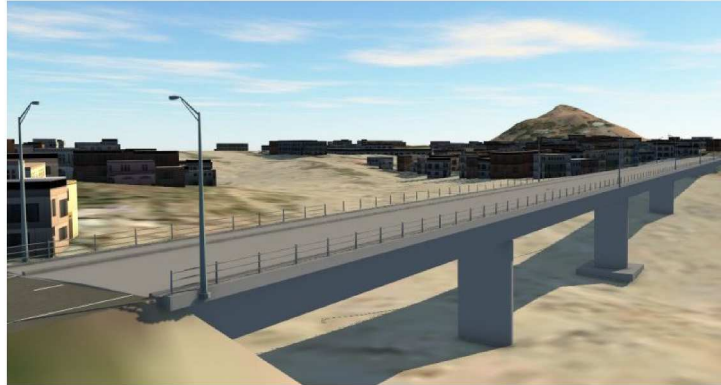


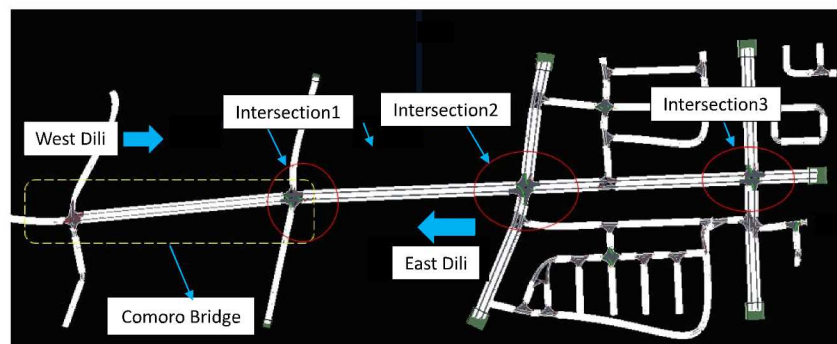
Figure 4. 11 Digital twin model

4.4.3. Digital Twin of Comoro Bridge for Traffic Flows Simulation

The Comoro Bridge connects to the existing road across the Comoro River as depicted in **Figure 12a**. Dili's main arterial roads are connected to multiple roads as depicted in **Figure 12b**, and they are forming a road traffic network. The development of the digital twin–BIM model of Dili's road network, specifying the road inflows and outflows from each road (**Figure 12c**) and traffic events (**Figure 12d**), enables the traffic flow simulation on existing road networks as depicted in **Figure 12e**. Such a traffic flow simulation was performed to verify the following objectives.



(a)



(b)

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Directed Demand:

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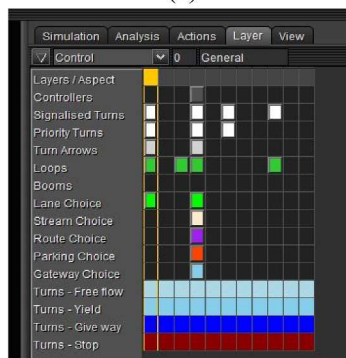
Profile	1	2	3	4	8	10	Total
1		24	20	10	23	7	90
2		50	15	20	10	7	108
3		20	10	40	6	3	83
4		100	30	15	10	3	162
8		15	10	10	10	3	52
10		50	30	10	100	10	213
11		10	10	7	20	6	56
19		10	25	14	30	8	101
Total	255	140	91	230	73	41	876

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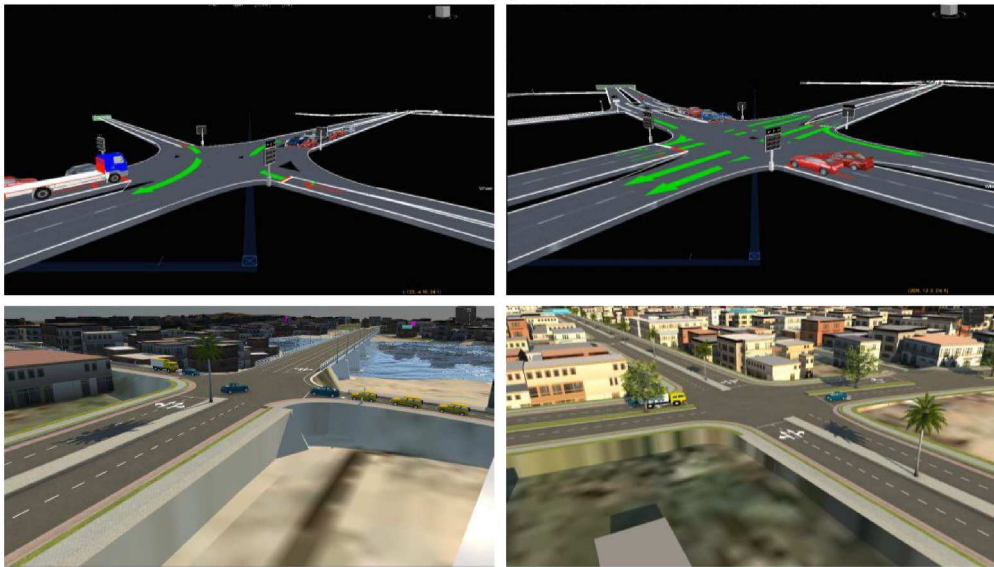
OK

Close

(c)



(d)



(e)

Figure 4. 12 Traffic flow simulation in BIM. (a) Target area; (b) overall area of traffic flow simulation; (c) traffic demand panels; (d) traffic control panel; (e) video simulations.

- To assess the effectiveness of the Comoro Bridge in mitigating traffic congestion in the City of Dili.

- To validate the capabilities of advanced BIM technology in designing and managing transportation infrastructure.
- To demonstrate the efficacy of BIM technology applications in the architecture, engineering, and construction (AEC) industry.

Since the purpose of this paper was to examine how to utilize digital twins for the Comoro Bridge, quantitative analysis results will be presented in another paper. However, preliminary studies predicted that the construction of the Comoro Bridge would alleviate traffic congestion in Dili City. Such traffic flow simulations are extremely useful not only for verifying the impact of the construction of a new bridge but also for predicting traffic congestion on surrounding roads during construction and for considering measures to alleviate traffic congestion at the planning stage.

4.5. Digital Twin of Comoro Bridge for Structural Performance Evaluation

4.5.1. Digital Twin–BIM Technology and Finite Element Analysis Interoperability

This study involved the interoperability between digital twin–BIM technology and finite element analysis (FEA), as depicted in **Figure 4.13**. The process of interoperability between digital twin–BIM technology and FEA are outlined as follows:

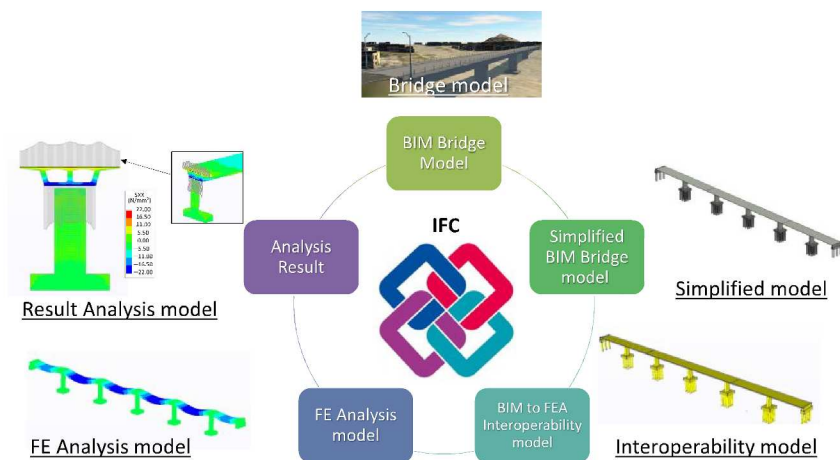


Figure 4.13 Digital twin–BIM and FEA interoperability

- The complete Comoro Bridge model was developed using BIM tools.
- A simplification process was conducted to remove secondary elements such as railings, electrical poles, pedestrians, and other nonessential components.
- The IFC format was utilized for seamless interoperability between BIM and FE analysis (FEA).
- After achieving interoperability, the bridge model was prepared for the FE analysis (FEA).
- The finite element analysis (FEA) was performed.

- Results and evaluations are conducted.

4.5.2. Structural Performance Evaluation Based on FE Analysis

- Full-Scale Model Creation for FE Analysis

The digital twin of the Comoro Bridge, developed in a BIM tool (Revit) and supported by visual programming (refer to **Figure 4.14**), facilitated the FE analysis of the full-scale model. Subsequently, the model was exported to IFC files for integration with FE software. Following this, it was necessary to install prestressing tendons along the PC box girder sections based on the construction drawings, as depicted in **Figure 4.15**.

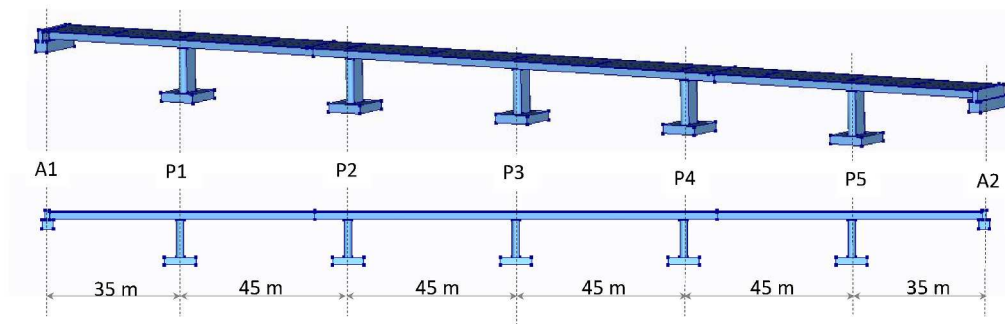


Figure 4. 14 Full-Scale Model

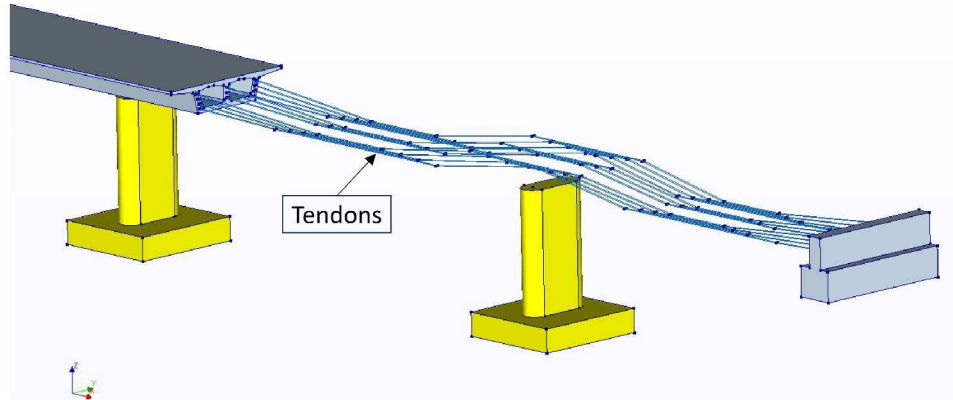


Figure 4. 15 Prestressed Tendons Installation

The Comoro Bridge model was composed of three PC-box superstructures, five piers, and two abutments as mentioned above. Each component was idealized by a solid element, and the bearing on the top of piers and abutments was idealized by spring elements, which represented the stiffness of six degrees of freedom in each direction. The prestressing tendons were idealized by the so-called embedded bar element coupled with the concrete superstructure. The embedded bar element was a virtual element representing the interaction behavior of the reinforcement inside the concrete members.

- Material Properties

The material properties of the concrete and prestressed tendons utilized for the FE analysis in this study are presented in **Table 4.1** and **Table 4.2** based on construction records, respectively.

Table 4. 1 Material properties of the concrete in the analysis.

No.	Type of Structure	Materials	
1	Superstructure	Concrete (fc)	36 MPa
		Poisson's ratio	0.2
		Mass density	2500 kg/m ³
2	Substructure	Concrete	30 MPa
		Poisson's ratio	0.2
		Mass density	2500 kg/m ³

Table 4. 2 Prestressed tendons.

Main Tendon		
Type	SWPR7BL 12S15.2mm	
Tensile stress	1850 (N/mm ²)	
Yield strength	1600 (N/mm ²)	
Allowable tensile stress	At the time of prestressing	1440 (N/mm ²)
	Just after prestressing	1295 (N/mm ²)
	Design load	1110 (N/mm ²)

▪ Boundary Conditions

The boundary conditions applied in this analysis were as follows:

- The bottoms of pile caps and abutments were idealized as fixed supports. They were rigidly connected to the ground with translations (T1, T2, and T3) constrained, as illustrated in **Figure 4.16**.
- The bearings were represented by spring materials, as depicted in **Figure 17**. Modeling the rotational boundary conditions as fully free poses challenges, hence rotational springs were adopted with a stiffness value of 10⁶ (kNm/rad) as indicated in **Table 3**.

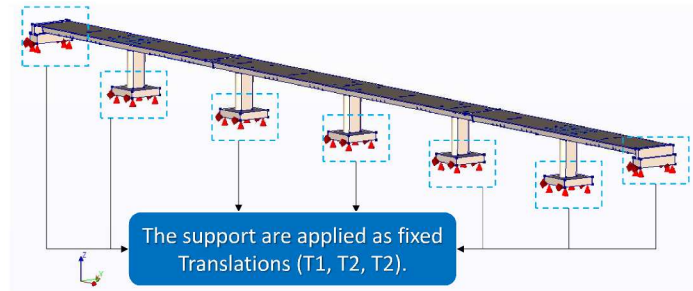


Figure 4. 16 Support

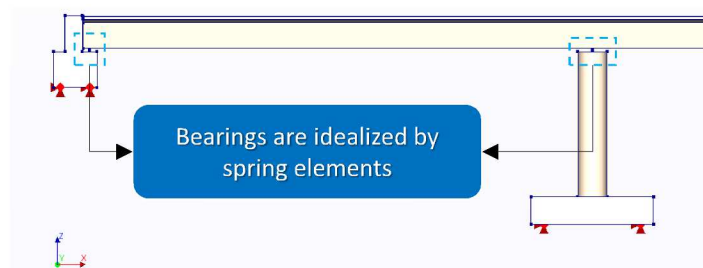


Figure 4. 17 Springs

Table 4. 3 Boundary conditions idealized as springs.

Location	Direction	Theoretical B. C.	Analysis	
			B. C.	Stiffness
A1	Sway deformation	X	Rigidly fixed by spring element	10^{10} (kN/m)
		Y		
		Z		
	Rotational deformation	R_X	Constrained by spring element	10^6 (kNm/rad)
		R_Y		
		R_Z		
P1-P5	Sway deformation	X	Rigidly fixed by spring element	10^{10} (kN/m)
		Y		
		Z		
	Rotational deformation	R_X	Constrained by spring element	10^6 (kNm/rad)
		R_Y		

		R_Z	Fix		
		X			
	Sway	Y	Fix	Rigidly fixed	10^{10} (kN/m)
	deformation	Z		by spring element	
A2		R_X	Fix		
	Rotational	R_Y	Free	Constrained	10^6 (kNm/rad)
	deformation	R_Z	Fix	by spring element	

▪ Loads

The loads considered in this analysis are depicted in **Figure 4.18** as follows:

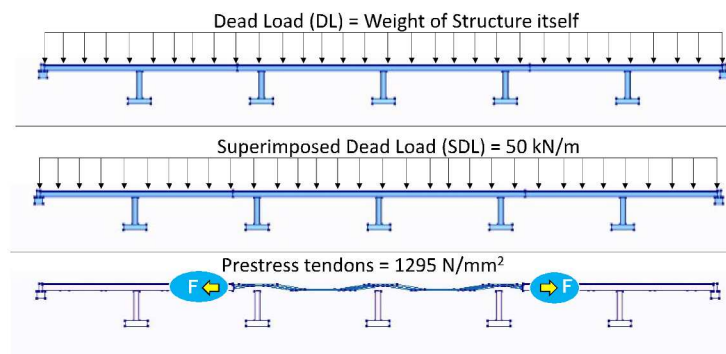


Figure 4. 18 Loads

1. Self-weight (DL): represents the weight of all structural elements of the bridge.
2. Superimposed dead load (SDL): Includes the weight of the steel railing, asphalt concrete pavement, safety fences, and other components. The combined value of this load was 50 kN/m.
3. Prestress Tendon (T): represents the tendons just after prestressing with a stress of 1295 N/mm².

▪ Discretization (Meshing)

A mesh is a discrete representation of a larger geometric domain using smaller cells. Meshes are commonly employed for solving partial differential equations, rendering computer graphics, and analyzing geographical and cartographic data. Meshing divides the space into elements (or cells or zones) on which the equations can be solved, providing an approximation of the solution across the larger domain. In this study, the meshing process was performed in DIANA FEA, using a mesh size of 0.25 m and a HEX/SQUAD meshing type, as illustrated in **Figure 4.19**.

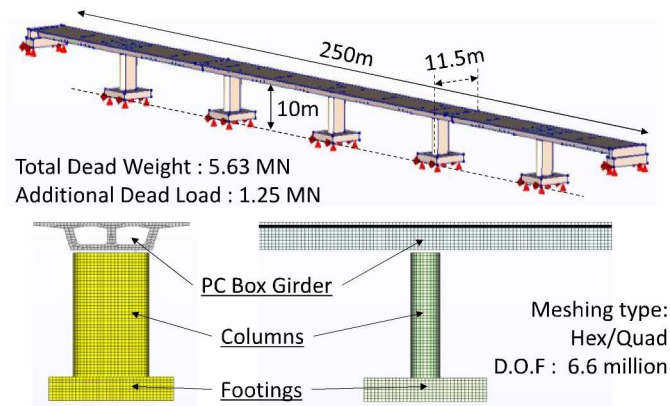


Figure 4. 19 Discretization

- Analysis Type

The types of FE analysis conducted in this study are presented in **Table 4**. Geometric nonlinear analyses were not performed.

Table 4. 4 FE analysis types.

Names	Types
Analysis	Linear static
Dimension	Three dimensions
Composed element	Solid
Mesh order	Linear
Mesh size	0.25 m
D.O. F	6.6 million

- Structural Evaluation for the state conditions of Comoro Bridge

When analyzing the Comoro Bridge model using an FE analysis, the obtained results can be compared to the theoretical values to evaluate the structural performance, as outlined below:

- Displacement

The displacement results from the dead load (DL + SDL) obtained from both the FE analysis and theoretical calculations are presented in **Figure 4.20**. The results indicated that the displacements obtained from both the FE analysis and theoretical calculations were quite similar in the internal spans. However, there was a slight variation in the displacements of the side spans due to the influence of the boundary.

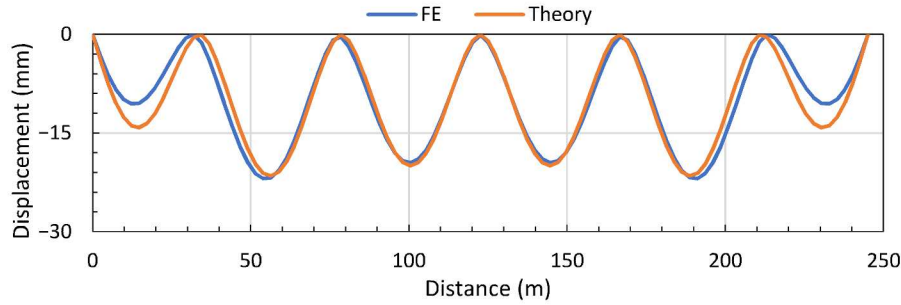


Figure 4. 20 Displacement due to the dead load (DL + SDL)

- Normal stress distribution

The results of the finite element analysis (FEA) can be utilized to assess the distribution of normal stress along the axis of the Comoro Bridge in comparison to the theoretical results. The normal stress distribution presented in this study was induced by the dead load (DL + SDL), as depicted in **Figure 4.21**. According to the Euler–Bernoulli theory, the normal stress is distributed according to the bending moment distribution along the bridge axis, resulting in peak values at the top of the piers. As observed in the figure, the normal stress distribution results obtained from both the FE analysis and theoretical calculations were consistent and nearly identical. However, the peak stress occurring at the top of the piers exhibited larger values than those predicted by the Euler–Bernoulli theory. The mechanisms underlying these differences are discussed later.

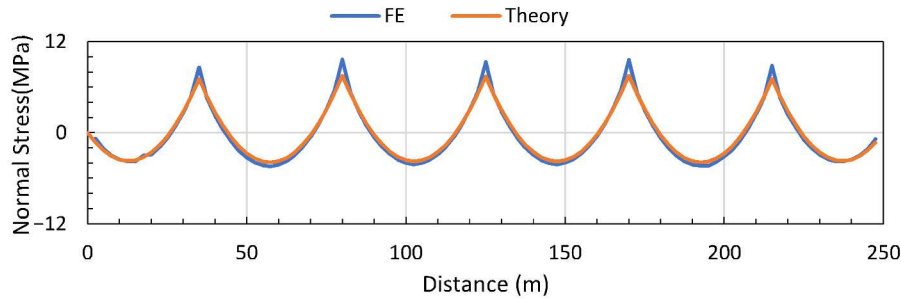
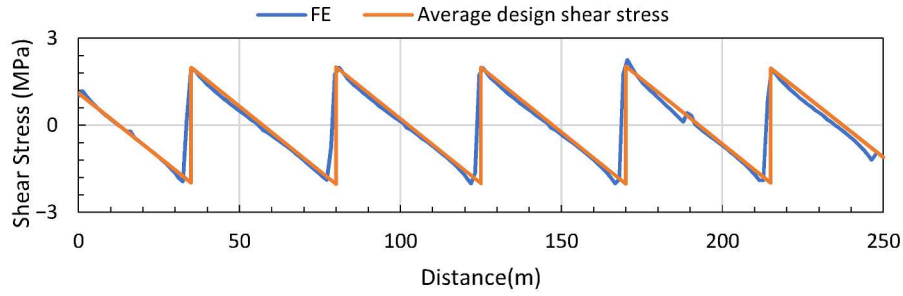


Figure 4. 21 Normal stress distributions due to the dead load (DL + SDL).

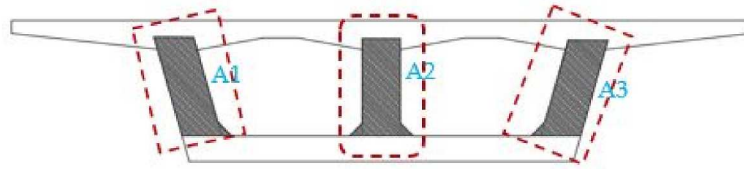
- Shear-Stress distribution

Due to the uniform load action of the dead load (DL) and superimposed dead load (SDL), the shear stress exhibited a linear distribution with a downward slope, as illustrated in **Figure 4.22a**. Furthermore, the average shear stress, calculated using Equation (1), by dividing the theoretical value of the acting shear force by the equivalent cross-sectional area of the highlighted region in **Figure 4.22b**, demonstrated an excellent agreement with the results obtained from the structural analysis. This phenomenon is attributed to the uniform concentration of the shear stress on the web of the prestressed-concrete (PC) box girder, as illustrated in **Figure 4.22c**. The detailed FE analysis results obtained using the overall bridge model consistently aligned with the theoretically expected results, providing conclusive evidence of the significant value and usefulness of the digital twin in the bridge analysis.

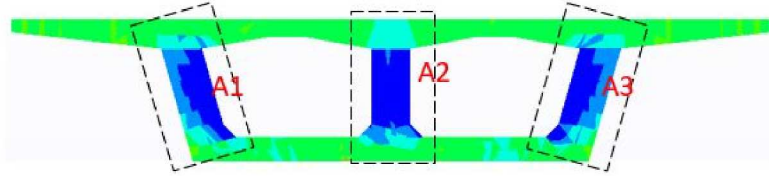
$$\tau^* = \frac{\text{Shear force}(Q)}{\text{Effective area}(A_{\text{eff}})} \quad (4.1)$$



(a)



(a)



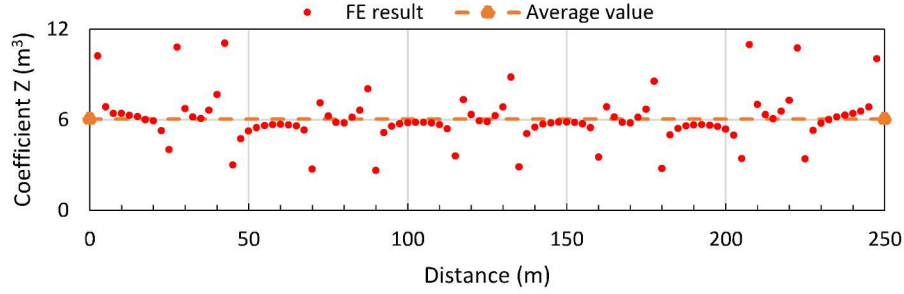
(c)

Figure 4. 22 Shear-stress distribution along the bridge axis. (a) Shear-stress distribution due to the dead load (DL + SDL); (b) effective area; (c) contour map of the effective area.

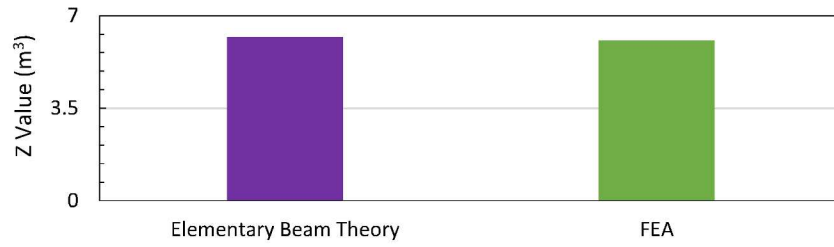
▪ Sectional force (Coefficient Z value)

The finite element analysis enabled the evaluation of the sectional coefficient Z along the bridge axis, obtained using **Equation (2)**, as depicted in **Figure 4.23a**. At certain locations, the coefficient Z was arbitrarily distributed; however, taking the average value results in a Z coefficient value of 6.059 m³. This value is closely aligned with the theoretical value of 6.195 m³ based on the Euler–Bernoulli theory, as illustrated in **Figure 4.23b**.

$$Z = \frac{\text{Inertia Moment}}{\text{neutral axis height}} = \frac{I}{y} \quad (4.2)$$



(a)



(b)

Figure 4. 23 Coefficient Z value. **(a)** Z value along the bridge axis; **(b)** Z value results from the FEA and theory.

- Nonuniform normal stress (Shear-lag) distribution on box-girder section

The phenomenon of the shear-lag effect can be evaluated in the box-girder section, as depicted in **Figure 4.24a,b**. The uniform normal stress distribution along the flange of thin-walled flexural members, such as box girders, is recognized as shear-lag effects [23, 24]. According to elementary beam theory (Bernoulli–Euler theory), the normal stress in the longitudinal direction resulting from a bending deformation is assumed to be proportional to the distance from the neutral axis. As a result, it is expected to be uniform across the flange width, as formulated in **Equation (3)**.

$$\sigma_x = \frac{M_y}{I_z} y = \frac{M}{z} \quad (4.3)$$

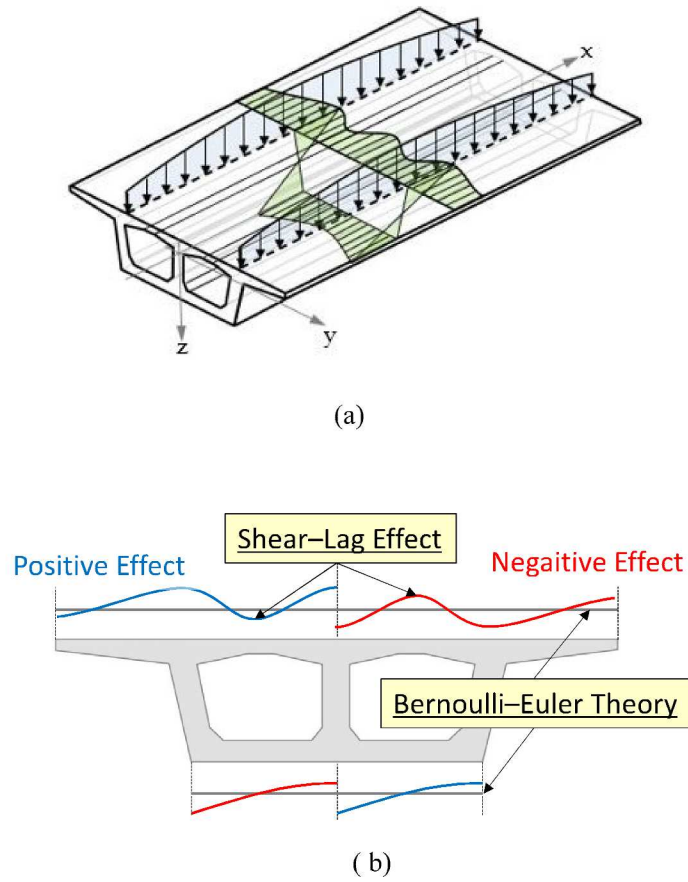


Figure 4. 24 Nonuniform normal stress distribution on box-girder section. (a) the distribution of nonuniform normal stress along the bridge axis. (b) Nonuniform normal stress distribution in the PC box-girder section

However, when the flange width increases, this assumption becomes invalid. The phenomenon of shear-lag effect can also be defined as the nonuniform distribution of normal stress in the wide flange. Nevertheless, the stress reaches its maximum value at the intersection of the flange and web, gradually decreasing towards the center of the flange [23,24].

- Shear-Lag Effect Evaluation on PC Box-Girder Section

To evaluate the shear-lag effect of the PC box-girder section, it is necessary to identify the target locations along the bridge axis. In accordance with **Figure 4.25**, the bridge span between pier 3 and pier 4 was selected for evaluation. The chosen evaluation locations included the top piers, the quarter-point along the span length, and the midspan.

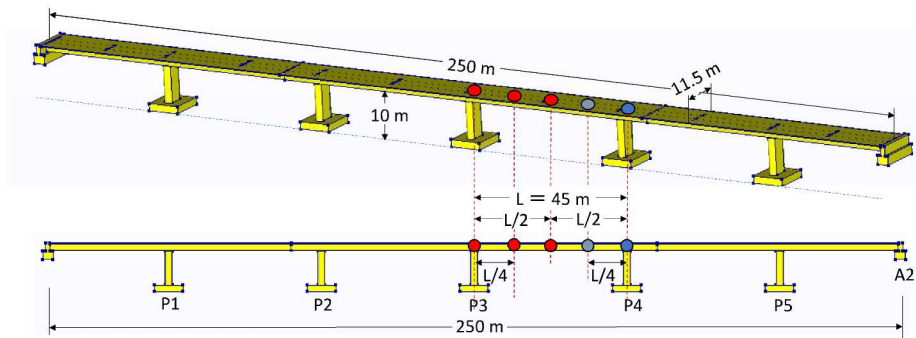


Figure 4.25 Evaluation Point of Shear-Lag Effect

■ Shear-lag effect Evaluation

The normal stress distribution at the top and bottom flanges of the box girder at pier 3 was evaluated and is depicted in **Figure 4.26a**. **Figure 4.26b,c** illustrates the occurrence of a nonuniform stress distribution at the top and bottom surface flanges, deviating from the predictions of the Euler–Bernoulli theory. Consequently, a significant shear-lag effect phenomenon was observed on the box-girder section at both the top and bottom flanges at pier 3.

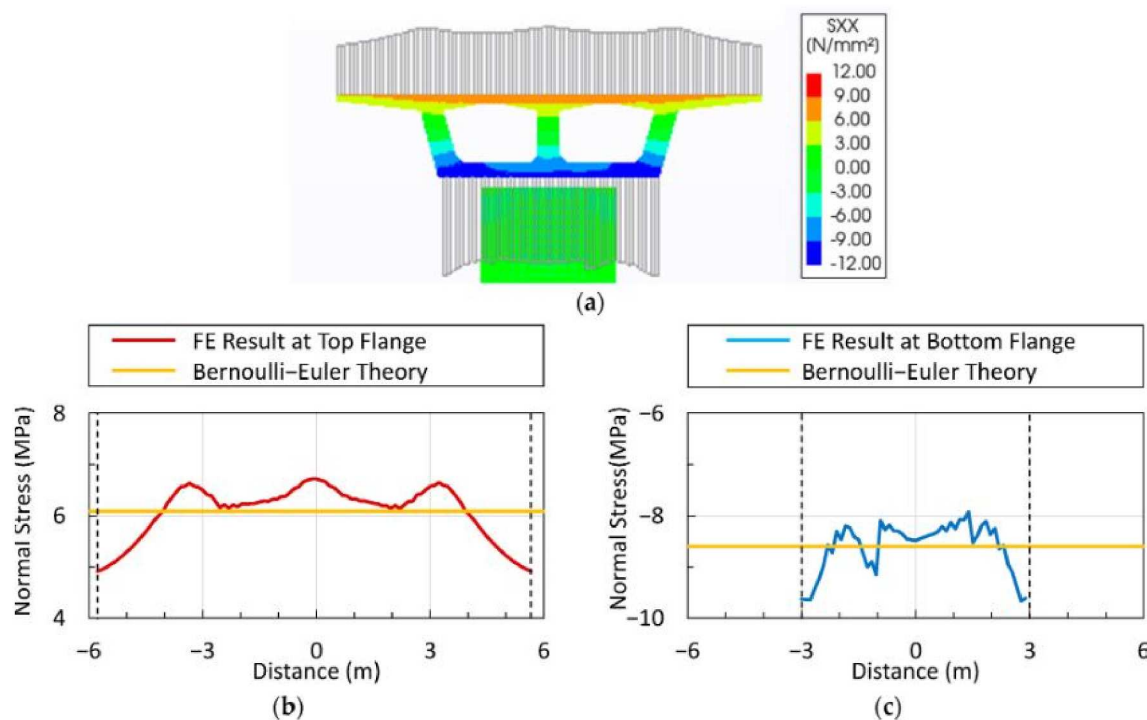


Figure 4.26 Normal stress distribution on the girder section at pier 3. (a) Contour map of the normal stress distribution; (b) at the top flange; (c) at the bottom flange.

The normal stress distribution at the top and bottom flanges of the box girder, positioned $1/4 L$ away from pier 3, is depicted in **Figure 4.27a**. **Figure 4.27b,c** demonstrate the occurrence of a nonuniform stress distribution at the top and bottom surface flanges, deviating from the predictions of the Euler–Bernoulli theory. Nevertheless, the shear-lag effect was notably diminished towards the midspan when considering the $1/4 L$ location.

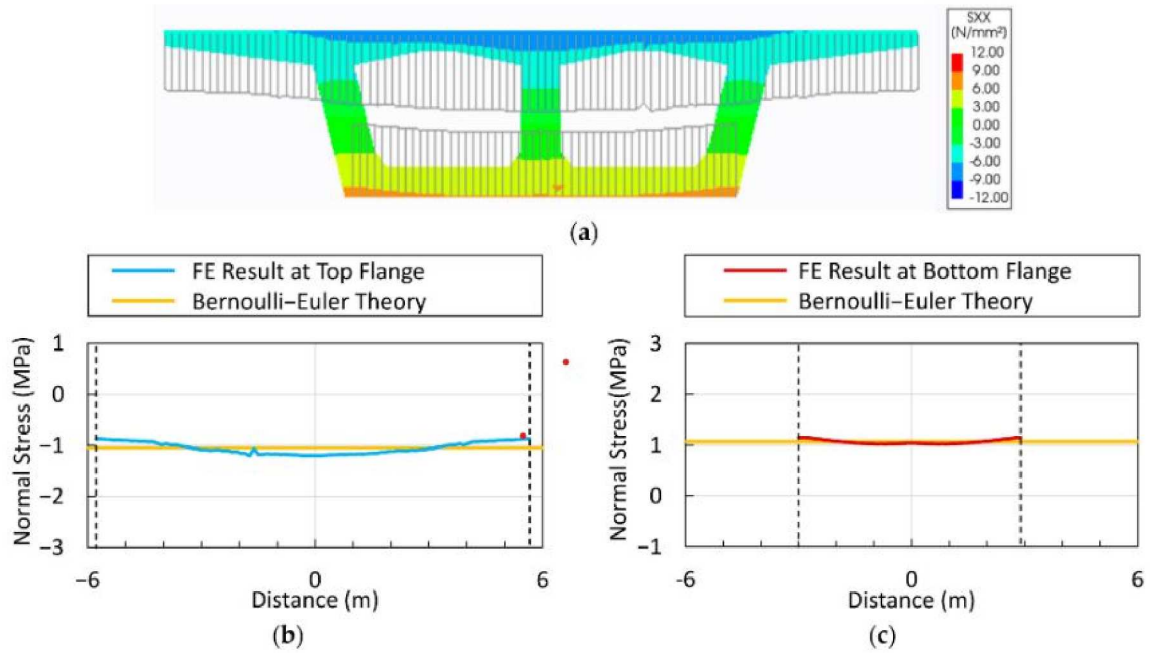


Figure 4. 27 Normal stress distribution on the girder section at $1/4 L$ from pier 3. (a) Contour map of the normal stress distribution; (b) at the top flange; (c) at the bottom flange.

The contour map of the stress distribution (**Figure 4.28a**) clearly illustrates that the shear-lag effects at both the bottom and top flanges of the midspan box girders were negligible, closely aligning with the assumptions of the Euler–Bernoulli beam theory (refer to **Figure 4.28b,c**). Consequently, given the limited occurrence of shear forces, the shear-lag effect could be disregarded in the midspan section of the box girder.

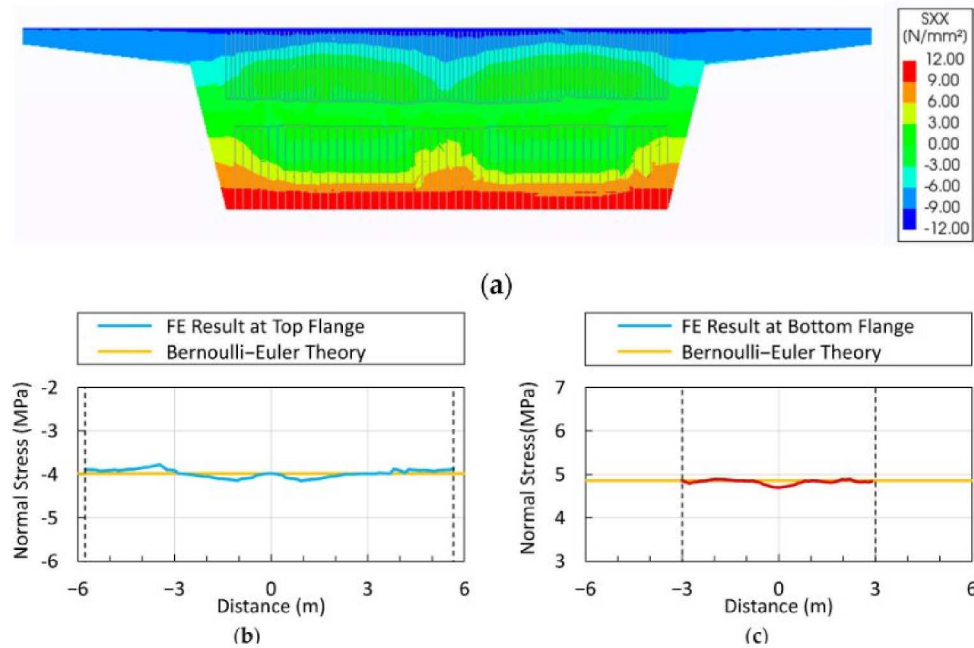


Figure 4. 28 Normal stress distributed on the girder section at midspan. (a) Contour map of the normal stress distribution; (b) at the top flange; (c) at the bottom flange.

Therefore, the assessment of the shear-lag effect for the PC box-girder section of the Comoro Bridge was as follows:

1. The nonuniform normal stress distribution due to the shear-lag effect obviously occurred at the top and bottom flanges.
 2. The shear-lag effect significantly occurred at the top of the piers, especially at the web and flanges interaction.
 3. However, when it moved towards the midspan, the shear-lag effect was diminished linearly and could even be neglected.
- Shear-Lag Effect on Double-Cell Box Vs. Single-Cell Box Girder

In order to investigate the shear-lag effect phenomenon on the PC box-girder bridge in Comoro, a double-cell box girder was designed to replicate the original configuration of the Comoro Bridge compared to a single-cell box girder. The single-cell box girder possessed identical dimensions and cross-sectional area. In the double-cell box girder, the middle web was removed and added to the left and right webs of the single-cell box girder, as illustrated in **Figure 4.29**. Consequently, the evaluation of shear-lag effects in both the double-cell and single-cell box girders was as follows:

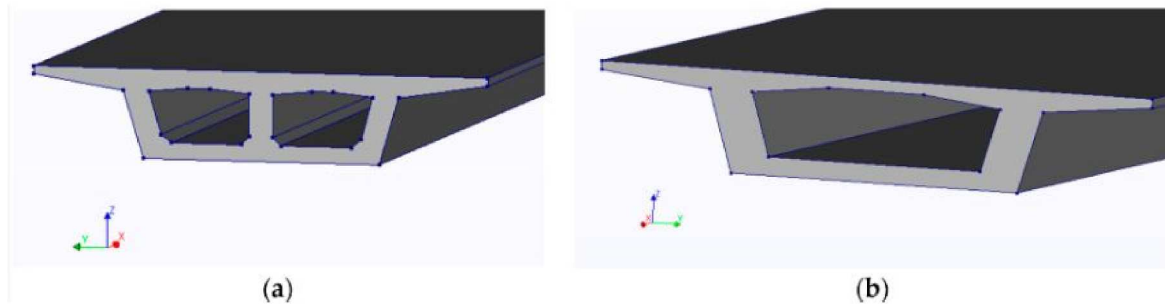


Figure 4.29 Double-Cell Box and Single-Cell Box Girder. (a) Double-Cell Box Girder; (b) Single-Cell Box Girder.

- The shear-lag effect was observable at the top and bottom flanges in the box-girder section located at the top of the piers, as depicted in **Figure 4.30a**.

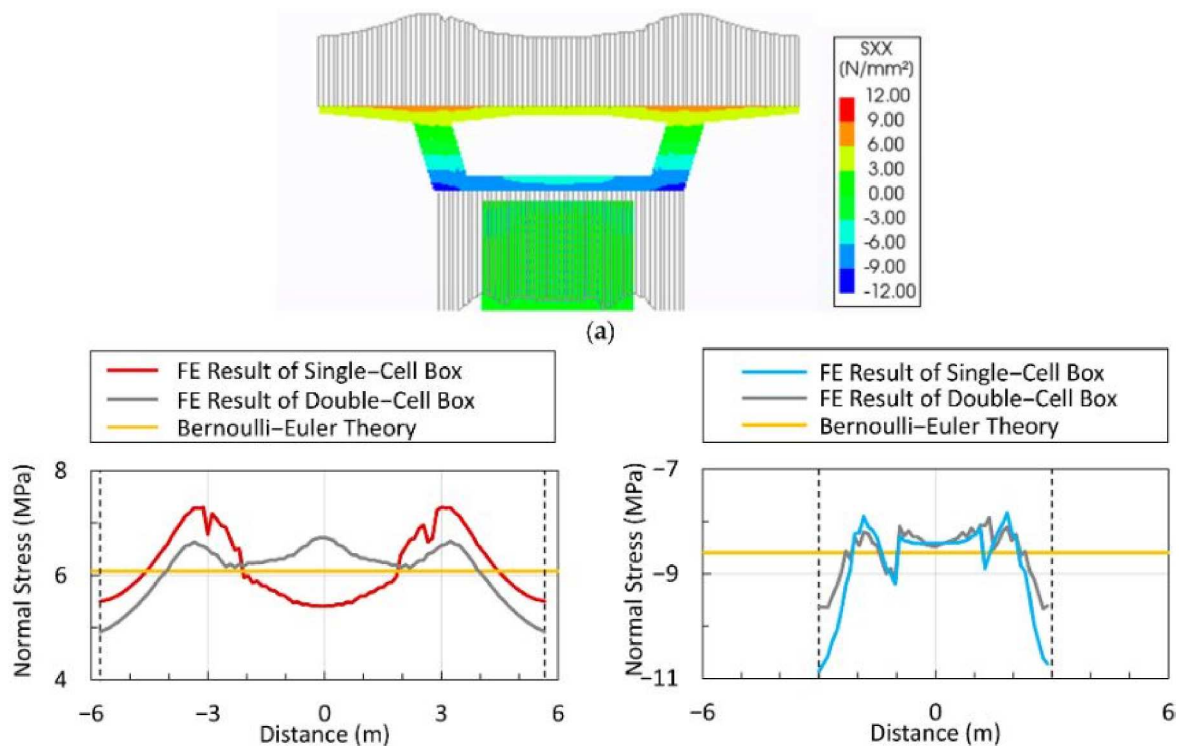


Figure 4.30 Normal stress distribution on the girder section at pier 3 (single-cell box-girder case). (a) Contour map of the normal stress distribution; (b) at the top flange; (c) at the bottom flange.

- The results indicated that the shear-lag effect was more prominent in the single-cell box compared to the double-cell box. This disparity was attributable to the geometrical differences, with the double-cell box featuring an intermediate web, while the single-cell box lacked one (refer to **Figure 4.30b,c**).

Consequently, the shear-lag effect was significantly more pronounced in the single-cell box girder. However, as the location transitions towards the midspan, the shear-lag effect diminished linearly and became aligned with the assumptions of the Euler–Bernoulli theory (refer to **Figure 4.31**).

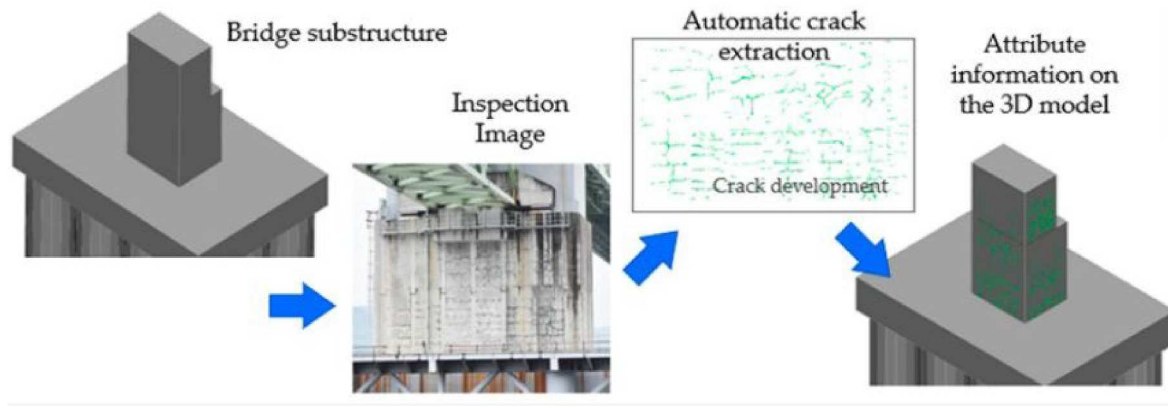


Figure 4. 31 Bridge digital twin for structure maintenance

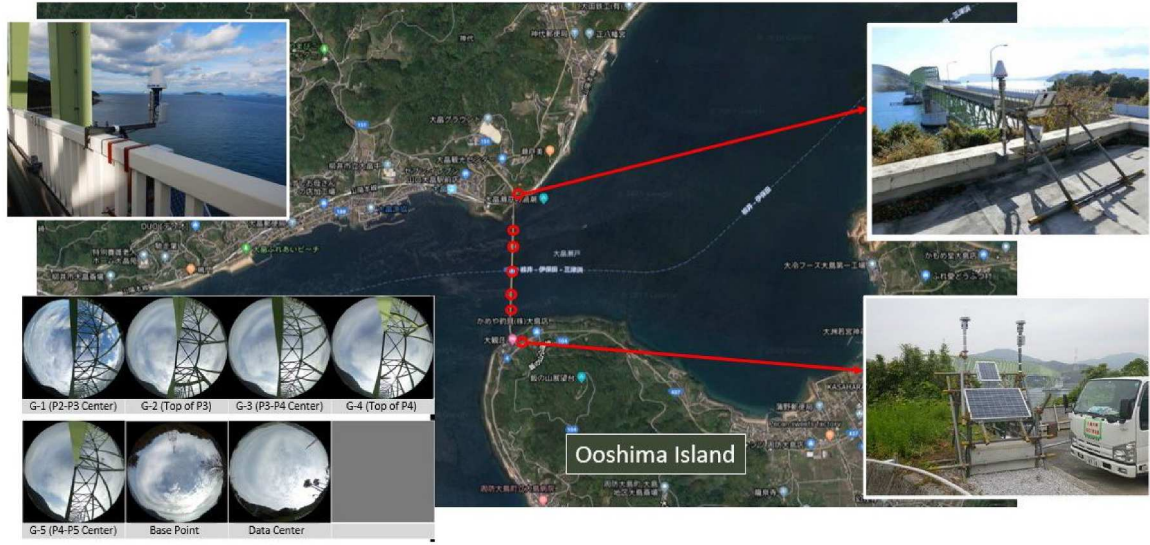
The evaluation results of the shear-lag effect for both the double-cell box and single-cell box were as follows:

1. Both the double-cell and single-cell boxes exhibited a shear-lag effect, especially at the top of the piers.
2. Both the double-cell and single-cell boxes exhibited a shear-lag effect, especially at the top of the piers.
3. Both the double-cell and single-cell boxes exhibited a shear-lag effect, especially at the top of the piers.

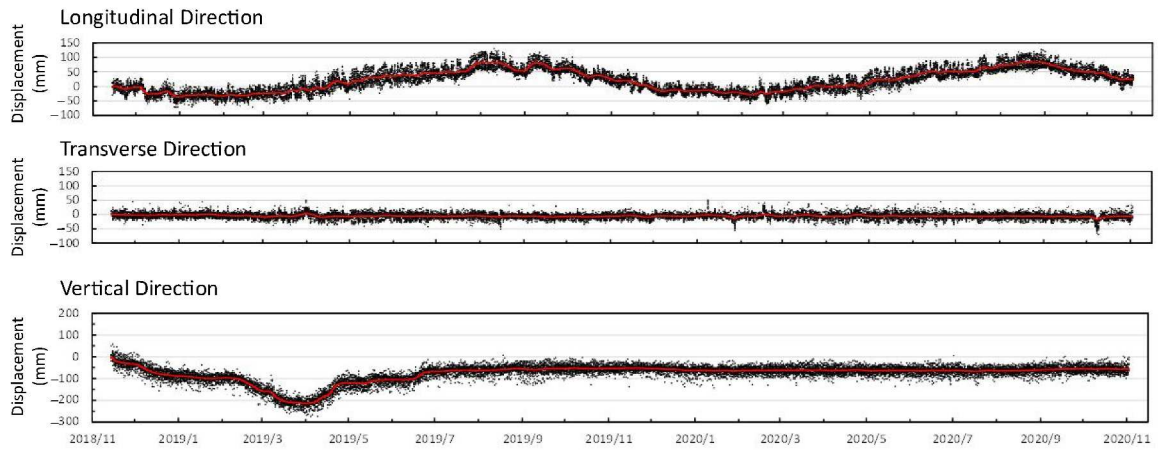
A comparative study can be performed using a full-scale bridge model, which is easily developed from the BIM technology.

4.6. Application of Bridge Digital Twin for Structure Maintenance

Digital twin–BIM technology can be utilized for the maintenance of bridge structures. As illustrated in **Figure 4.32**, it is feasible to automatically extract crack information (maintenance data) from captured image data during inspections and incorporate it as attribute information into the 3D model of the structure. This enables the storage and management of maintenance information using BIM technology. Hence, digital twin–BIM technology plays a vital role in managing the complete life cycle of the bridge. Additionally, as mentioned in the **Section 1**, structural health monitoring has been planned based on the GNSS data observation as depicted in **Figure 32**. This figure shows the setup of the monitoring system and observation data in past research. By a continuous 3D displacement monitoring of bridges, it is expected that valuable data will be available for the maintenance of the bridge.



(a)



(b)

Figure 4. 32 Implementation of GNSS monitoring for bridges in past research. (a) Setup of GNSS monitoring system; (b) observation data from the GNSS monitoring system.

4.7. Conclusion

This chapter established the DT-BIM-based digital representation and physics-based validation components of the proposed operational digital twin framework for bridge infrastructure. Through a case study of the Comoro PC box-girder bridge, a detailed BIM model was developed and integrated with finite element analysis to evaluate fundamental structural performance characteristics. The results demonstrated that the DT-BIM model provides a reliable and physically consistent baseline for representing bridge behavior, supporting visualization, information management, and structural assessment. By positioning BIM-based

modeling and FEA-based validation as foundational elements, this chapter provides the necessary digital and physical groundwork for subsequent GNSS-based monitoring, uncertainty-aware state estimation, and decision-support functions addressed in the following chapters.

- The development and application of digital twin-BIM technology for bridge management offer significant advantages in the field of infrastructure maintenance and operation. By integrating the capabilities of digital twin technology with building information modeling (BIM), bridge managers can create a comprehensive virtual representation of the bridge, capturing its physical and functional attributes.
- Digital twin-BIM technology enables the landscape visualization of the Comoro Bridge with the surrounding environment, traffic flow simulation at the area of the target bridge, a finite element analysis for bridge structure performance evaluation, and bridge structure maintenance. Therefore, digital twin-BIM technology has the potential and ability to access accurate and up-to-date information about the bridge's condition that enhances asset management practices, optimizes maintenance schedules, and extends the lifespan of the structure.
- Additionally, digital twin-BIM technology promotes an effective collaboration among stakeholders involved in bridge management, allowing seamless data exchange, information sharing, and coordinated decision-making. This enhances communication, reduces errors, and streamlines workflows, leading to improved efficiency and cost-effectiveness in bridge maintenance and operation.
- Furthermore, the utilization of digital twin-BIM technology in bridge management contributes to enhanced safety by enabling the evaluation of the structural integrity, the assessment of risk factors, and the implementation of preventive measures. This proactive approach minimizes the likelihood of bridge failures, ensuring the safety of users and surrounding areas.

Overall, the combination of digital twin and BIM technologies presents a powerful tool for bridge management, offering enhanced insights, improved decision-making, and optimized asset performance. As technology continues to advance, it holds enormous potential for revolutionizing the way bridges are designed, built, monitored, and maintained, leading to safer and more efficient infrastructure systems.

4.8. References

1. Tao, F.; Zhang, H.; Liu, A.; Nee, A.Y.C. Digital Twin in Industry: State-of-the-Art. *IEEE Trans. Ind. Inform.* **2019**, *15*, 2405–2415.
2. Turner, C.J.; Oyekan, J.; Stergioulas, L.; Griffin, D. Utilizing Industry 4.0 on the Construction Site: Challenges and Opportunities. *IEEE Trans. Ind. Inform.* **2021**, *17*, 746–756.
3. Broo, D.G.; Bravo-Haro, M.; Schooling, J. Design and implementation of a smart infrastructure digital twin. *Autom. Constr.* **2022**, *136*, 104171.
4. Sanfilippo, F.; Thorstensen, R.T.; Jha, A.; Jiang, Z.; Robbersmyr, K.G. A Perspective Review on Digital Twins for Roads, Bridges, and Civil Infrastructures. In Proceedings of the 2022 International

Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME), Maldives, 16–18 November 2022; pp. 1–6.

5. Gao, Y.; Qian, S.; Li, Z.; Wang, P.; Wang, F.; He, Q. Digital Twin and Its Application in Transportation Infrastructure. In Proceedings of the 2021 IEEE 1st International Conference on Digital Twins and Parallel Intelligence (DTPI), Beijing, China, 15 July–15 August 2021; pp. 298–301.
6. Opoku, D.-G.J.; Perera, S.; Osei-Kyei, R.; Rashidi, M. Digital twin application in the construction industry: A literature review. *J. Build. Eng.* **2021**, *40*, 102726.
7. Salamone, S.; Bartoli, I.; Phillips, R.; Nucera, C.; di Scalea, F.L. Health Monitoring of Prestressing Tendons in Posttensioned Concrete Bridges. *Transp. Res. Rec. J. Transp. Res. Board* **2011**, *2220*, 21–27.
8. Yu, S.; Li, D.; Ou, J. Digital twin-based structure health hybrid monitoring and fatigue evaluation of orthotropic steel deck in cable-stayed bridge. *Struct. Control Health Monit.* **2022**, *29*, 2976.
9. Gao, Y.; Li, H.; Xiong, G.; Song, H. AIoT-informed digital twin communication for bridge maintenance. *Autom. Constr.* **2023**, *150*, 104385.
10. Jiang, F.; Ma, L.; Broyd, T.; Chen, K. Digital twin and its implementations in the civil engineering sector. *Autom. Constr.* **2021**, *130*, 103838.
11. Dan, D.; Ying, Y.; Ge, L. Digital Twin System of Bridges Group Based on Machine Vision Fusion Monitoring of Bridge Traffic Load. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 22190–22205.
12. Hidayat, F.; Supangkat, S.H.; Hanafi, K. Digital Twin of Road and Bridge Construction Monitoring and Maintenance. In Proceedings of the 2022 IEEE International Smart Cities Conference (ISC2), Pafos, Cyprus, 26–29 September 2022; pp. 1–7.
13. Sofia, H.; Anas, E.; Faiz, O. Mobile Mapping, Machine Learning and Digital Twin for Road Infrastructure Monitoring and Maintenance: Case Study of Mohammed VI Bridge in Morocco. In Proceedings of the 2020 IEEE International Conference of Moroccan Geomatics (Morgeo), Casablanca, Morocco, 11–13 May 2020; pp. 1–6.
14. Rios, A.J.; Plevris, V.; Nogal, M. Bridge management through digital twin-based anomaly detection systems: A systematic review. *Front. Built Environ.* **2023**, *9*, 1176621.
15. Zhao, H.; Tan, C.; O'Brien, E.J.; Zhang, B.; Uddin, N.; Guo, H. Developing Digital Twins to Characterize Bridge Behavior Using Measurements Taken under Random Traffic. *J. Bridg. Eng.* **2022**, *27*, 04021101.
16. Mahmoodian, M.; Shahriyar, F.; Setunge, S.; Mazaheri, S. Development of Digital Twin for Intelligent Maintenance of Civil Infrastructure. *Sustainability* **2022**, *14*, 8664.
17. Kaewunruen, S.; AbdelHadi, M.; Kongpuang, M.; Pansuk, W.; Remennikov, A.M. Digital Twins for Managing Railway Bridge Maintenance, Resilience, and Climate Change Adaptation. *Sensors* **2022**, *23*, 252.

18. Nicoletti, V.; Martini, R.; Carbonari, S.; Gara, F. Operational Modal Analysis as a Support for the Development of Digital Twin Models of Bridges. *Infrastructures* **2023**, *8*, 24.
19. Shim, C.-S.; Dang, N.-S.; Lon, S.; Jeon, C.-H. Development of a bridge maintenance system for prestressed concrete bridges using 3D digital twin model. *Struct. Infrastruct. Eng.* **2019**, *15*, 1319–1332.
20. Ye, C.; Kuok, S.-C.; Butler, L.J.; Middleton, C.R. Implementing bridge model updating for operation and maintenance purposes: Examination based on UK practitioners' views. *Struct. Infrastruct. Eng.* **2021**, *18*, 1638–1657.
21. Nishimura, Y.; Watanabe, G.; Arii, K.; Imada, Y. Real-Time Trend Estimation of Daily Fluctuation Based on Gns Displacement Observation on a Steel Truss Bridge. In Proceedings of the Transaction of the Ai-Data Science Symposium, Tokyo, Japan, 16–17 November 2022; Volume 3, pp. 621–630. (In Japanese).
22. Arii, K.; Watanabe, G.; Takechi, K.; Shimizu, N. *Automatic Continuous 3D Displacement Monitoring of Bridges Using Static Positioning System*; In Press; JSCE: Tokyo, Japan, 2023; Volume 79. (In Japanese)
23. Lin, Z.; Zhao, J. Revisit of AASHTO Effective Flange-Width Provisions for Box Girders. *J. Bridg. Eng.* **2011**, *16*, 881–889.
24. Lertsima, C.; Chaisomphob, T.; Yamaguchi, E. Stress concentration due to shear lag in simply supported box girders. *Eng. Struct.* **2004**, *26*, 1093–1101.

5. System-Level Traffic Management Using Digital Twin–BIM Technology: A Case Study in Dili, Timor-Leste

Overview

Rapid urbanization in Dili, the capital of Timor-Leste, has intensified traffic congestion and associated air quality degradation, highlighting the need for data-driven and evidence-based traffic management strategies. This study develops and implements a Digital Twin (DT)–based traffic management framework by integrating Building Information Modeling (BIM) with traffic simulation tools to create a dynamic virtual representation of the urban road network. The proposed framework enables the analysis of traffic demand, congestion patterns, and operational performance during morning, afternoon, and evening peak periods. To extend the Digital Twin beyond mobility assessment, a box model approach is employed to estimate near-ground concentrations of traffic-related air pollutants, including **CO**, **NO_x**, **PM_{2.5}**, and **SO₂**. The results reveal distinct vehicle-dependent emission characteristics, with motorcycles contributing predominantly to CO emissions, while diesel-powered heavy vehicles dominate NO_x and PM_{2.5} concentrations. Emission levels consistently peak during morning traffic hours, indicating that traffic volume is the primary driver of pollutant accumulation. The findings demonstrate that the proposed DT–BIM framework is an effective decision-support tool for integrated traffic and environmental management, particularly in rapidly urbanizing and data-scarce urban contexts.

5.1. Introduction

As urban populations grow, the confluence of transportation and environmental issues increasingly impacts economies and livelihoods. Urban growth has a significant impact on traffic dynamics, congestion, and air pollution. Global factors such as economic shifts, evolving transportation infrastructure, and the rise of ridesharing and delivery services further complicate these challenges[1,2].

Research on the economic impact of traffic congestion in U.S. metropolitan areas highlights its negative impact on job growth and productivity, underscoring the need to prioritize economically important trips or increase travel capacity [3]. In addition, the effectiveness of traffic management strategies (TMS) on urban air quality and pollution-related health outcomes has been studied and shows limited evidence to support emission reduction schemes such as urban road pricing and low-emission zones (LEZs)[4]. Therefore, the effective traffic management is emerging as a critical global policy concern, crucial to avert economic losses due to lost productivity and increased air pollution from increased emissions [5].

To address these challenges, innovative traffic management systems are needed, especially those that utilize digital twin technology. Digital twin can analyze and visualize queue lengths and traffic flows and assess how the installation or removal of various traffic signs affects the traffic system, thereby facilitating traffic flow optimization and environmental impact assessment. Digital twin can also be integrated with various image sensors to simulate traffic based on real-time data, predict the occurrence of traffic congestion,

and reduce congestion by controlling traffic signals. By enabling the assessment of traffic conditions, digital twin is expected to provide quantitative insights for evidence-based traffic management policies (EBTMP) [6,7,8,9].

The Dili city area, the capital of Timor-Leste, has suffered from uncontrolled urbanization, traffic congestion, and environmental problems that have hampered economic activities due to the lack of comprehensive measures to address urban issues, in addition to the lack of social infrastructure due to rapid population growth. JICA is supporting the preparation of a comprehensive urban development master plan to address these issues in the Dili metropolitan area and is working to contribute to the formation and growth of a sustainable city with industrial vitality [10].

This study aims to provide an alternative solution to the challenges of traffic management in the city of Dili through the application of digital twin technology. By using actual traffic volume data to assess traffic dynamics, bottlenecks, and emissions, the digital twin BIM technology accurately simulates peak hours, congestion, delays, and pollutants such as CO₂, NO_x, and PM₁₀. As a result, digital twin - BIM technology can provide a reliable solution to the traffic challenges in Dili City, Timor-Leste.

5.2. Digital Twin–BIM Strategies for System-Level Traffic Management

5.2.1. Digital twin for traffic management

Digital twins are increasingly being used in traffic management to replicate the physical traffic network into a digital model. The digital twin combines real-time traffic data for simulation in order to provide a holistic understanding of traffic dynamics, enabling better decision-making. The vast potential of information technology in the field of road transportation allows for the real-time integration of digital and physical road systems for traffic modeling and analysis [11, 12, 13]. This kind of integration is commonly known as the digital twin concept, which considers the merging of the virtual (digital) and the real world [14]. As such, DT applications provide viable solutions to the issue of the increasing complexity of transportation systems and the idea of tracking them throughout their lifecycle.

In the early stages of design, construction, reconstruction, traffic planning or control, and numerous other analysis purposes, real-time bi-directional interaction between the physical system and corresponding digital replicas is made possible by a continuously synchronized digital twin model with its physical counterpart. As a result, digital twin has demonstrated great promise in a number of domains and is attracting considerable attention from industry and academia[15]. For example, some researchers are exploring the use of digital twins in transportation, with a particular focus on the real-time synergy of simulation and traffic data streams to visualize motorway dynamics[16]. Where they used the Geneva Highway Digital Twin Model (DT-GM) to integrate real-time data into microscopic roadway simulations, introducing a new paradigm. The DT-GM integrates highly refined real-world traffic data through constant synchronization and calibration with the SUMO simulator, allowing simulation-based control optimization to occur while the system is in operation. Therefore, digital twins are increasingly used in traffic management to build virtual replicas of real traffic networks [17, 18]. With the help of these digital twins, which integrate simulation and real-time traffic data, traffic dynamics can be fully understood, allowing for improved control and decision-making. By modeling and predicting traffic conditions, they can be used to optimize cities by facilitating adjustments to traffic signals, route planning, and resource allocation. Therefore, in this study, a

digital twin is used to simulate traffic management in the city of Dili, particularly in the Cathedral Zone, to provide evidence-based traffic management for decision-making.

5.2.2. BIM for traffic management

Building Information Modeling (BIM) is increasingly being used in traffic management and transportation infrastructure, providing benefits to the various stakeholders involved in the decision-making process. In civil engineering, BIM serves as a digital management system that facilitates collaborative working techniques to create, maintain, and use data and information about transportation assets throughout their lifecycle [19, 20]. The benefits that BIM brings to the following stakeholders include:

- **Urban Planners:** BIM assists urban planners in analyzing transportation systems and improving road design. By integrating urban traffic data, land use data, and traffic management information, BIM promotes a more efficient decision-making process related to transportation infrastructure development and urban planning.
- **Transportation Engineers:** BIM enables transportation engineers to create engineering-level models of transportation infrastructure to facilitate transportation system analysis, simulation, and design optimization. By providing a digital representation of the transportation network, BIM helps transportation engineers identify bottlenecks, optimize traffic flow, and evaluate the effectiveness of traffic management strategies.
- **Policy Makers:** BIM contributes to evidence-based decision-making for policymakers involved in traffic management and urban development. By integrating real-time traffic data and simulation technology, BIM enables policymakers to assess the impact of proposed traffic management policies and infrastructure projects before they are implemented. This enables informed decision-making and the development of effective strategies to address traffic congestion and environmental issues.
- **City Administrator:** BIM assists city administrators in managing transportation assets and optimizing urban mobility. By providing a digital twin of the urban transportation network, BIM facilitates real-time monitoring, analysis, and optimization of traffic flows. Municipalities can use BIM to make data-driven decisions to increase transportation efficiency, improve road safety, and reduce environmental impact.

As a result, BIM helps improve the decision-making process for city planners, transportation engineers, policy makers, and city administrators involved in traffic management and urban development initiatives.

5.3. Rapid urbanization and traffic management issues in Dili, Timor-Leste

This study focuses on the traffic problems in the city of Dili, the capital of Timor Leste, specifically in the Cathedral Zone, as shown in **Figure. 5.1**. In this area, chronic traffic delays and congestion occur throughout the day, especially during peak hours. This reduces urban mobility and increases economic losses and air pollution. To address these challenges, it is imperative to implement Digital Twin – BIM technology to help optimize traffic management.

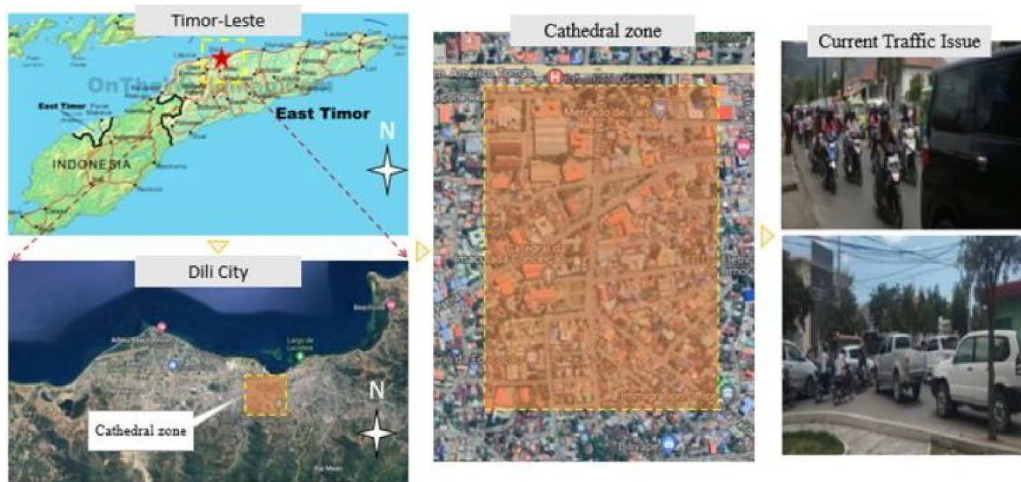


Figure 5. 1 Study Area

Dili, the capital of Timor-Leste, is the country's economic, administrative, and educational center. Since its independence from Indonesia in 2002, the city has played a prominent role in the country's affairs and has experienced rapid and sustained population growth. According to "Timor-Leste's 2022 Population and Housing Census", Dili's population reached 324,269 out of a total national population of 1,340,434, or 24.2% of the total population. Despite its relatively small area of 14,954 square kilometers, Dili has a population density of about 90 people per square kilometer [21].

The concentration of the population in urban areas, particularly in Dili, has increased significantly in recent years. This trend is clearly visible in **Figure 5.2**, a satellite image of Dili, which highlights the limited land in the city as a center of urbanization. Dili's population density is extremely high at 1,177 people per square kilometer, a figure well above the national average for Timor-Leste.

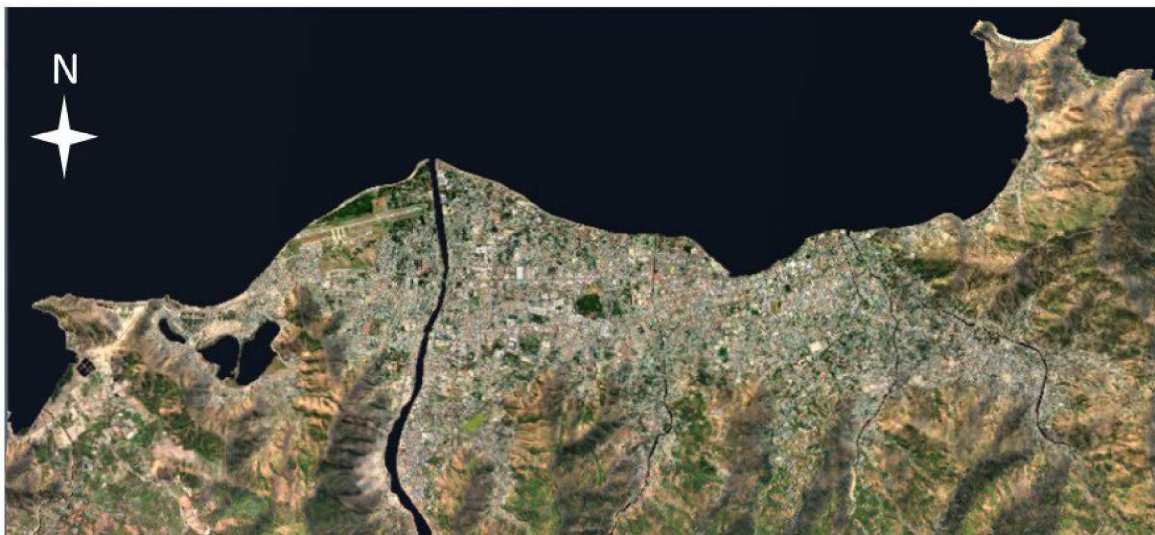


Figure 5. 2 Satellite Image of Dili City

As previously stated, traffic congestion not only decreases transportation mobility but also logistics productivity, economic losses, and even increases air pollution. Therefore, it is expected that the introduction of digital twin technology enables optimizing traffic management resulting in the economic growth and the decrease in air pollution.

5.4. Development of a Digital Twin-BIM workflow for traffic Management

The development of a Digital Twin - Building Information Modeling (DT-BIM) workflow for traffic management is an important aspect of this research. Digital twin technology involves the creation of a virtual replica of a physical system or process, enabling simulation, analysis, and optimization. Building Information Modeling (BIM), on the other hand, is a digital representation of the physical and functional characteristics of a building or infrastructure element. The integration of digital twin and BIM technologies provides a comprehensive approach to traffic management, enabling detailed simulation, analysis, and decision-making. The workflow shown in **Figure 5.3** outlines the steps involved in developing a DT-BIM workflow for traffic management:

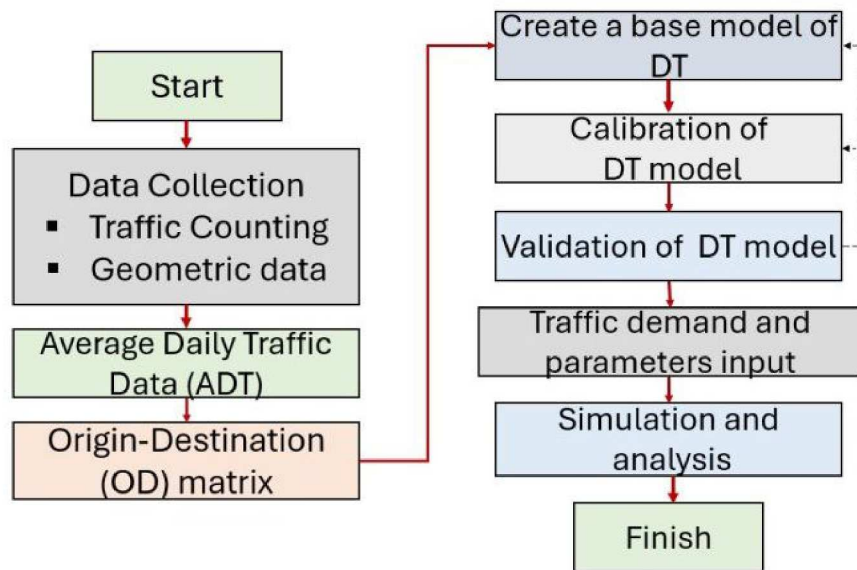


Figure 5.3 DT-BIM workflow for traffic management

- Data collection (traffic counting and geometric data)
- Evaluate Average Daily Traffic (ADT)
- Evaluate the Origin-Destination matrix (OD)
- Create a base model for Digital Twin.
- Verification of the DT model

- Calibration of the DT model
- Validation of the DT model
- Traffic demand and parameters input
- Simulation of and analysis

(1) Data collection

A comprehensive traffic data collection has been initiated by a team of students from the Department of Civil Engineering of the National University of Timor-Leste. The study period was set for one week, from September 3 to 9, 2020, to study representative traffic volumes in the city of Dili. Comprehensive data collection was conducted by a team of students from the Department of Civil Engineering of the National University of Timor-Leste. Focusing on the Cathedral Zone, the downtown area of Dili, the team diligently collected important information, including traffic and geometric data. The goal of this effort was to obtain traffic data that could be used to evaluate the traffic management system in Dili, particularly in the Cathedral Zone.

➤ Traffic data

Traffic data was collected by conducting traffic counts, focusing on the Cathedral Zone. The counting period covered seven days, starting at 7 a.m. and ending at 6 p.m., as depicted in **Figure 5.4**. The reason why traffic counts were only conducted during the day was because traffic is usually very low at night.

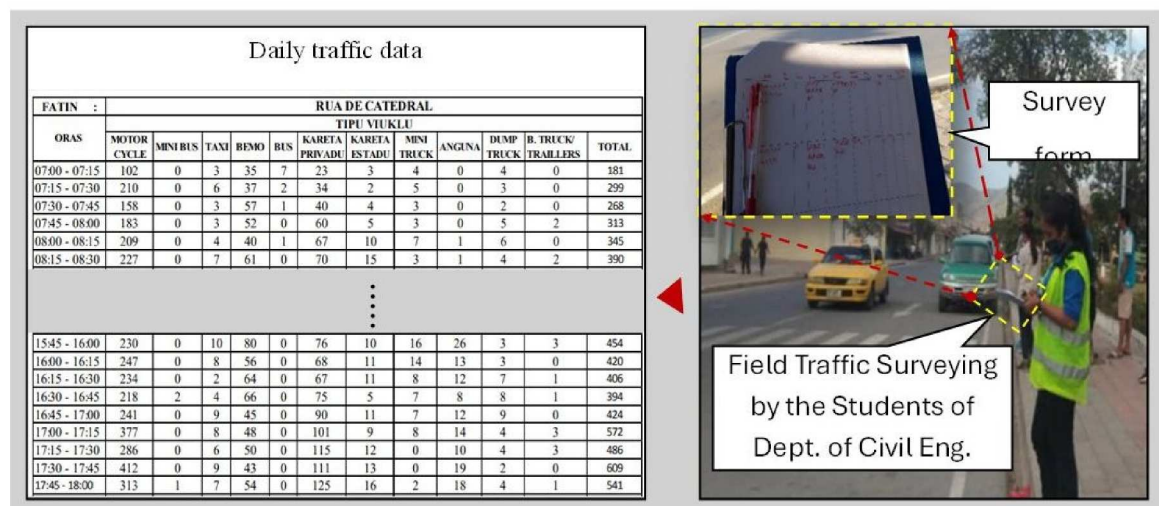


Figure 5. 4 Daily Traffic Counting

Traffic data sets were collected at 15-minute intervals for various types of vehicles commonly used in Dili, including motorcycles, minibuses, taxis, small mini-buses, buses, private cars, government cars, mini-trucks, anguna, dump trucks, and trailers. A comprehensive dataset was obtained from ten different road segments, namely Av. Villa Verde, Rua de Caju Laran, Rua de Tuana Laran, Av. 20 de Maio, Rua de

Cathedral 1, Av. D. Ricardo da Silva 1, Av. D. Ricardo da Silva 2, Beco Hermanina, Av. de Colmera, and Rua de Cathedral 2, as shown in **Figure 5.5**. Subsequently, this dataset was used to calculate the Average Daily Traffic (ADT) and determine the peak hour for each road segment.

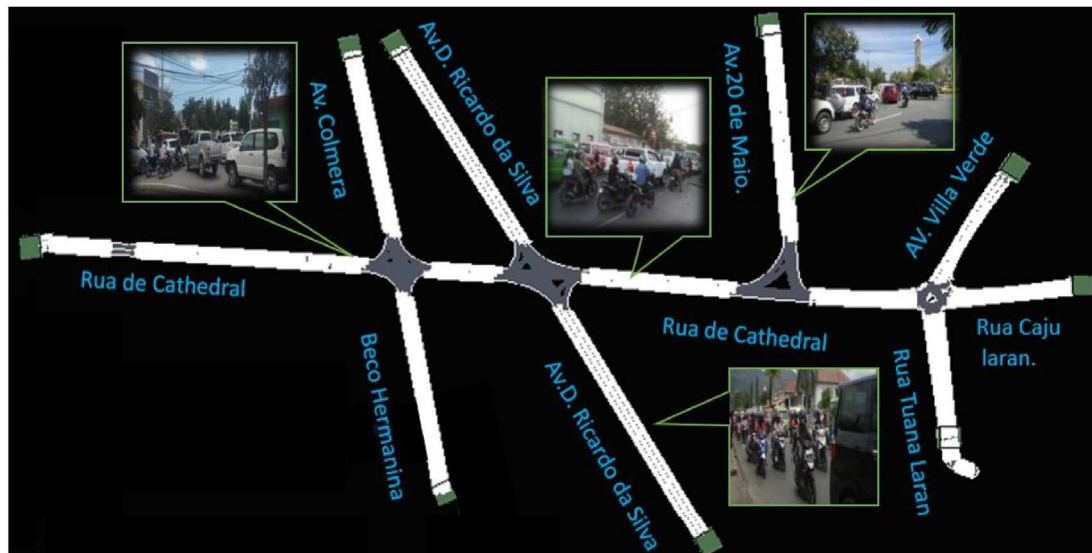


Figure 5. 5 Target Zone

➤ Geometric data

Furthermore, geometric data for road segments in the Cathedral zone was collected to fully comprehend the issue of traffic flow in that zone, as illustrated in **Table 5.1**. This includes the following information presented in columns: (1) the number of road segments, (2) road segment names, (3) road types, and (4) road widths. This information is essential as the foundation for creating a base model of the Digital Twin.

Table 5. 1 Geometric Data

Geometric data			
No	Road section	Roda type	Road Width(m)
1	Avenida Villa-Verde	2 lanes 1 direction (2/1)	9.3
2	Rua de Caju laran	2 lanes 2 directions (2/2)	7.8
3	Rua de Tuana laran	2 lanes 2 directions (2/2)	10.7
4	Avenida 20 de maio	2 lanes 1 direction (2/1)	9.15
5	Rua de Cathedral	2 lanes 1 direction (2/1)	8.2
6	Avenida D.Ricardo da Silva	2 lanes 2 directions (2/2)	8.6
7	Avenida D.Ricardo da Silva	2 lanes 1 direction (2/1)	9.2
8	Beco de Hemanina(Bebora)	2 lanes 2 directions (2/2)	6.1
9	Rua de Colmera	2 lanes 1 direction (2/1)	9.5
10	Rua de Cathedral (Rotunda mandarin)	2 lanes 1 direction (2/1)	8.8

(2) Average daily traffic (ADT)

Once traffic data has been collected, the next task is to calculate Average Daily Traffic (ADT), a crucial step in determining peak traffic periods. ADT, also known as average daily traffic, is the average number of vehicles that pass through a given roadway location over a brief period, usually seven days or less. It is obtained by dividing the total daily volume for a given period by the number of days in that period, as shown in **Equation 5.1**.

$$ADT = \frac{1}{n} \sum_{i=1}^n VOL_i \quad (5.1)$$

VOL_i : daily volume in the i^{th} day, n : the number of whole days over the observation period.

In this study, **Table 5.2** presents the Average Daily Traffic (ADT) data, with the following information arranged in columns: (1) number of vehicle types operating in the downtown Dili, (2) vehicle types and names, (3) vehicle categories, and (4) average daily traffic for different vehicle types on the 10 road segments within the designated target zones. These ADT data will be used for traffic simulation and traffic management analysis.

Table 5. 2 Average Daily Traffic (ADT)

Average daily traffic (ADT) for target zone			
No	Vehicle type	Category	ADT
1	Motorcycle	Motocycles (MC)	27081
2	Taxi	Light Vehicles (LV)	874
3	Mikrolet		2909
4	Private car		6025
5	Government car		1776
6	Anguna		787
7	Mini Truck		477
8	Mini Bus		139
9	Bus	Heavy/Big Vehicles (HV)	95
10	Dump truck		199
11	Big Truck/Traillers		79
	Total		40441

(3) Peak hour volume (PHV)

PHV represents the maximum number of vehicles passing a point in both directions in one hour. The equation for PHV is shown in **Equation 5.2**.

$$PHV = \frac{MHV}{DS} \quad (5.2)$$

Where:

- *PHV* is the Peak Hour Volume
- *MHV* is the Maximum Hourly Volume. It is the highest number of vehicles passing the point in both directions during anyone-hour period.
- *DS* is a Directional Split. It is the number of traffic moving in a specific direction during the peak hour.

Figure 5.6 illustrates the peak hour volume in the Cathedral Zone of the city of Dili, which serves as the target area for our research. In addition, we have highlighted three peak hours: morning peak hour (08:00~09:00), afternoon peak hour (12:00~13:00), and evening peak hour (17:00~18:00), which can be used in DT-BIM for simulation and analysis. **Table 5.3** shows the selected detailed peak hour data from **Figure 5.6**, which includes the following columns: (1) traffic sources from ten road segments in the research target zone, (2) traffic volume from each road segment for the morning peak hour, (3) traffic volume for the afternoon peak hour, and (4) traffic volume for the evening peak hour.

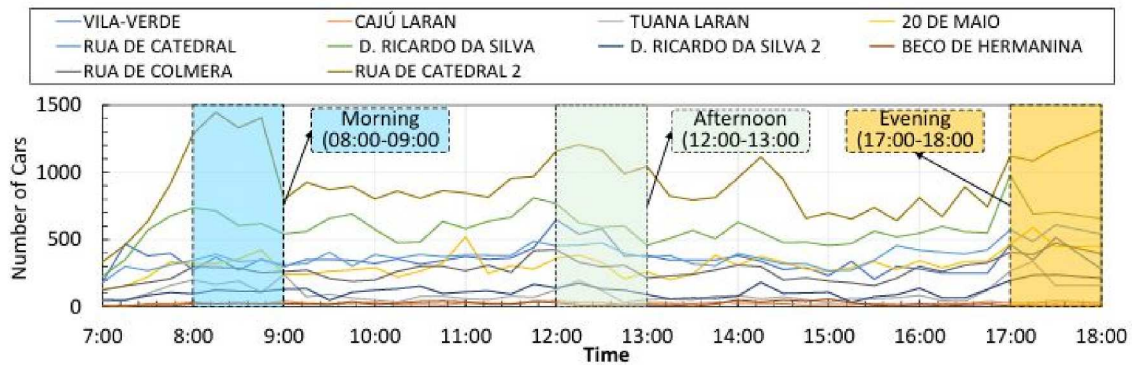


Figure 5. 6 Peak Hour

Table 5. 3 Selected peak Hour

Traffic Source	Peak Hours		
	08:00 - 09:00	12:00 -13:00	17:00 -18:00
Av. Villa Verde	1268	2144	1606
Rua de Caju Laran	104	119	130
Rua de Tuana Laran	664	472	918
Av. 20 de Maio	1414	1278	1954
Rua de Cathedral 1	1416	1783	2208
Av. D. Ricardo da Silva 2	2671	2582	3028
Av. D. Ricardo da Silva 1	448	570	881
Beco de Hermanina	101	68	49
Rua de Colmera	1128	1359	1663
Rua Cathedral 2	5472	4518	4705

(4) Origin - Destination (OD) matrix.

An Origin-Destination (OD) matrix is a key method in transportation planning and management. It shows the flow of trips within a transportation network between different origin-destination pairs.

The matrix represents the movement of vehicles from an origin to a destination in each zone.

The OD matrix is commonly used to study travel patterns, identify congestion hotspots, plan transportation infrastructure improvements, and optimize traffic management systems.

The general form of an OD matrix is a square matrix with rows representing origins, columns representing destinations, and cells representing the number of trips. The following mathematical formulas can be used to calculate an Origin-Destination (OD) matrix, as shown in **Equation 3**.

$$P_T = \begin{bmatrix} T_{11} & T_{12} & \dots & T_{1n} \\ T_{21} & T_{22} & \dots & T_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ T_{n1} & T_{n2} & \dots & T_{nn} \end{bmatrix} \quad (5.3)$$

Where:

- T_{ij} : represents the number of trips from origin i to destination j
- i : ranges from 1 to n for origins
- j : ranges from 1 to n for destinations

In this study, three Origin-Destination (OD) matrices are presented in **Tables 5.4, 5.5, and 5.6**, corresponding to different peak hours that can later be input into the DT-BIM model. **Table 5.4** outlines the OD matrix for the morning peak hour, which spans from 08:00 to 09:00. **Table 5.5** provides insight into the afternoon peak hour, covering the period from 12:00 to 13:00. Finally, **Table 5.6** shows the OD matrix for the evening peak hour, extending from 17:00 to 18:00. In addition, the data collected to determine the number of trips from origin-destination was difficult to obtain in the field. Therefore, the percentage of traffic for each roadway segment was used to determine the OD matrix as shown in **Tables 5.4, 5.5, and 5.6**. In addition, as shown in the OD tables, some rows contain zeros. This indicates that, due to the characteristics of the roadway, vehicles did not reach those destinations. For example, the section of Av. Villa Verde is a one-way road, while Av. D. Ricardo da Silva 2 has two lanes and two directions (2/2). Thus, these matrices serve as the basis for simulations and analyses aimed at evaluating traffic issues and environmental impacts. They have played a crucial role in the development of an Evidence-Based Traffic Management Policy (EBTMP).

Table 5. 4 Origin-Destination (OD) matrix for Morning Peak Hour

	Morning Peak Hour (08:00 - 09:00)											Total	%
	Origin- Destination (OD) matrix												
	Destinations												
	Av. Villa Verde	Rua de Caju Laran	Rua de Tuana Laran	Av. 20 de Maio	Rua de Catedral 1	Av. D. Ricardo da Silva 2	Av. D.Ricardo da Silva 1	Beco de Hermanina	Rua de Colmera	Rua Catedral 2			
Origin	Av. Villa Verde	70	119	0	183	292	0	70	0	534	1268	8.6%	
	Rua de Caju Laran	0	11	0	16	25	0	7	0	45	104	0.7%	
	Rua de Tuana Laran	0	49	0	108	165	0	49	0	292	664	4.5%	
	Av. 20 de Maio	0	78	132	205	325	0	78	0	595	1414	9.6%	
	Rua de Catedral 1	0	0	0	0	467	0	123	0	828	1416	9.6%	
	Av. D. Ricardo da Silva 2	0	0	0	0	0	0	92	0	2583	2671	18.2%	
	Av. D.Ricardo da Silva 1	0	0	0	0	0	448	0	0	0	448	3.1%	
	Beco de Hermanina	0	0	0	0	0	0	0	0	101	101	0.7%	
	Rua de Colmera	0	0	0	0	0	0	0	61	1067	1128	7.7%	
	Rua Catedral 2	0	0	0	0	0	0	0	0	5472	5472	37.3%	

Table 5. 5 Origin-Destination (OD) matrix for Afternoon Peak Hour

Afternoon Peak Hour (12:00 - 13:00)													
Origin- Destination (OD) matrix											Total	%	
	Destination												
	Av. Villa Verde	Rua de Caju Laran	Rua de Tuana Laran	Av. 20 de Maio	Rua de Catedral 1	Av. D. Ricardo da Silva 2	Av. D. Ricardo da Silva 1	Beco de Hermanina	Rua de Colmera	Rua Catedral 2			
origin	Av. Villa Verde		146	196	0	385	500	0	138	0	779	2144	14.4%
	Rua de Caju Laran	0		13	0	23	91	0	9	0	45	119	0.8%
	Rua de Tuana Laran	0	41		0	93	119	0	39	0	180	472	3.2%
	Av. 20 de Maio	0	87	117		230	298	0	82	0	464	1278	8.6%
	Rua de Catedral 1	0	0	0	0		617	0	102	0	1063	1783	12.0%
	Av. D. Ricardo da Silva 2	0	0	0	0	0		78	0	2504	2582	17.3%	
	Av. D. Ricardo da Silva 1	0	0	0	0	0	570		0	0	570	3.8%	
	Beco de Hermanina	0	0	0	0	0	0	0		0	68	68	0.5%
	Rua de Colmera	0	0	0	0	0	0	0	95		1321	1359	9.1%
	Rua Catedral 2	0	0	0	0	0	0	0	0	0		4518	30.3%

Table 5. 6 Origin-Destination (OD) matrix for Evening Peak Hour

	Evening Peak Hour (17:00 - 18:00)												
		Destination									Total	%	
		Av. Villa Verde	Rua de Caju Laran	Rua de Tuana Laran	Av. 20 de Maio	Rua de Catedral 1	Av. D. Ricardo da Silva 2	Av. D. Ricardo da Silva 1	Beco de Hermanina	Rua de Colmera			Rua Catedral 2
origin	Av. Villa Verde		107	181	0	602	379	0	100	0	536	1606	9.4%
	Rua de Caju Laran	0		16	0	26	32	0	10	0	45	130	0.8%
	Rua de Tuana Laran	0	82		0	193	237	0	78	0	327	918	5.4%
	Av. 20 de Maio	0	131	221		668	461	0	121	0	652	1954	11.4%
	Rua de Catedral 1	0	0	0	0		782	0	200	0	1227	2208	12.9%
	Av. D. Ricardo da Silva 2	0	0	0	0	0		0	103	0	2925	3028	17.7%
	Av. D. Ricardo da Silva 1	0	0	0	0	0	281		0	0	0	881	5.1%
	Beco de Hermanina	0	0	0	0	0	0	0		0	49	49	0.3%
	Rua de Colmera	0	0	0	0	0	0	0	53		1610	1663	9.7%
	Rua Catedral 2	0	0	0	0	0	0	0	0	0		4705	27.4%

(5) Create a base model DT

The digital twin model plays an important role in traffic simulation, particularly within the Cathedral Zone in the city of Dili, Timor-Leste. By carefully replicating the actual conditions of the road and its components, using advanced Building Information Modeling tools, this process ensures accurate simulations. The application goes beyond modeling by providing a comprehensive view of traffic congestion and environmental implications within the Cathedral Zone. The result of the digital twin model is depicted in **Figure 5.7**. In addition, the DT model not only provides good simulation results but also makes a significant contribution to Evidence-Based Traffic Management Policy (EBTMP). The integration of traffic management

principles into the digital twin framework does not stop at simulation but actively contributes to the improvement of traffic management practices. The insights gained from this approach provide a foundation for informed decision-making, promoting sustainable and efficient urban mobility solutions that are tailored to the dynamic complexity of the target research zone and its surroundings.



Figure 5. 7 DT model Creation

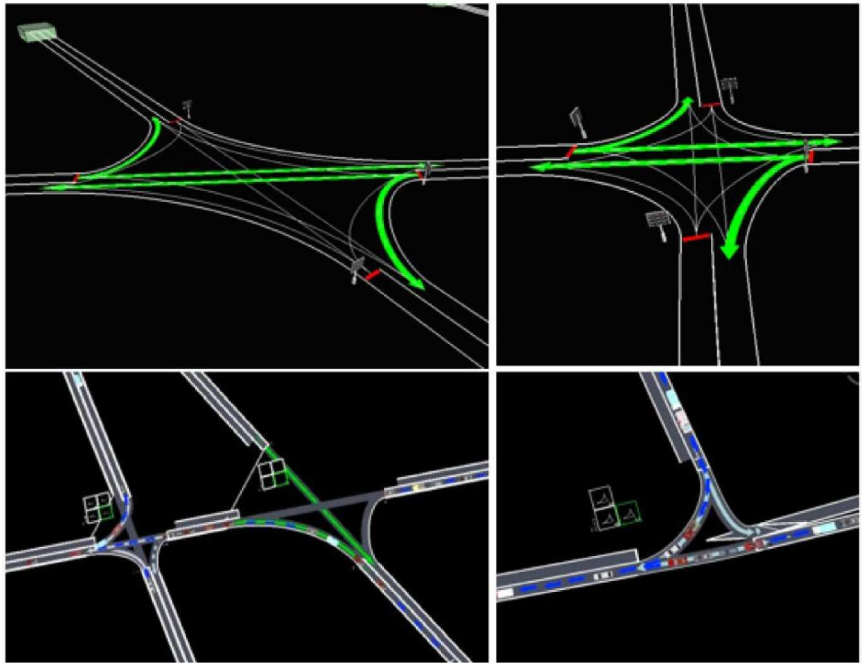


Figure 5. 8 Calibration and verification of the DT model

(6) Calibration and Verification of the DT model

Once the DT model is created in the BIM tools, it is important to calibrate and validate the model itself to be similar to the real condition for each road section in the Cathedral Zone, as shown in **Figure 5.8**. This zone contained 10 road sections with each type as elaborated below:

- Av. Villa Verde: 2 lanes, 1 direction
- Rua Caju Laran: 2 lanes, 2 directions
- Rua de Tuana Laran: 2 lanes, 2 directions
- Avenida 20 de maio: 2 lanes, 2 directions
- Rua de Cathedral: 2 lanes, 1 direction
- Avenida D.Ricardo da Silva 2: 2 lanes, 2 directions
- Avenida D. Ricardo da Silva 1: 2 lanes, 1 direction
- Beco de Hermanina: 2 lanes, 2 directions
- Rua de Colmera: 2 lanes, 1 direction
- Rua de Cathedral 2 (Rotunda Mandarin): 2 lanes, 1 direction.

Thus, by calibrating and verifying the DT model according to real-world conditions, later simulation and analysis results can be achieved accurately.

(7) Traffic demand and parameters input

Traffic demand refers to the number of vehicles seeking to travel, expressed as several vehicle trips in the traffic simulation tool [22]. Therefore, inputting actual traffic in the form of OD matrix data into the BIM tool becomes an essential step in the traffic simulation process. Subsequently, it is crucial to input and configure parameters, including intersections, traffic lights, and signalization, as shown in **Figures 5.9, 5.10, and 5.11**, respectively. The primary goal of this data entry and parameter setting is to create a realistic traffic simulation model. This model facilitates optimal traffic outcomes and allows for easy identification of congestion points and environmental impacts in the surrounding area. Accurate simulations are essential for producing meaningful results that are essential for developing an Evidence-Based Traffic Management Policy (EBTMP) that effectively informs the decision-making process. This comprehensive approach ensures a solid foundation for urban planning, promoting sustainable solutions and informed policies to improve traffic management.

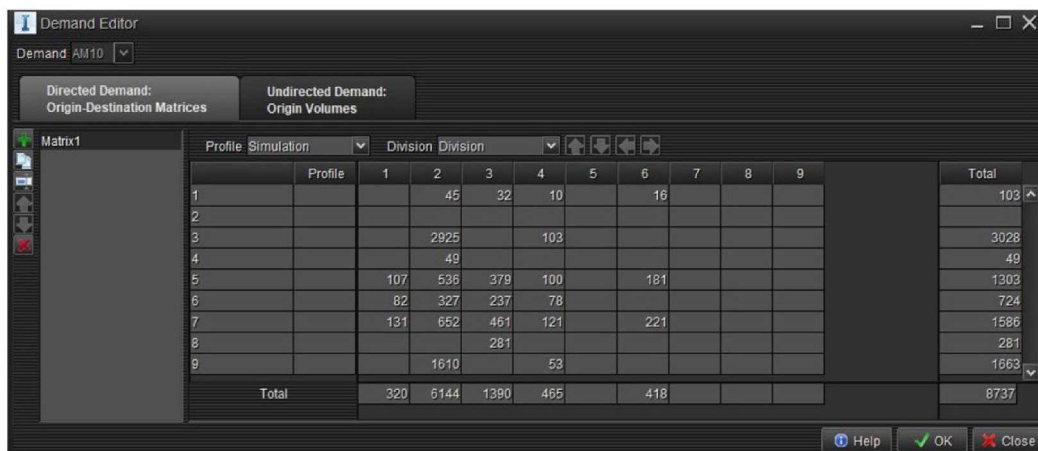


Figure 5. 9 Traffic Demand Editor for OD matrix input

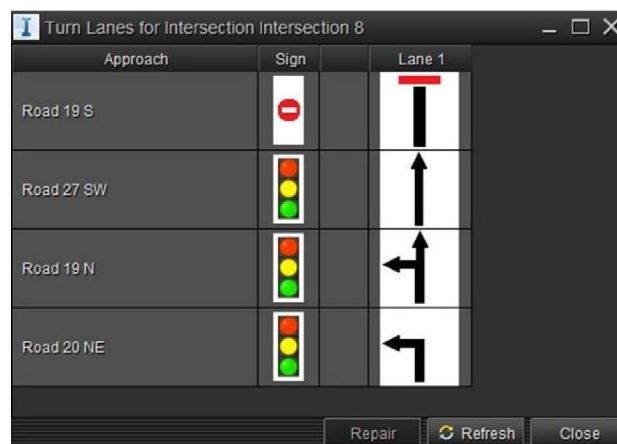


Figure 5. 10 Signalization and Intersections

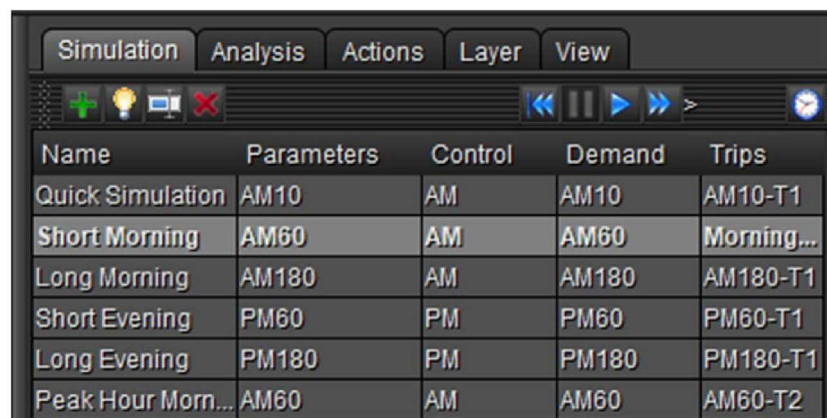


Figure 5. 11 Simulation Settings panel

5.5. Traffic Simulation and Analysis

(1) Simulation theory

Car following models are theoretical frameworks used to describe and predict the behavior of individual vehicles as they travel in traffic and follow other vehicles on the road[18, 23]. These models are essential in traffic engineering and transportation planning to understand how traffic flows arise and develop strategies to improve traffic efficiency and safety. The basic idea behind car following models is to represent the driver's behavior in relation to the vehicle in front of him. These models usually consider factors such as vehicle speed, distance to the previous vehicle, acceleration, deceleration, driver reaction time, and other relevant variables.

Thus, traffic simulation in BIM tools is used in microscopic traffic models, which simulate individual vehicles and their interactions in the traffic flow. The BIM tools for traffic simulation contain three car-following models: Gipps, Wiedemann, and Fritzsche's models. Both the Wiedemann and Fritzsche's models are psycho-physical models where the driver is assumed to change his behavior at certain thresholds, as shown in **Figure 5.12**.

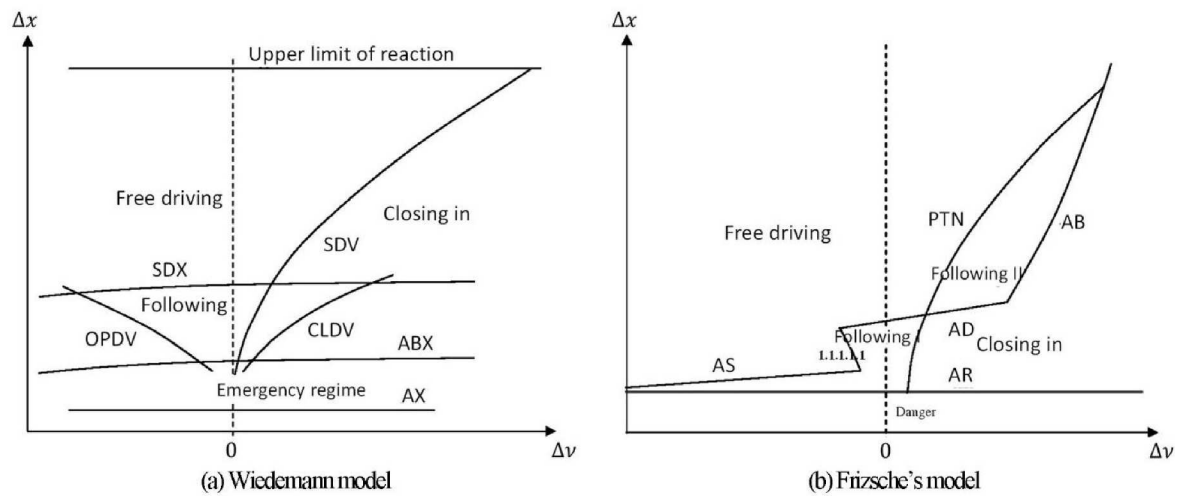


Figure 5.12 A psycho-physical model assumes a driver changes behavior at certain thresholds[23].

The Wiedemann car-following model was first introduced in 1974 and has been continuously refined ever since [18, 23-26]. This model consists of five different driving states as follows:

- Free Driving: The driver maintains the desired speed.
- Following: The driver follows the lead vehicle, unconsciously accelerating and decelerating.
- Approaching: The driver's speed adapts to the lower speed of the lead vehicle. Deceleration continues until the speed difference is zero, i.e., the driver has reached his desired safety distance.
- Breaking: If the desired safety distance is significantly reduced, for example, if the lead vehicle abruptly changes speed, the driver decelerates noticeably.

- Emergency: High deceleration is applied to avoid a collision with the vehicle in front.

Subsequently, the car following model of the car developed by Fritzche in 1994 also consists of five different driving states as follows:

- Danger: The driver uses maximum deceleration to increase the distance to the leading vehicle because the distance between the vehicles is perceived to be too small.
- Closing in: The driver decelerates to match the speed of the lead vehicle when the headway equals the safe gap distance.
- Following 1: The driver takes no conscious action.
- Following 2: The driver notices that he is closing on the lead vehicle but takes no action due to the large gap.
- Free driving: The follower accelerates to achieve the desired speed. The driver's inability to maintain a constant speed is modeled with a parameter.

These models track the movement and behavior of each vehicle separately, considering factors such as acceleration, deceleration, lane changes, and interactions with other vehicles. The Gipps model is one of the microscopic models commonly used in traffic simulation. The Gipps model, developed by Michael Gipps, describes the acceleration behavior of each vehicle as a function of the desired speed, the speed of the surrounding vehicles, and the distance to the vehicle ahead. The model aims to capture driver's behavior in a more realistic way by considering factors such as driver anticipation and reaction time. In contrast, the Wiedemann and Fritzsche models are more often associated with mesoscopic or macroscopic approaches to traffic modeling. Mesoscopic models consider traffic flow at an intermediate level, focusing on groups of vehicles or road sections, while macroscopic models analyze traffic flow at a broader level, often using aggregate variables such as traffic density and traffic speed.

So, in this study, the microscopic traffic simulation model based on the Gipps is adopted.

(2) Results of simulation and analysis

After conducting simulations and analyses for the Cathedral Zone using peak-hour data, including the morning peak (08:00-09:00), afternoon peak (12:00-13:00), and evening peak (17:00-18:00), the traffic simulation was performed using a digital twin model based on Building Information Modeling tools, as depicted in **Figure 5.13**. Further details of the morning peak results are illustrated in **Figure 5.14**, and the assessment status is presented in **Table 7**. The traffic assessment showed that of the ten road segments within the target zone during the morning peak, eight segments were congested while only two were uncongested.

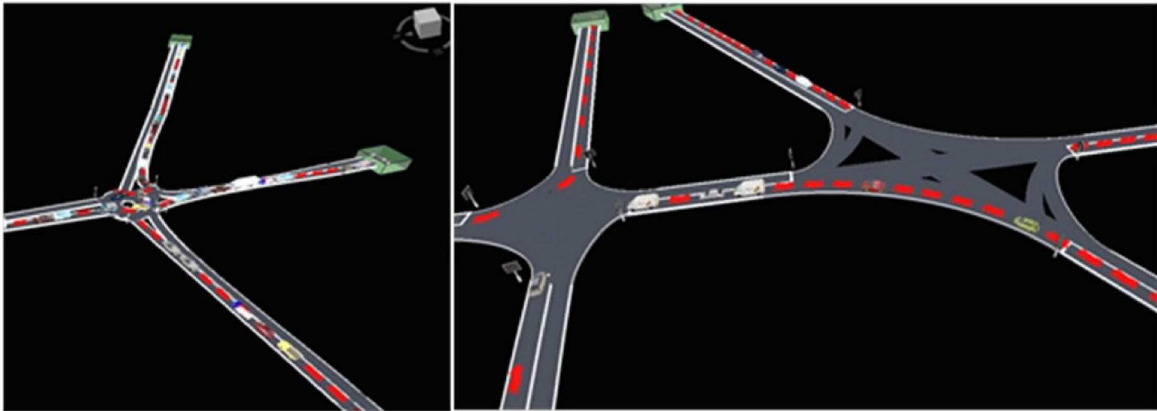


Figure 5. 13 Traffic Simulation



Figure 5. 14 Simulation results of the morning peak hour.

Table 5. 7 Assessment result of the morning peak hour simulation

Morning Peak Hour 08:00 - 09:00					
Traffic Source	Average delay (Second)	Delay Treshold(second)	Queue(m)	Observation	Status
Av. Villa Verde	140	55	163.5	Yes	Congested
Rua de Caju Laran	11	55	84.8	No	Not Congested
Rua de Tuana Laran	95	55	93.3	Yes	Congested
Av. 20 de Maio	189	55	164	Yes	Congested
Rua de Cathedral 1	80	55	84.2	Yes	Congested
Av. D. Ricardo da Silva 2	289	55	186.7	Yes	Congested
Av. D. Ricardo da Silva 1	86	55	109.4	Yes	Congested
Beco de Hermanina	78	55	80	Yes	Congested
Rua de Colmera	114	55	98.4	Yes	Congested
Rua Cathedral 2	24	55	189	NO	Not Congested

In addition, the afternoon peak hour simulation, as depicted in **Figure 5.15** and detailed in **Table 8**, indicated that nine road segments were congested, with one segment remaining uncongested. Finally, the evening peak hour simulation in **Figure 5.16** and **Table 9** showed that seven road segments were congested, while three were uncongested. Thus, the simulation and analysis results clearly indicate a serious traffic problem in the study area. This information is crucial for decision makers as evidence to support the development of a future Evidence-Based Traffic Management Policy (EBTMP) in Dili City, Timor-Leste.

**Figure 5. 15** Simulation result of the afternoon peak hour.

Table 5. 8 Assessment result of the afternoon peak hour simulation

Afternoon Peak Hour 12:00 - 13:00

Traffic Source	Average delay (Second)	Delay Treshold(second)	Queue(m)	Observation	Status
Av. Villa Verde	286	55	163.3	Yes	Congested
Rua de Caju Laran	119	55	88.5	Yes	Congested
Rua de Tuana Laran	149	55	97.7	Yes	Congested
Av. 20 de Maio	178	55	173.1	Yes	Congested
Rua de Cathedral 1	89	55	84.7	Yes	Congested
Av. D. Ricardo da Silva 2	285	55	191.2	Yes	Congested
Av. D.Ricardo da Silva 1	92	55	111.2	Yes	Congested
Beco de Hermanina	76	55	82	Yes	Congested
Rua de Colmera	298	55	98.3	Yes	Congested
Rua Cathedral 2	45	55	190	No	Not Congested



Figure 5. 16 Simulation result for evening peak hour

Table 5. 9 Assessment result of evening peak hour.

Evening Peak Hour 17:00 - 18:00					
Traffic Source	Average delay (Second)	Delay Threshold(second)	Queue(m)	Observation	Status
Av. Villa Verde	120	55	160	Yes	Congested
Rua de Caju Laran	33	55	92.1	No	Not Congested
Rua de Tuana Laran	14	55	92.6	No	Not Congested
Av. 20 de Maio	202	55	184.9	Yes	Congested
Rua de Cathedral 1	79	55	84.5	Yes	Congested
Av. D. Ricardo da Silva 2	288	55	193.3	Yes	Congested
Av. D.Ricardo da Silva 1	95	55	110	Yes	Congested
Beco de Hermanina	71	55	85	Yes	Congested
Rua de Colmera	139	55	99.2	Yes	Congested
Rua Cathedral 2	23	55	195	No	Not Congested

(3) Estimation of Traffic-Related Air Pollutant Concentrations Using a Box Model

To estimate concentrations of air pollutants near the ground surface generated by road traffic, this study adopted the **Box Model Method**. The box model is a simplified atmospheric assessment technique that represents the computational domain as a three-dimensional control volume and assumes uniform pollutant concentrations within that volume. This method is widely used for local to regional air quality assessments, particularly for estimating average or worst-case concentrations in traffic-affected areas, when the primary focus is not on understanding detailed atmospheric transport processes such as advection and turbulence (Seinfeld and Pandis, 2016) [27].

▪ Definition of the Box Model

In this study, the **horizontal extent of the box** corresponds to the traffic analysis zone defined within the digital twin–BIM framework. Based on geographic analysis, the planning area for the target zone is **382,910.06 m²**, encompassing the major road segments and intersections included in the traffic simulation as demonstrated in **Figure 5.17**. All vehicle activity occurring within this zone during the analyzed peak period was treated as an internal emission source.

The **vertical extent of the box** was set to **5 m**, resulting in a total air volume of **1,914,550.3 m³**. This fixed control volume was applied consistently across all peak-hour scenarios and vehicle categories. Traffic-related emissions were calculated using vehicle-kilometer-traveled (VKT) values derived from the traffic simulation and emission factors based on Indonesian national and regional references. The total mass of each pollutant was divided by the box volume to obtain the corresponding mass concentration.

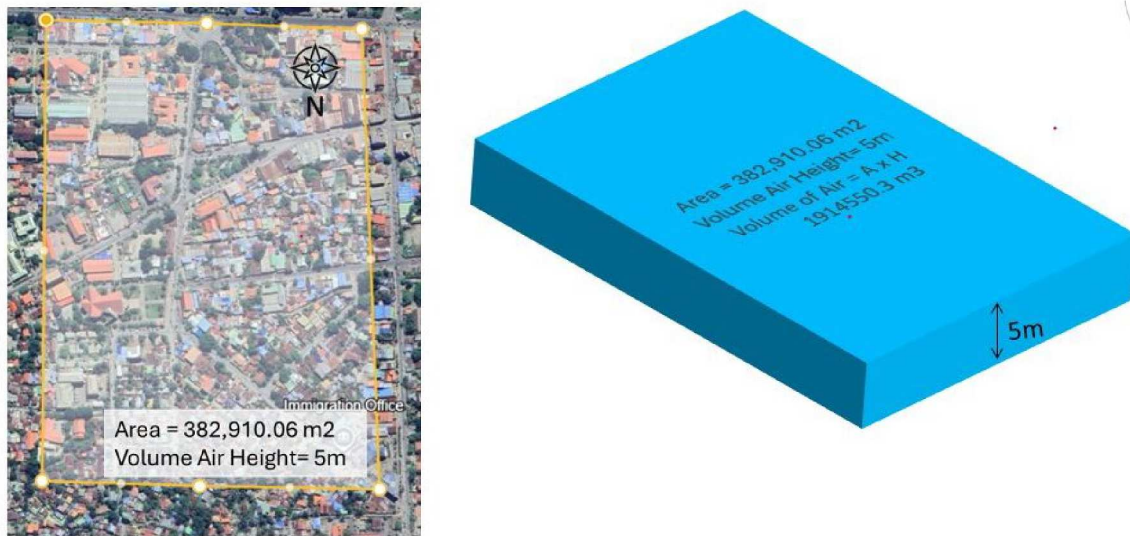


Figure 5. 17 Box model of the study area.

The calculated concentrations of CO , NO_x , $\text{PM}_{2.5}$, and SO_2 for the morning, afternoon, and evening peak hours demonstrate the following.

- **Physical Basis for the 5 m Box Height Assumption**

The selection of a **5 m vertical height** represents a conservative assumption intended to capture **pollutant accumulation near the ground under stable atmospheric conditions**. Vertical dispersion of traffic-related pollutants is strongly influenced by atmospheric stability, which is commonly classified using the **Pasquill stability classes**, as illustrated in **Figure 5.18**. This figure shows the relationship between the distance of horizontal advection (x) and the vertical diffusion parameter (σ_z), which governs the extent of vertical mixing in the atmosphere.

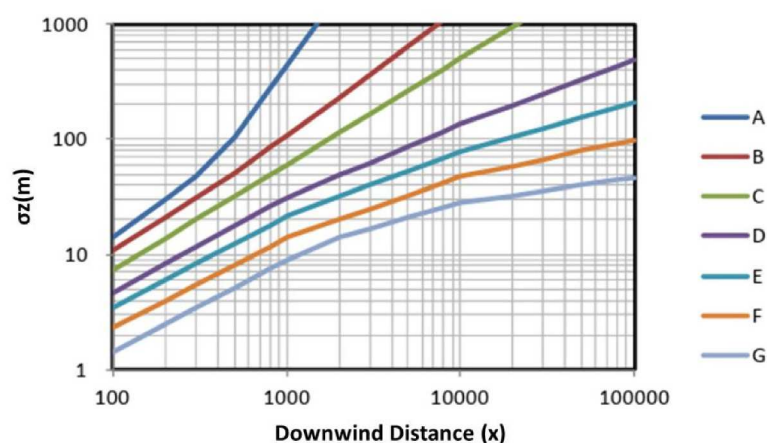


Figure 5. 18 σ_y and σ_z as a function of downwind distance

Under very stable conditions, corresponding to **Pasquill stability classes F or G**, vertical mixing is significantly suppressed due to the presence of surface-based temperature inversion layers. As a result, pollutants emitted from traffic sources tend to remain confined within a shallow layer near the surface, leading to elevated ground-level concentrations. Such behavior is well documented in atmospheric dispersion studies and represents a realistic worst-case scenario for near-road air quality assessment (Turner, 1994; NOAA, 2023) [28, 29].

For calculation domains with horizontal scales on the order of several hundred meters, approximately **600 m in this study**, empirical relationships between downwind distance and the vertical diffusion parameter σ_z indicate that vertical diffusion under extremely stable conditions is limited to only a few meters. According to established dispersion guidelines, σ_z values of approximately **5 m** are consistent with such conditions at this spatial scale (Ministry of the Environment, Japan, 2012) [30]. Defining the box height to match this diffusion scale allows the model to represent the effective mixing layer in which pollutants accumulate near the surface.

By adopting this shallow box height, the concentration values presented in the tables and figures represent **upper-bound or worst-case estimates** of ground-level pollutant concentrations during peak traffic periods. This assumption is appropriate for assessing potential environmental and public health impacts, particularly in urban areas where traffic congestion and stable atmospheric conditions may occur simultaneously.

▪ Calculate the Concentrations

To calculate the air pollutant concentration, key parameters must be considered, such as the Emission Factor (EF) (as detailed in **Table 5.10**). Given the lack of Timor-Leste-specific data, we utilize the Indonesian reference by Rizki, M et al., 2021 [31] for these emission factors.

Table 5. 10 Emission Factor (EF)

Vehicle Category	CO (g/km/vehicle)	NOx (g/km/vehicle)	PM2.5 (g/km/vehicle)	SO ₂ (g/km/vehicle)
Motorcycle	69.40	0.29	0.23	0.1
Light Vehicle (cars, vans, minibuses, gasoline)	39.00	1.10	0.05	0.026
Heavy Vehicle (diesel trucks & buses)	4.50	12.60	1.20	0.93

The second critical parameter for calculating air pollutant concentration is the Volume of air measured from the target area. As illustrated in Figure 5.17, the target area for this study has been defined by: Area (A): 382,910.06 m³, Height (H): 5m. The total Volume of Air (V) used in this study is calculated by multiplying the area by the height: V = 1,914,550.3 m³.

Lastly, the Vehicle Kilometer Travelled (VKT) is crucial as it quantifies the total activity of the emission sources (vehicles) within the defined urban zone. The VKT is specifically determined by considering the travel distance of different vehicle categories across the three major periods of peak traffic flow: Morning Peak Hour, Afternoon Peak Hour, and Evening Peak Hour, as demonstrated in **Table 5.11**

Table 5. 11 Vehicle Kilometer Travel (VKT)

VMT(Vehicle Kilometer Travel) in km			
Vehicle Category	Morning Peak Hour (08:00-09:00)	Afternoon Peak Hour (12:00-13:00)	Evening Peak Hour (15:00- 16:00)
MC	75.42	67.69	62.11
LV	75.42	67.69	62.11
HV	75.42	67.69	62.11

▪ **Equation for Mass Concentration**

Mass Concentration (C) of Pollutant is calculated by taking the total mass emitted (M) and dividing it by the Volume of the mixing zone (V_{air}).

$$M_{i,k} = EF_{i,k} \cdot VKT_i \quad (5.4)$$

$$C_{i,k} = M_{i,k} / V_{air} \quad (5.5)$$

Where :

- $M_{i,k}$: Mass pollutant emitted from the source i for the pollutant k (g)
- $EF_{i,k}$: Emission factor of source i for the pollutant k (g/km)
- VKT_i : Vehicle Kilometers Traveled from source i (km)
- $C_{i,k}$: Mass concentration of the pollutant k contributed by the source i (g/m³)

▪ **Result calculation of Mass Emitted (M) and Concentration (C).**

This study analyzes vehicular emissions across four major pollutants **CO**, **NO_x**, **PM_{2.5}**, and **SO₂**, categorized by vehicle type and peak traffic hours. The results highlight a clear correlation between fuel type, vehicle weight, and the specific pollutants emitted as presented in **Table 5.12**.

Table 5. 12 Mass Emitted (M) and Concentration (C).

Vehicle Category	Morning Peak hour (08:00-09:00)							
	CO		NO _x		PM _{2.5}		SO ₂	
	Mass Emmited (M) g	Concentrat ion (C) mg/m3	Mass Emmited (M) g	Concentrat ion (C) µg/m3	Mass Emmited (M) g	Concentrat ion (C) µg/m3	Mass Emmited (M) g	Concentrat ion (C) µg/m3
Motorcycle	5234.15	2.73	21.87	11.42	17.35	9.06	7.542	3.939
Light Vehicle (cars, vans, minibuses, gasoline)	2941.38	1.54	82.96	43.33	3.77	1.97	1.96092	1.024
Heavy Vehicle (diesel trucks & buses)	339.39	0.18	950.29	496.35	90.50	47.27	70.1406	36.636
	Afternoon Peak hour (12:00-13:00)							
	CO		NO _x		PM _{2.5}		SO ₂	
	Mass Emmited (M) g	Concentrat ion (C) mg/m3	Mass Emmited (M) g	Concentrat ion (C) µg/m3	Mass Emmited (M) g	Concentrat ion (C) µg/m3	Mass Emmited (M) g	Concentrat ion (C) µg/m3
Motorcycle	4697.69	2.45	19.63	10.25	15.57	8.13	6.769	3.536
Light Vehicle (cars, vans, minibuses, gasoline)	2639.91	1.38	74.46	38.89	3.38	1.77	1.75994	0.919
Heavy Vehicle (diesel trucks & buses)	304.61	0.16	852.89	445.48	81.23	42.43	62.9517	32.881
	Evening Peak hour (17:00-18:00)							
	CO		NO _x		PM _{2.5}		SO ₂	
	Mass Emmited (M) g	Concentrat ion (C) mg/m3	Mass Emmited (M) g	Concentrat ion (C) µg/m3	Mass Emmited (M) g	Concentrat ion (C) µg/m3	Mass Emmited (M) g	Concentrat ion (C) µg/m3
Motorcycle	4310.43	2.25	18.01	9.41	14.29	7.46	6.211	3.244
Light Vehicle (cars, vans, minibuses, gasoline)	2422.29	1.27	68.32	35.69	3.11	1.62	1.61486	0.843
Heavy Vehicle (diesel trucks & buses)	279.50	0.15	782.59	408.76	74.53	38.93	57.7623	30.170

The result identifies a specialized emission profile for each vehicle class. **Motorcycles** are the primary contributors to **Carbon Monoxide (CO)** levels, with a peak mass emission of 5234.15g and a concentration of 2.73 mg/m³ during the morning peak. This suggests that gasoline-powered two-wheelers, while smaller, significantly impact urban CO levels.

In contrast, **Heavy Vehicles (Diesel)** are the dominant source of high-toxicity pollutants. They contribute the highest mass and concentration for **NO_x**(496.35µg/m³), **PM_{2.5}** (47.27µg/m³), and **SO₂**(36.636µg/m³). Notably, the PM_{2.5} concentration from heavy vehicles is approximately **24 times higher** than that of light gasoline vehicles, underscoring the severe environmental impact of diesel engines regarding particulate matter.

A consistent temporal pattern is observed across all categories. Emission levels are highest during the Morning Peak (08:00–09:00), followed by a moderate decrease during the Afternoon Peak (12:00–13:00), and reach their lowest values during the Evening Peak (17:00–18:00). Across all pollutants, emissions decrease uniformly by approximately 17.6% from the morning to the evening peak. This consistency indicates that variations in emissions are predominantly driven by fluctuations in traffic volume, rather than by changes in driving behavior or environmental conditions.

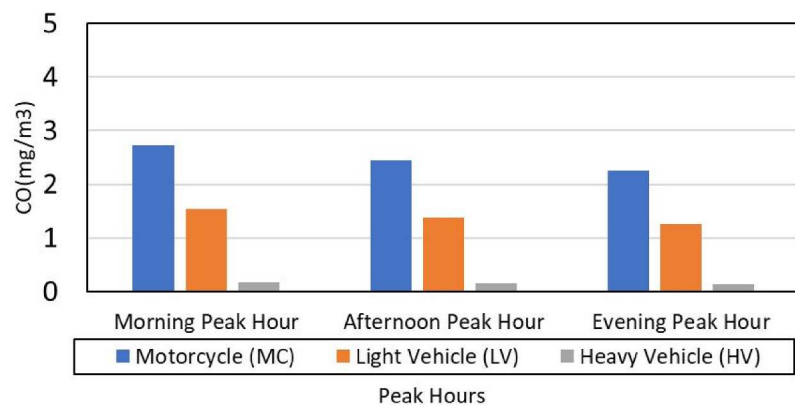
The findings indicate that air quality interventions should be pollutant-specific. Strategies aimed at reducing CO emissions should primarily target motorcycle fleets, whereas mitigation of *NO_x* and *PM_{2.5}* should prioritize the regulation of diesel-powered heavy vehicles. Moreover, the morning peak period remains the most critical time window for elevated exposure risks.

▪ Result air pollutant concentration

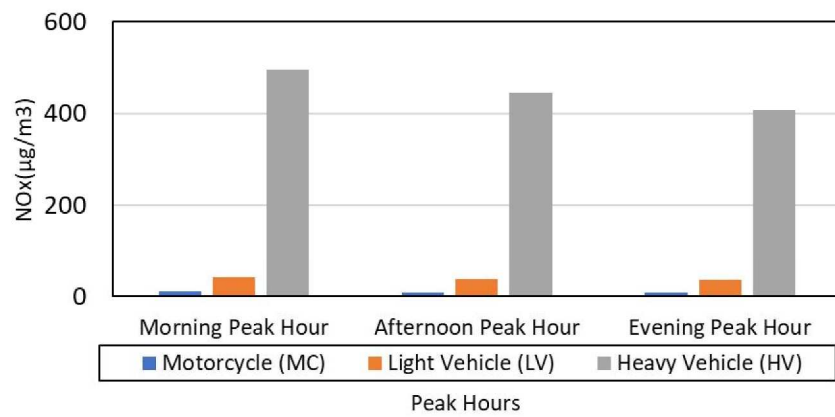
The concentration values shown in the **Table 5.13** and **Figure 5.19** represent the atmospheric concentration levels of CO (mg/m³), NO_x (µg/m³), PM_{2.5} (µg/m³) and SO₂(µg/m³) emitted by different vehicle categories (motorcycles (MC), light vehicles (LV), heavy vehicles (HV)) during morning, afternoon, and evening peak periods. These figures quantify the extent to which emitted pollutants disperse into the surrounding air, indicating the degree to which each vehicle type contributes to regional air quality deterioration.

Table 5. 13 air pollutant concentration

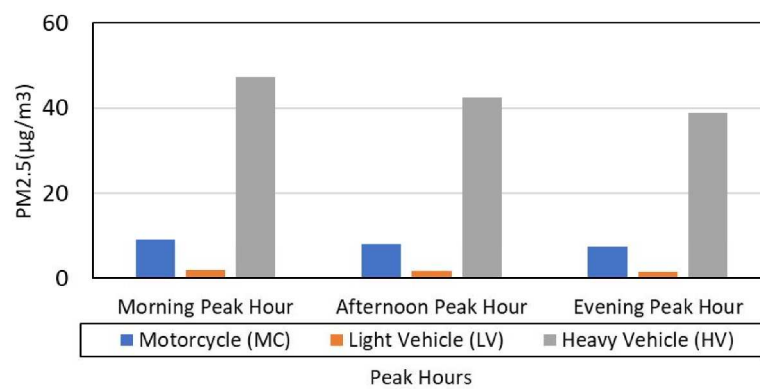
Type	CO(mg/m3)			NOx (µg/m3)			PM2.5 (µg/m3)			SO2 (µg/m3)		
	08:00 - 09:00	12:00 -13:00	17:00 - 18:00	08:00 - 09:00	12:00 -13:00	17:00 - 18:00	08:00 - 09:00	12:00 -13:00	17:00 - 18:00	08:00 - 09:00	12:00 -13:00	17:00 - 18:00
	Morning Peak Hour	Afternoon Peak Hour	Evening Peak Hour	Morning Peak Hour	Afternoon Peak Hour	Evening Peak Hour	Morning Peak Hour	Afternoon Peak Hour	Evening Peak Hour	Morning Peak Hour	Afternoon Peak Hour	Evening Peak Hour
Motorcycle (MC)	2.73	2.45	2.25	11.42	10.25	9.41	9.06	8.13	7.46	3.94	3.54	3.24
Light Vehicle (LV)	1.54	1.38	1.27	43.33	38.89	35.69	1.97	1.77	1.62	1.02	0.92	0.84
Heavy Vehicle (HV)	0.18	0.16	0.15	496.35	445.48	408.76	47.27	42.43	38.93	36.64	32.88	30.17



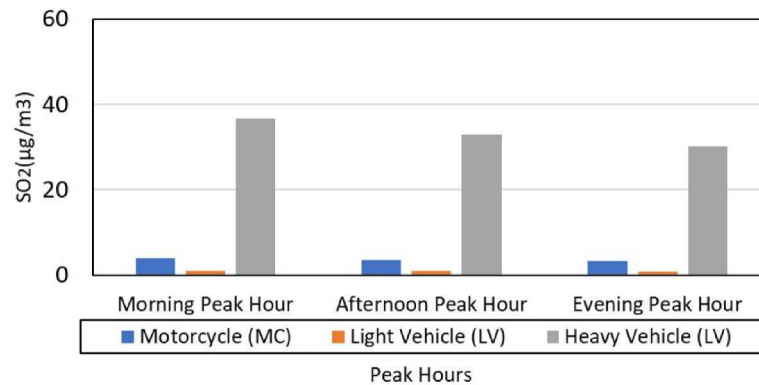
(a) Carbon Monoxide (CO)



(b) Nitrogen Oxides (Nox)



(c) Fine Particulate Matter (PM2.5)



(d) Sulfur Dioxide (SO₂)

Figure 5. 19 Result of Air pollution concentration

▪ **Comparison of Air Pollutant results**

Table 5.14 and **Figure 5.20** present a comparative analysis of the calculated 1-hour average concentrations of key air pollutants—CO, NO₂, PM_{2.5}, and SO₂—against the air quality standards established by the World Health Organization (WHO), Japan, and Indonesia. This comparison aims to assess the air quality condition of the target area and identify potential exceedances relative to regulatory thresholds.

Table 5. 14 Comparison result

Air Pollutants for 1 Hour time	Calculation result	Japan Standard	Indonesian Standard	WHO	Status
CO(mg/m3)	4.45	11.5	10	35	SAFE
NO ₂ (µg/m3)	440.89	113	200	200	HIGHLY EXCEEDED
PM _{2.5} (µg/m3)	58.30	35	55	15	EXCEEDED
SO ₂ (µg/m3)	41.60	105	150	40	EXCEEDED (WHO)

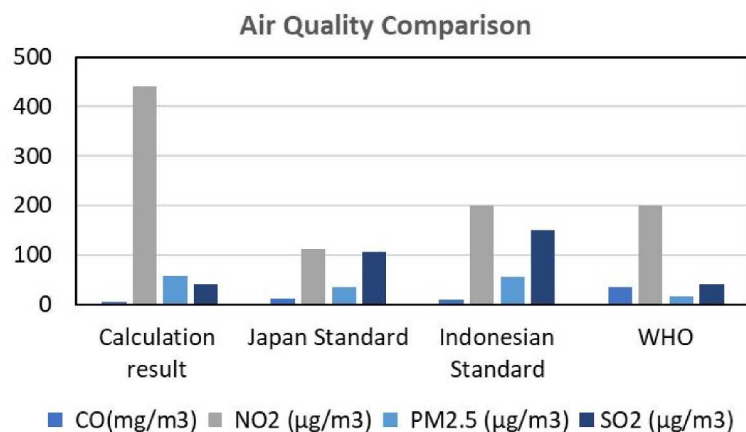


Figure 5. 20 Result of comparison

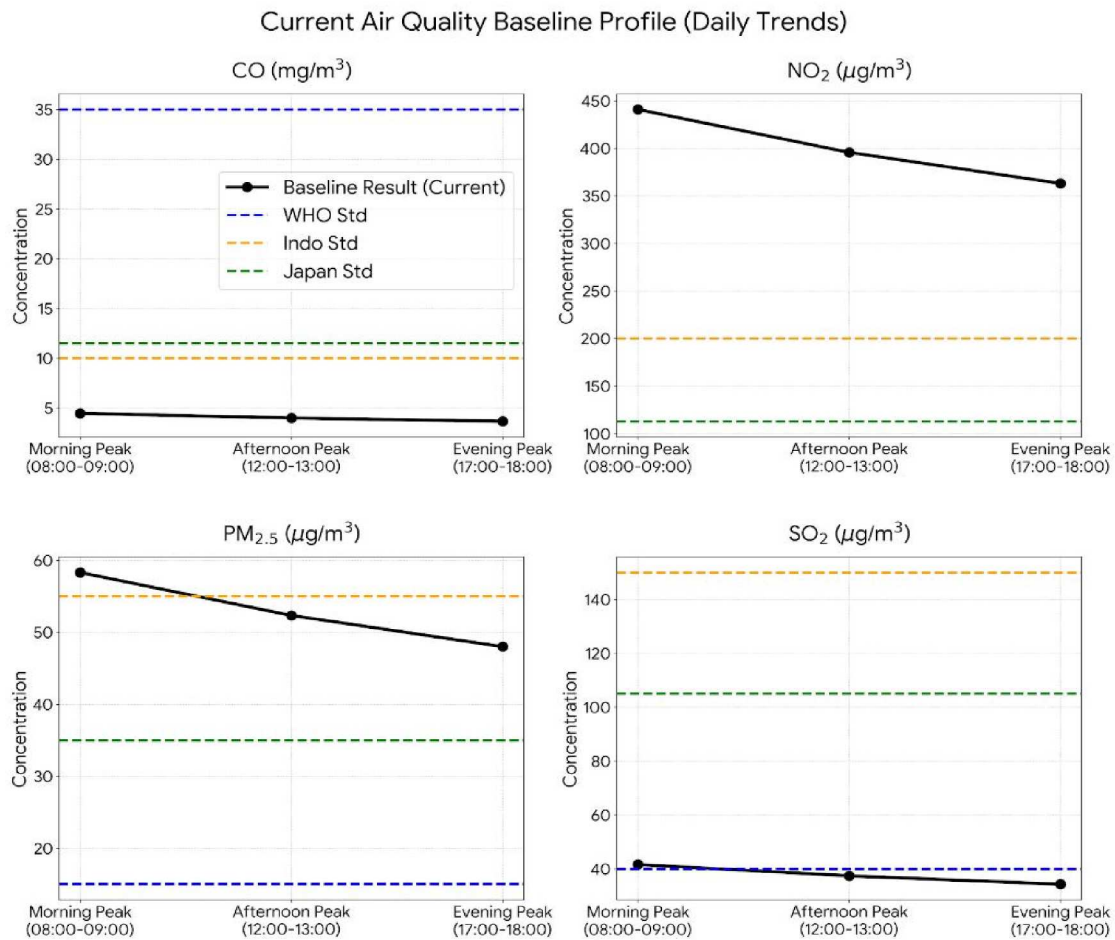


Figure 5. 21 Result of temporal variation

As shown in **Table 5.14**, the calculated concentration of carbon monoxide (CO) is 4.45 mg/m³, which remains well below the permissible limits set by WHO (35 mg/m³), Japan (11.5 mg/m³), and Indonesia (10 mg/m³). Consequently, CO levels in the study area can be classified as safe for the assessed period.

In contrast, nitrogen dioxide (NO₂) exhibits a significantly elevated concentration of 440.89 μg/m³, far exceeding the standards prescribed by WHO and Indonesia (200 μg/m³) as well as Japan (113 μg/m³). This indicates a critical exceedance of NO₂ levels, suggesting strong influences from traffic emissions or combustion-related activities within the area.

For particulate matter (PM_{2.5}), the calculated concentration of 58.30 μg/m³ exceeds the WHO guideline value of 15 μg/m³ and the Japanese standard of 35 μg/m³, while slightly surpassing the Indonesian limit of 55 μg/m³. This result highlights a considerable particulate pollution burden, which poses potential health risks, particularly for sensitive populations.

Similarly, sulfur dioxide (SO₂) shows a concentration of 41.60 μg/m³, which exceeds the WHO guideline value of 40 μg/m³, although it remains below the Japanese (105 μg/m³) and Indonesian (150 μg/m³)

standards. This indicates that while SO₂ levels are generally compliant with national regulations, they marginally violate the stricter WHO guideline.

Figure 5.21 further illustrates the temporal variation of pollutant concentrations during morning, afternoon, and evening peak periods, alongside the corresponding regulatory limits. CO concentrations remain consistently below all standards throughout the day. However, NO₂ and PM_{2.5} levels remain above permissible thresholds across all time intervals, with peak values typically occurring during the morning period, likely due to increased traffic density. SO₂ concentrations show a decreasing trend from morning to evening and approach the WHO limit, reinforcing the findings presented in Table 5.14.

Overall, the results demonstrate that while CO pollution does not pose a concern in the study area, NO₂ and PM_{2.5} concentrations significantly exceed international and national air quality standards, indicating degraded air quality conditions. These findings underscore the need for targeted mitigation strategies, particularly addressing vehicular emissions and particulate matter sources, to improve ambient air quality in the target area.

5.6. Conclusion and Future Work

This study extends the Digital Twin (DT) paradigm from individual asset monitoring to a system-level urban transportation application by developing and implementing a DT-BIM-based traffic management framework for Dili, Timor-Leste. The proposed workflow successfully integrates Building Information Modeling with traffic simulation tools, enabling the creation of a dynamic and data-driven virtual representation of the urban road network.

Through peak-hour simulations, the framework provides quantitative insights into traffic demand, congestion patterns, and operational performance during morning, afternoon, and evening periods. In addition to mobility analysis, the study demonstrates the capability of the Digital Twin to support environmental assessments by incorporating a box model approach to estimate traffic-related air pollutant concentrations.

The results highlight clear relationships between vehicle type, traffic volume, and pollutant emissions, confirming the applicability of Digital Twin technology as a decision-support tool for evidence-based urban planning and infrastructure policy, particularly in data-scarce and rapidly urbanizing contexts.

Despite these contributions, several opportunities remain to further enhance the framework's operational relevance and analytical accuracy. Future research should prioritize the integration of real-time traffic data from IoT sensors, GNSS-enabled probe vehicles, or connected infrastructure to transition from periodic simulations to continuous, real-time Digital Twin operation.

Additionally, while the box model provides conservative estimates of near-ground pollutant concentrations, the adoption of more advanced atmospheric dispersion or Computational Fluid Dynamics (CFD) models would enable a more detailed representation of pollutant transport in complex urban environments. Scaling the Digital Twin from a localized study area to a city-wide or regional network would further support system-level traffic optimization, rerouting strategies, and emergency response planning. Finally, the incorporation of machine learning-based calibration techniques using observed traffic data could improve predictive accuracy and adaptability under varying traffic conditions, seasonal effects, and special events.

5.7. Reference

1. Lu, J., Li, B., Li, H., & Al-Barakani, A.: Expansion of city scale, traffic modes, traffic congestion, and air pollution, *Cities*, Vol. 108, 102974, 2021. DOI: 10.1016/j.cities.2020.102974
2. Wang, M., & Debbage, D.: Urban morphology and traffic congestion: Longitudinal evidence from US cities, *Computers, Environment, and Urban Systems*, Vol. 89, 101676, 2021. DOI: 10.1016/j.compen-vurbsys.2021.101676
3. Sweet, M.: Traffic Congestion's Economic Impacts: Evidence from US Metropolitan Regions, *Urban Studies*, Vol. 51, Issue 10, pp. 2088-2110, 2014. DOI: 10.1177/0042098013505883
4. Bigazzi, A. Y., & Rouleau, M.: Can traffic management strategies improve urban air quality? A review of the evidence, *Journal of Transport & Health*, Vol.7, Part B, pp. 111-124, 2017. DOI: 10.1016/j.jth.2017.08.001
5. Bigazzi, A. Y., Rouleau, Figliozi, M. A., & Clifton, K. J.: Traffic Congestion and Air Pollution Exposure for Motorists: Comparing Exposure Duration and Intensity, *International Journal of Sustainable Transportation*, Vol. 9, Issue 7, pp. 443-456, 2015. DOI: 10.1080/15568318.2013.805345
6. Tao, F., Zhang, H., Liu, A., & Nee, A. Y. C.: Digital Twin in Industry: State-of-the-Art, *IEEE Transactions on Industrial Informatics*, Vol. 15, no. 4, pp. 2405-2415, 2018. DOI: 10.1109/TII.2018.2873186
7. Gao, Y., Qian, S., Li, Z., Wang, P., & Wang, F. He, Q., "Digital Twin and Its Application in Transportation Infrastructure.", 2021 IEEE 1st International Conference on Digital Twins and Parallel Intelligence (DTPI), pp.298 301, 2021.
8. Elfrido, E. T., Watanabe, G., Shao, P., & Arie, K.: Development and Application of Digital Twin-BIM Technology for Bridge Management, *Applied Sciences*, Vol. 13, Issue 13, 7435, 2023. DOI: 10.3390/app13137435
9. Golubev, K., Zagarskikh, A., and Karsakov, A.: A framework for a multi-agent traffic simulation using combined behavioral models, *Procedia Computer Science*, Vol. 136, pp. 443-452, 2018. DOI: 10.1016/j.procs.2018.08.267
10. Project for Study on Dili Urban Master Plan (in Japanese) <https://www.jica.go.jp/oda/project/1200320/index.html>
11. Liao, X., Wang, Z., Zhao, X., Han, K., and Tiwari, P., Barth, M. J., and Wu, G.: Cooperative ramp merging design and field implementation: a digital twin approach based on vehicle-to-cloud communication, *IEEE Transactions on Intelligent Transportation Systems*, Vol. 23, Issue 5, pp.1-11, 2021. DOI: 10.1109/TITS.2020.3045123
12. Dasgupta, S., Rahman, M., Lidbe, A.D., Lu, W., and Jones, S.: A Transportation Digital-Twin Approach for Adaptive Traffic Control Systems, *Physics and Society*, p.15, 20 21. DOI: 10.47550/arXiv.2109.10863

13. J. Argota Sánchez-Vaquerizo.: Getting Real: The Challenge of Building and Validating a: Large-Scale Digital Twin of Barcelona's Traffic with Empirical Data, *International Journal of Geo-Information*, Vol.11, Issue 1, 2022. DOI: 10.3390/ijgi11010024
14. White, G., Zink, A., Codecá, L., and Clarke, S.: A digital Twin smart city for citizen feedback, *Cities*, Vol. 110, 1030 64, 2021. DOI: 10.1016/j.cities.2020.103064
15. Liu, M., Fang, S., Dong, H., and Xu, C.: Review of digital twin about concepts, technologies, and industrial applications, *J. Manuf. Syst*, Vol. 58, pp.346-361, 2021. DOI: 10.1016/j.jmsy.2020.06.017
16. Kušić, K., Schumann, R., and Ivanjko, E.: A digital twin in transportation: Real-time synergy of traffic data streams and simulation for virtualizing motorway dynamics, *Advanced Engineering Informatics*, Vol. 55, 101858, 2023. DOI: 10.1016/j.aei.2022.101858
17. Storani, F., Pace, R. D. and Luca, S. D.: A hybrid traffic flow model for traffic management with human-driven and connected vehicles, *Transportmetrica B: Transport Dynamics*, Vol. 10, Issue 1, pp. 1151-1183, 2022. DOI: 10.1080/21680566.2022.2026836
18. Avramovic, S., and Johnsson, E.: Evaluation of Autodesk InfraWorks 360 and PTV Vissim: A comparative study of two traffic simulation software products, *Chalmers University of Technology*, p. 85, 2017. <https://odr.chalmers.se/server/api/core/bitstreams/022a4148-ef5a-4307-90a9-34243cc0d520/content>
19. Schlosser, T., Schlosser, P., Zuzulová, A., Cápayová, S., and Bálint, G.: Traffic Planning as a Preliminary Tool in Project Documentation for BIM, *Buildings*, Vol. Issue 12, 381, 2022. DOI: 10.3390/buildings12030381
20. Castañeda, K., Sánchez, O., Herrera, R. F., Pellicer, E., and Porras, H.: BIM-based traffic analysis and simulation at road intersection design, *Automation in Construction*, Vol. 131, 103911, 2021. DOI: 10.1016/j.autcon.2021.103911
21. Timor-Leste: Population and Housing Census 2022. https://timor-leste.unfpa.org/sites/default/files/pub-pdf/censuspreliminaryresults2022_4.pdf
22. Autodesk, Infraworks for Analysis and Simulation, Autodesk Infraworks, 2023, <https://www.autodesk.com/products/infraworks/analysis-and-simulation>, (2024/03/14).
23. J. J.Olstam, J. J., and Tapani, A.: A. Comparison of Car Following Models, *Swedish National Road and Transport Research Institute*, p.41, 2004.
24. Fritzsche, H.: A Model for Traffic Simulation, *Traffic Engineering & Control*, Vol. 5, pp. 317-321, 1994.
25. Lochrane, T. W. P., Dailey, D., Al-Deek, H., and Krause, C.: Modeling Driver Behavior in Work and Nonwork Zones - Multidimensional Psychophysical Car-Following Framework, *Journal of the Transportation Research Board*, No. 2490, pp. 116-125, 2015. DOI: 10.3141/2490-13
26. Soria, I., Elefteriadou, L., and Kondyli, A.: Assessment of Car-Following Models by Driver Type and under Different Traffic, Weather Conditions Using Data from an Instrumented Vehicle, *Simulation Modeling Practice and Theory*, Vol. 40, pp. 208-220, 2024. DOI: 10.1016/j.simpat.2013.10.002

27. Seinfeld, J. H., & Pandis, S. N. (2016). *Atmospheric Chemistry and Physics: From Air Pollution to Climate Change*. Wiley.
28. Turner, D.B. (1994). *Workbook of Atmospheric Dispersion Estimates: An Introduction to Dispersion Modeling*, Second Edition (2nd ed.). CRC Press. <https://doi.org/10.1201/9780138733704>
29. NOAA (2023). *Pasquill Stability Classes*. Ready NOAA Air Resources Laboratory & (Draxler, R.R., Estimating vertical diffusion from routine meteorological tower measurements, *Atmospheric Environment*, 13, 1559-1564 (1979); see [https://doi.org/10.1016/0004-6981\(79\)90065-9](https://doi.org/10.1016/0004-6981(79)90065-9)).
30. Ministry of the Environment, Japan (2012). *Guidelines for Mobile Source Emission Inventory Development*.
31. Rizki, M., J. Syahputri, N. Noor, P.G. Gan, R. Wihanesta. 2021. "Indonesia Zero Emissions Application (EMISI): Methodology for Calculating Individual Emissions from Goods Deliveries, and Marine and Aviation Transport." Technical Note. Jakarta, Indonesia: World Resources Institute. Available online at: <https://doi.org/10.46830/writn.20.00150>

6. Operational Digital Twin Application under Abnormal and Emergency Conditions

Overview

This chapter demonstrates the application of the proposed operational digital twin framework under abnormal and emergency conditions through a real-world post-accident bridge case study. Focusing on displacement monitoring and structural assessment after an unexpected damage event, this chapter illustrates how BIM-aided digital twin models and GNSS-based monitoring can be integrated to support engineering interpretation when structural behavior deviates from normal conditions. In such situations, observation data are often limited, noisy, and temporally constrained, making conventional evaluation methods insufficient. By leveraging a digital twin that couples monitoring data with structural models, this chapter shows how post-accident structural responses can be interpreted in a systematic and physically meaningful manner. The presented case study highlights the role of the operational digital twin as a decision-support system for rapid structural assessment, safety evaluation, and subsequent maintenance planning under non-standard conditions.

6.1. Introduction

Bridges are fundamental elements of national infrastructure, providing critical connectivity, enabling the efficient transport of people and goods, and fostering socio-economic development [1, 2]. In geographically complex countries such as Japan, bridges play an especially vital role due to the need to span numerous rivers, valleys, and coastal inlets. However, the deterioration of aging infrastructure has become a growing concern. Many of Japan's bridges were constructed during periods of rapid economic growth, and a significant portion has now exceeded 50 years of service. According to Japan's Ministry of Land, Infrastructure, Transport and Tourism (MLIT), more than 75% of bridges will surpass this age threshold by 2040 [3], underscoring the urgent need for proactive, predictive, and cost-effective maintenance strategies.

Conventional bridge inspection practices, typically based on periodic visual assessments, are labor-intensive and may fail to detect early-stage structural deterioration, particularly in large or complex structures [4]. The recent advances in digital technology, such as Building Information Modeling (BIM), sensor networks, and satellite positioning systems are bringing a new paradigm to infrastructure management. BIM enables the creation of parametric 3D models that encompass the geometric and semantic attributes of physical assets. At the same time, sensor-based monitoring technologies such as Global Navigation Satellite Systems (GNSS) provide high-precision real-time displacement data that reflects the operational behavior of structures under environmental and load conditions [5]–[8]. By integrating these technologies into a digital twin framework, it is possible to develop cyber-physical systems that reproduce the real-time or near-real-time state of physical infrastructure [9]–[13]. Such systems not only enhance visibility into asset conditions but also support data-driven decision-making for maintenance and risk mitigation. The importance of these approaches is reflected in national-level initiatives promoting digital transformation aimed at improving infrastructure sustainability and disaster resilience, such as Japan's i-Construction and National

Resilience Plan [14]. In this study, we applied a BIM-based digital twin framework with GNSS displacement monitoring for the Oshima Bridge, a long-span Pratt truss bridge located in Yamaguchi Prefecture. This bridge experienced a serious structural accident in 2018 due to a collision with a ship, exposing the limitations of the conventional inspection system and highlighting the need for continuous, real-time monitoring. In response, this study proposes a new integrated approach for bridge lifecycle management, aiming to achieve early detection of abnormalities, optimization of maintenance schedules, and ultimately, improved structural resilience. The implemented framework focuses on unidirectional data integration from the GNSS monitoring system to the digital model but lays the groundwork for future developments. This includes bidirectional data synchronization, semantic interoperability, and closed-loop feedback systems that support autonomous maintenance actions and actuator-based interventions. This chapter focuses on asset-level digital twin development for a damaged bridge. The digital twin integrates BIM, GNSS deformation data, and linear FEA to interpret post-accident behavior. By demonstrating this approach through the case study of Oshima Bridge, this study contributes to the advancement of smart bridge management practices in Japan and presents a scalable model applicable to aging infrastructure systems worldwide.

6.2. Research Strategy

In this study, we propose an integrated digital twin framework for monitoring the structural integrity of Oshima Bridge, as shown in **Figure 6.1**. This strategy consists of four main components: parametric modeling, immersive visualization, displacement monitoring, and structural simulation. First, we develop a detailed 3D model of the bridge using building information modeling (BIM). This model serves as the geometric and semantic foundation of the digital twin, capturing the bridge's structural layout, material properties, and component relationships. To enhance interaction with the model and communication among stakeholders, the BIM model is integrated into a virtual reality (VR) environment. This immersive visualization enables intuitive spatial analysis and scenario-based inspections, particularly for complex structural elements and areas with restricted access. Next, real-time displacement monitoring is conducted using global navigation satellite system (GNSS) technology. High-precision GNSS sensors are placed at key locations on the bridge to capture longitudinal, lateral, and vertical displacements, allowing for the detection of potential structural anomalies. Finally, Finite Element Analysis (FEA) is performed to assess the structural stability of the bridge based on the observed displacement data. The FEA model calculated with field data helps verify the structure's stability and confirm the accuracy of the digital twin's predictive capabilities. Even though BIM, GNSS, and FEA are all established technologies, combining them creates a new collaborative approach that is specifically for monitoring the lifecycle of bridges. This framework paves the way for expanding digital twin implementation from static visualization to active monitoring and simulation-based decision support. Future research aims to expand the framework with AI-driven anomaly detection and automatic model update technologies to achieve predictive maintenance and closed-loop feedback within the digital twin architecture.

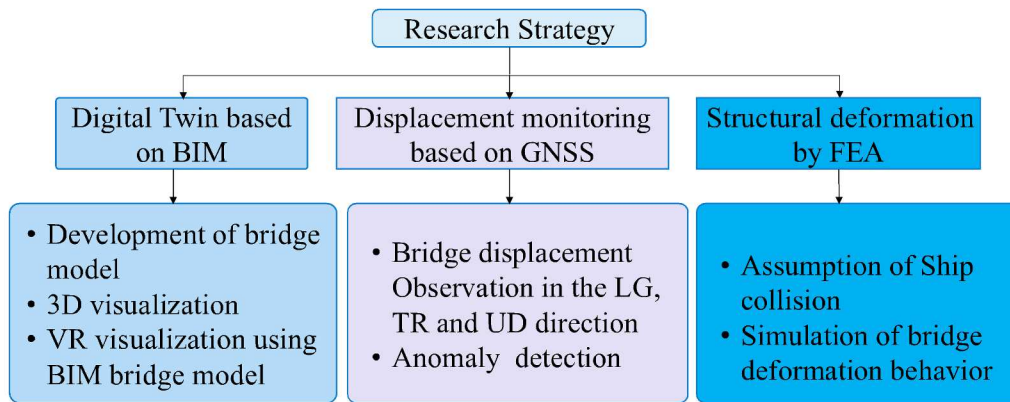


Figure 6. 1 Research Strategy

▪ BIM and Digital Twin

(1) BIM

BIM is a digital methodology that utilizes a standardized 3D model to represent and manage both the functional and physical characteristics of infrastructure assets. It enhances decision-making and promotes collaboration among stakeholders throughout all phases of a project's lifecycle [5,7,8]. As shown in **Figure 6.2**, BIM supports activities from planning and conceptual design to detailed design, construction, operation, maintenance, rehabilitation, and eventual decommissioning. In this context, the BIM-based project lifecycle is referred to as building information management

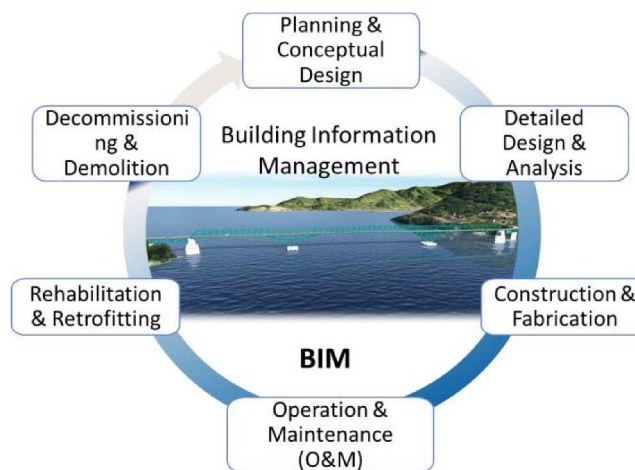


Figure 6. 2 Building Information Modeling

(2) Digital Twin

A digital twin is an advanced technology central to the realization of smart infrastructure and Industry 4.0 [7]. In bridge engineering, a digital twin is a virtual model that mirrors the physical structure by integrating real-time sensor data to simulate performance, detect anomalies, and support lifecycle management [7,10]. In this study, a digital twin of a Long-Span Pratt truss bridge is developed using BIM to establish a geometrically and semantically accurate, data-rich model. As illustrated in **Figure 6.3**, (a) shows the physical structure captured by the drone, and (b) displays the corresponding BIM-based digital twin. Real-time GNSS displacement data further enhances the digital twin by enabling three-dimensional monitoring, thereby improving anomaly detection and informing maintenance strategies across the bridge's lifecycle.



(a) Real World (Drone)



(a) Cyber Space (BIM)

Figure 6.3 Digital Twin of Bridge

▪ Overview of the Oshima Bridge and the 2018 Vessel Collision Accident

The Oshima Bridge, located in Yamaguchi Prefecture, is a critical transportation link connecting Yanai City to Suō-Ōshima Town. The total bridge length is 1,020 meters, with its main span consisting of a three-span continuous steel truss with a through-type lower chord structure. The central spans measure 200 m + 325 m + 200 m, for a total of 729 meters, as shown in **Figure 6.4**. At the time of construction, its central span was the second-longest Pratt truss span in the world and remains the fourth-longest in Japan [15].

Originally constructed by the former Japan Highway Public Corporation, the bridge was built using marine floating cranes (block assembly method) for the side spans, and the cantilever method with traveler cranes for the central span.

Transferred to the Yamaguchi Prefecture Road Corporation in 1987, the bridge now forms part of National Route 437 and serves as the sole land route for approximately 17,000 residents. This region is characterized by tidal currents reaching up to 10 knots [14]. On October 22, 2018, a foreign-registered cargo vessel collided with the bridge, causing severe structural damage as depicted in **Figure 6.4**. The incident underscored the vulnerability of maritime infrastructure in high-traffic tidal zones and reaffirmed the bridge's critical role in regional connectivity and emergency response [16].

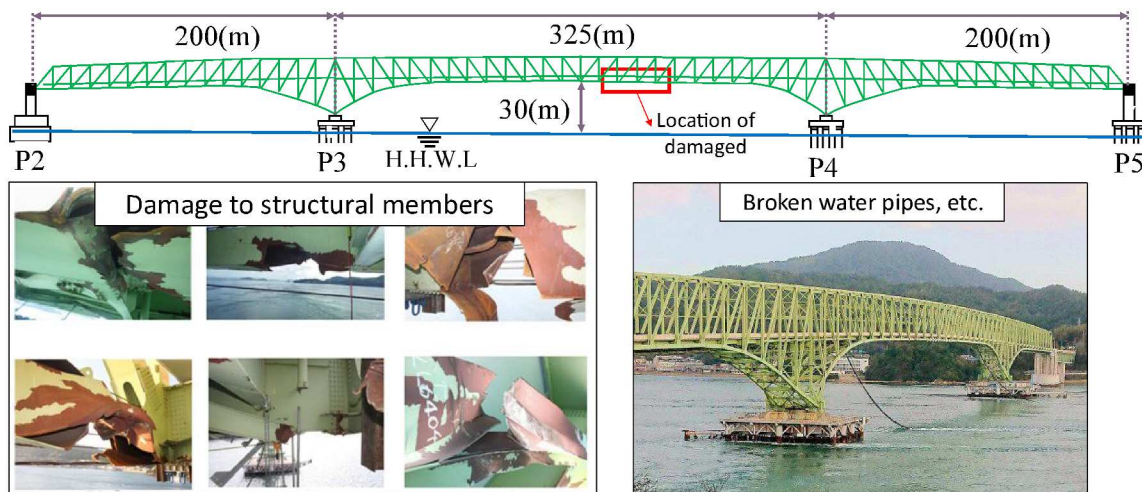


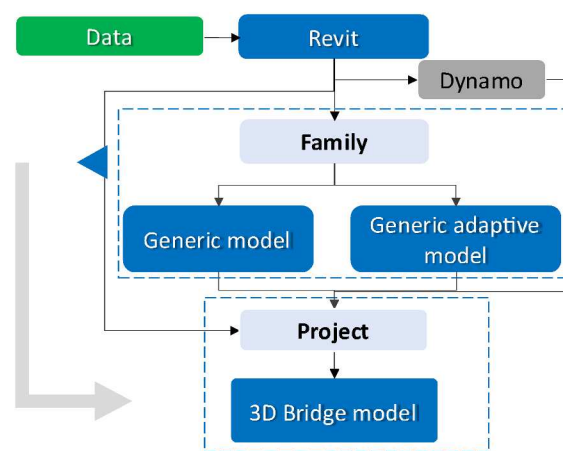
Figure 6. 4 Overview of the Oshima Bridge and the 2018 Vessel Collision Accident

▪ Development of a Digital Twin based on BIM

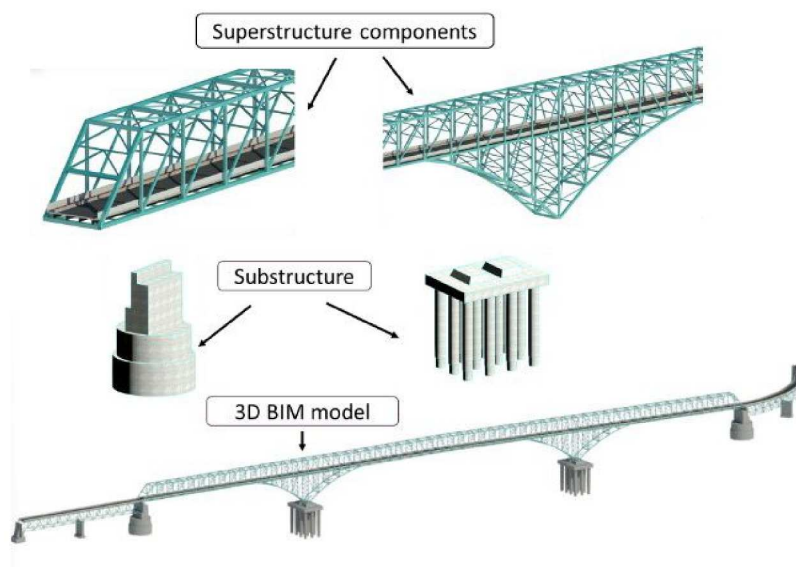
The development of the digital twin of the Oshima Bridge, based on BIM, follows the workflow illustrated in **Figure 6.5(a)**. Key steps in the modeling process are as follows:

- Data acquisition: Accurate representation of the existing structure requires comprehensive data collection, including design reports, as-built drawings, and construction records. These documents are typically sourced from the asset owner or relevant public authorities to ensure model fidelity.

- BIM modeling using Autodesk Revit: Both substructure and superstructure elements are modeled as BIM components, referred to as Revit families. These components are assembled within a unified project environment to construct an integrated 3D model of the bridge system. The final digital twin is shown in **Figure 6.5(b)**.
- Parametric design automation: To improve efficiency, the Dynamo visual programming interface is used to automate repetitive tasks and enable dynamic parameter control. This interaction with the Revit API significantly enhances productivity for modelers and engineers.



(a) Digital Twin model development Workflow



(b) Details of Bridge Models

Figure 6. 5 Development of a Digital Twin based on BIM

- **Virtual Reality (VR) visualization using BIM bridge model**

By integrating virtual reality (VR) with BIM-based digital twins, immersive 3D visualization of bridge models can be achieved, as shown in **Figure 6.6**. Stakeholders can interact with the structure in the virtual environment to deepen their understanding of design characteristics, simulate maintenance scenarios, and support lifecycle planning. Using tools such as VR headsets and Microsoft HoloLens, engineers and decision-makers can remotely assess the condition of the structure, collaborate in real time, and intuitively identify potential issues. This integration supports diverse applications such as technical training, safety assessments, and data-driven decision-making throughout the operational lifespan of a bridge, making it a valuable asset in modern infrastructure management.

However, the current implementation primarily relies on qualitative feedback, with potential for improvement in spatial understanding and communication among stakeholders. Future research will include structured usability studies to quantitatively evaluate the impact of VR on decision-making accuracy, task completion time, and error rates, compared to traditional two-dimensional inspection methods.

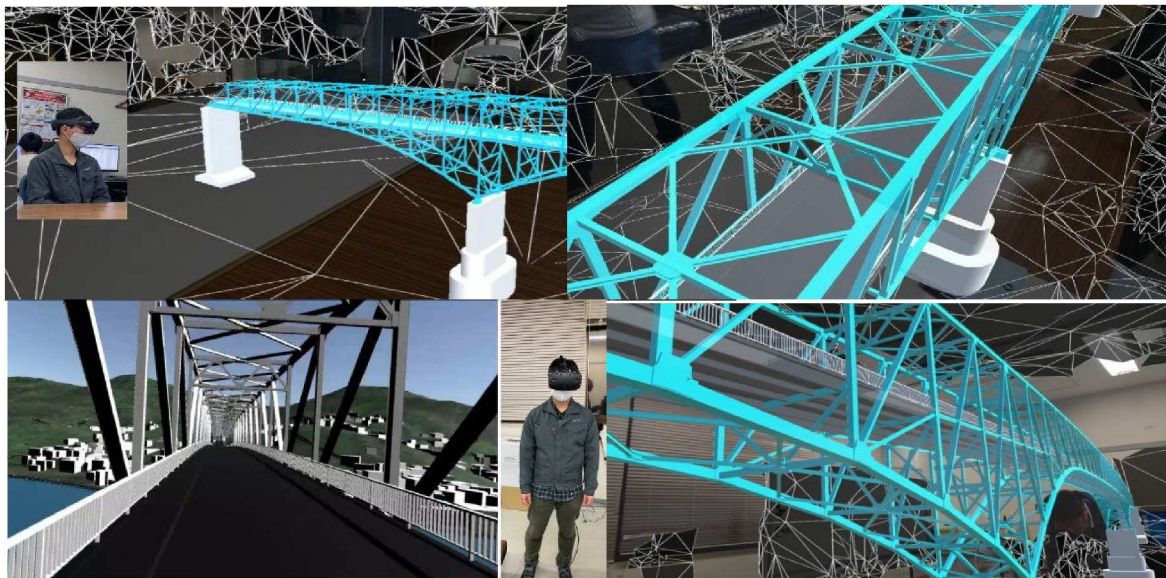


Figure 6. 6 Virtual Reality(VR) of Oshima Bridge

6.3. GNSS Displacement Monitoring

- **Overview of GNSS observation on the target bridge**

A three-span continuous steel Pratt truss bridge at Yamaguchi Prefecture, Japan. In October 2018, the bridge sustained damage when a cargo vessel collided with its center span. To monitor the structural recovery following the incident, GNSS displacement observations were conducted, as illustrated in **Figure 6.7**. GNSS receivers were strategically installed at five locations, specifically at the center of each span and on the piers (G1, G2, G3, G4, and G5). The data acquired from these observations provide valuable insights

for identifying structural anomalies and evaluating the bridge's deformation behavior over time. The GNSS displacement monitoring was carried out over a period of two years, from November 14, 2018, to November 3, 2020. The collected data included both RTK and static displacement measurements in three dimensions: longitudinal, transverse, and vertical directions. In this study, however, only the static positioning data are utilized for analysis due to their higher accuracy and reliability in capturing long-term displacement trends.

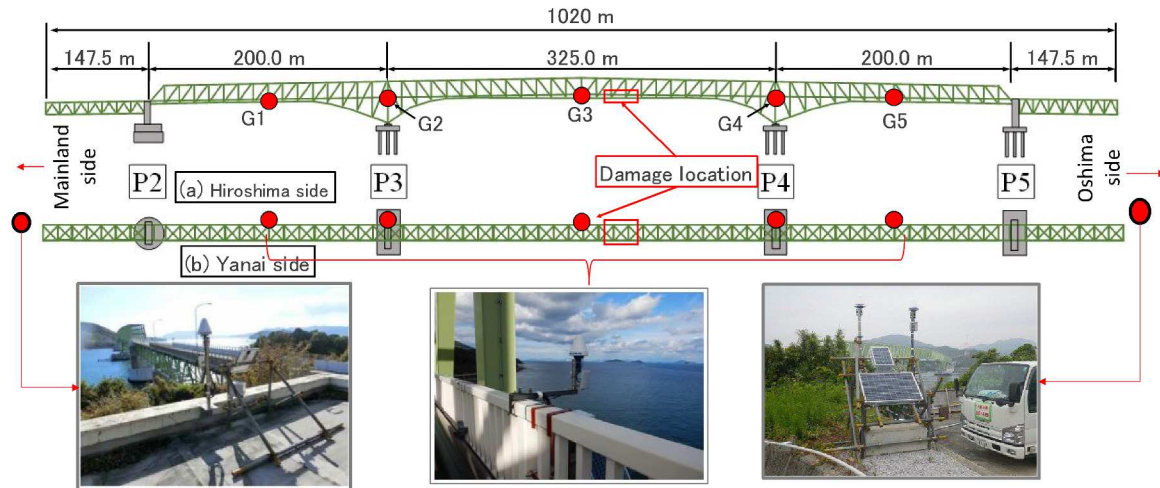


Figure 6. 7 Overview of GNSS observation

▪ Longitudinal(LG) displacement at the observation point

The results of the bridge deformation in the longitudinal direction, based on GNSS observations at the Oshima Bridge, are shown in **Figure 6.8**. The figure illustrates that observation point G1 experienced minimal deformation along the longitudinal axis. Point G2 exhibited noticeable deformation in the same direction, while point G3 showed only minor displacement. In contrast, significant longitudinal deformation was observed at points G4 and G5, indicating a greater structural response in those observation points.

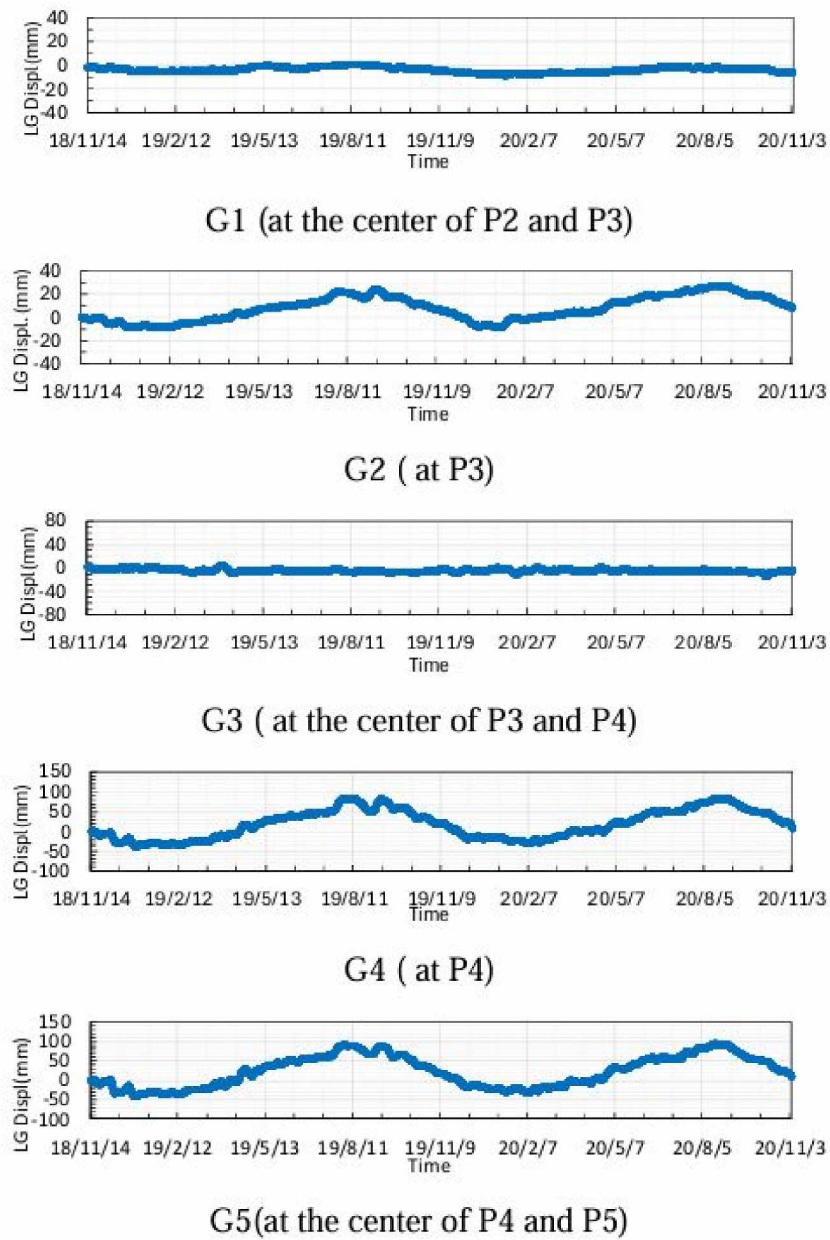


Figure 6. 8 Bridge deformation in the LG direction at the GNSS observation point

▪ **Transversal(TR) displacement at the observation point**

The results of bridge deformation in the transverse direction, as observed through GNSS measurements, are presented in **Figure 6.9**. Point G1 exhibited minimal deformation, while Point G2 showed slight displacement, though not significant. Points G3 and G4 also recorded very small deformations and Point G5 displayed similarly negligible movement. Overall, the GNSS observations indicate that transverse

deformation across all monitoring points was minimal and did not significantly affect the structural integrity of the bridge. This indicates that the bridge responded well in terms of lateral stability during the post-collision monitoring period.

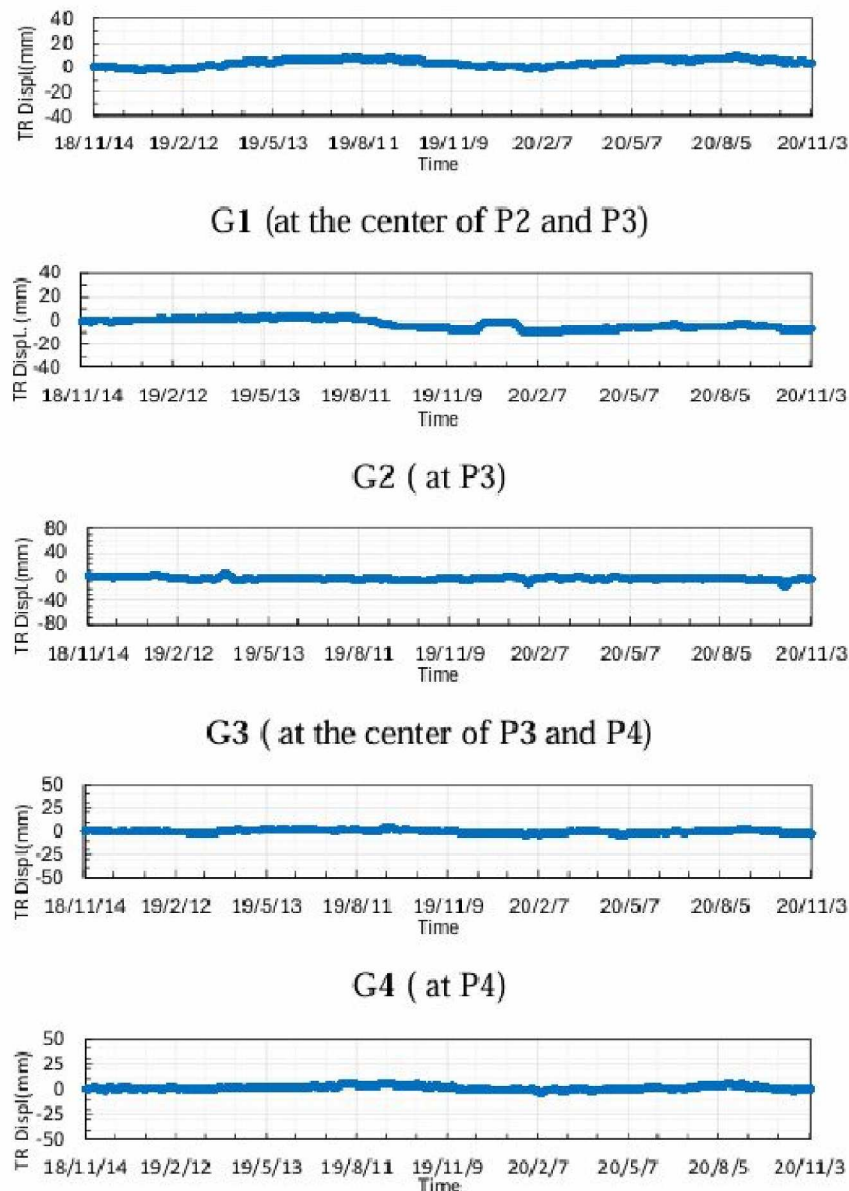


Figure 6. 9 Bridge deformation in the TR direction at the GNSS observation point

- **Up and Down displacement at the observation point**

In the case of vertical (up-and-down) deformation, a critical displacement was observed at the G3 location, as shown in **Figure 6.10**. This point corresponds to the area where the cargo vessel collided with the

bridge. The impact caused significant damage to several structural members at this location, resulting in excessive vertical displacement. Due to the severity of the damage, the bridge was temporarily closed to all traffic to allow for emergency inspections, maintenance, and structural rehabilitation. The critical deformation observed at G3 highlights the vulnerability of the structure at the impact zone and underscores the importance of continuous monitoring during recovery efforts.

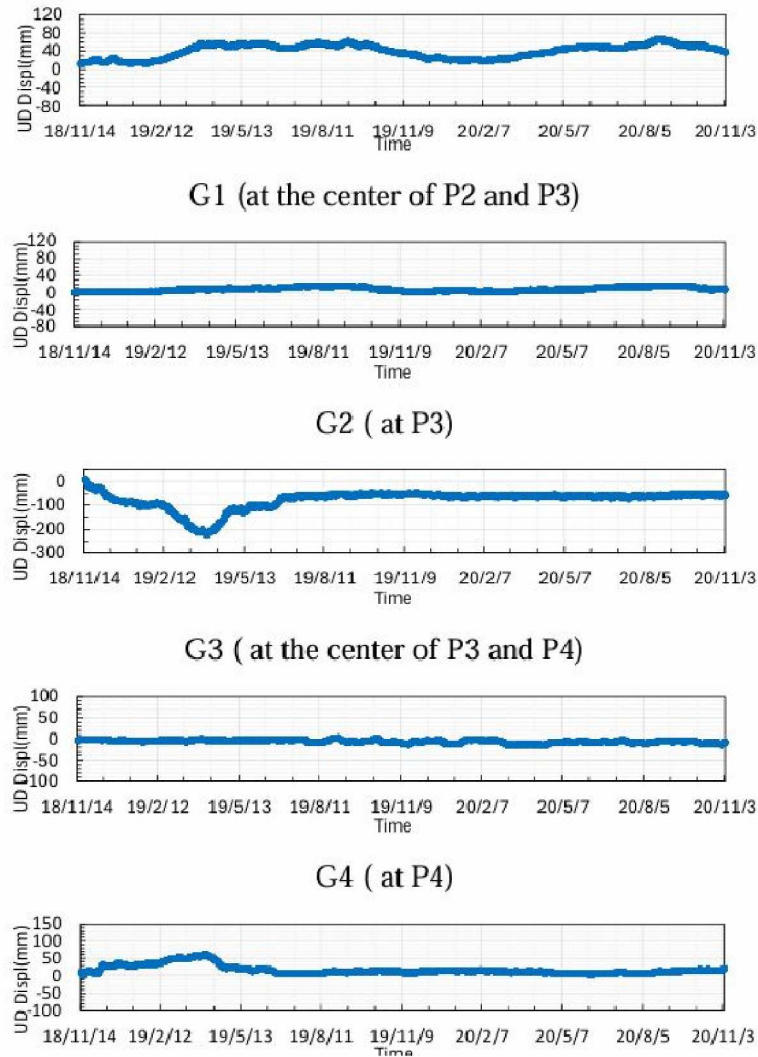


Figure 6. 10 Bridge deformation in the Up and Down direction at the GNSS observation point

6.4. Structural Simulation and Validation

▪ Ship Collision Assumption

In this study, structural damage was assumed in specific bridge members, and the resulting deformation of the entire bridge system was assessed, as illustrated in **Figure 6.11**. Case 1 involved reconstructing the

actual accident, serving as the baseline damage scenario. Cases 2 and 3 simulated hypothetical collisions occurring on the Oshima side, where the lower chord and lower horizontal members were designated as damaged elements. In Case 4, a more severe collision scenario was considered, positioned further along the Oshima side compared with Case 3. In this case, damage was assigned to the lower chord, lower horizontal members, and the diagonal members to represent a higher-impact condition. A linear elastic model was adopted for all simulations, consistent with the analytical scope of this chapter. While linear modeling adequately captures global deformation tendencies and comparative behavior across scenarios, it does not fully represent the nonlinear mechanisms associated with collision events. Realistic impact behavior typically involves contact interactions, material plasticity, local buckling, and potential crack initiation. Incorporating these nonlinear effects would enhance the accuracy and fidelity of the simulation; however, such advanced modeling is reserved for future research as part of the planned development of a more comprehensive digital twin framework.

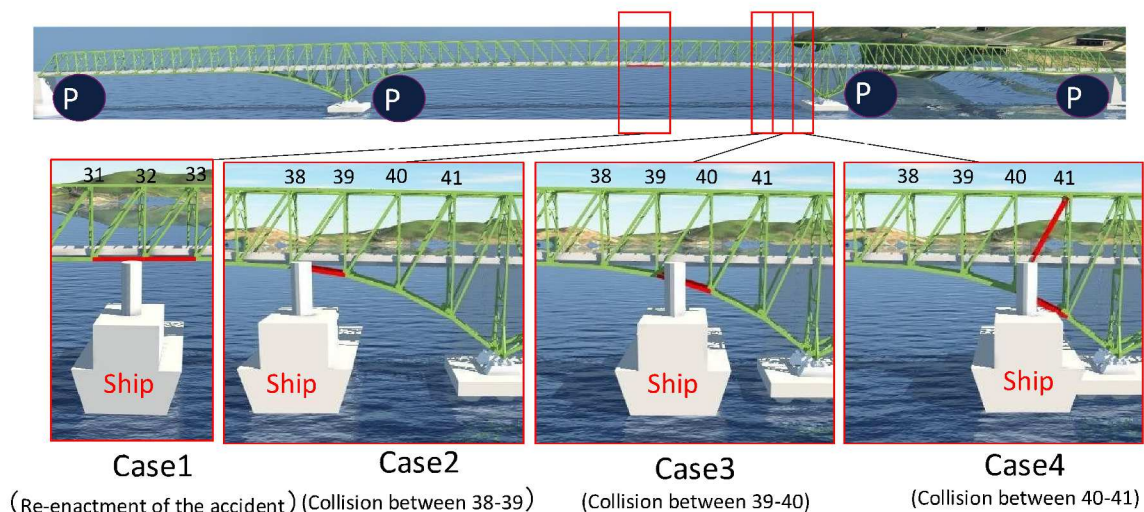


Figure 6. 11 Ship Collision Assumption

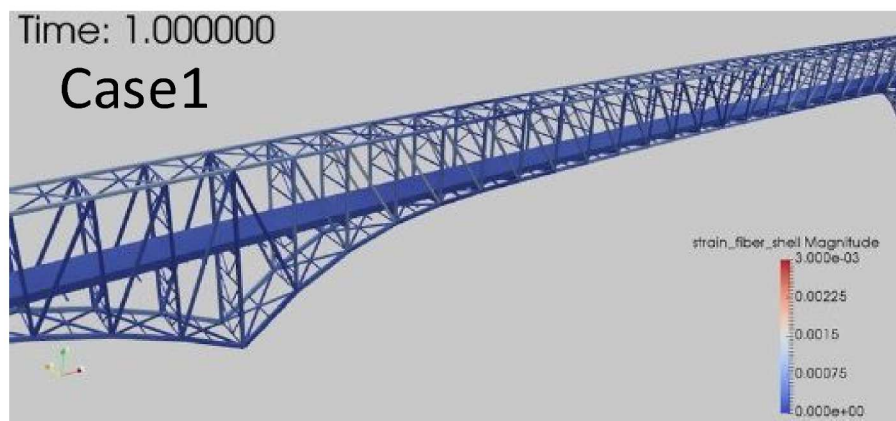
▪ Simulation of Structural Deformation Behavior

The linear analysis of FEA was used to simulate the deformation response of the bridge. The simulation results showed the following main observations, as illustrated in **Figure 6.12**.

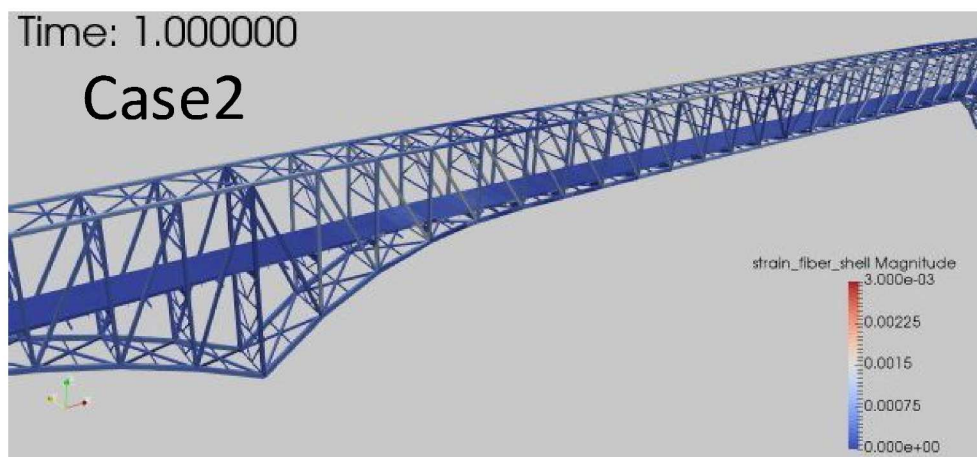
- In Case 1, the structure maintained complete stability, and no significant deformation occurred.
- In Cases 2 and 3, despite localized beam damage, additional displacement was minimized, demonstrating sufficient redundancy and load redistribution capability.
- In Case 4, overall deformation increased significantly in the central region and connection nodes near the particularly affected or collided area.

The results indicate that a critical loss of stiffness occurred approximately 3 seconds after the impact, indicating a threshold beyond which structural stability is compromised. These results emphasize the

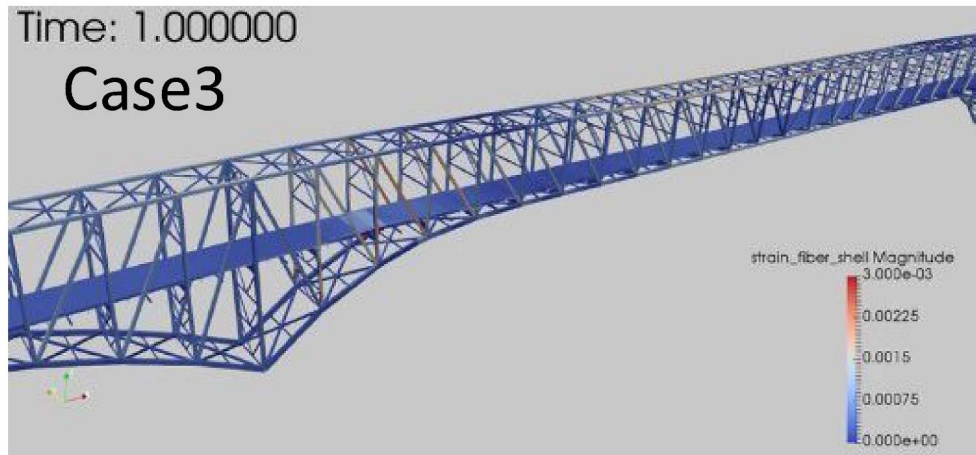
importance of appropriately capturing nonlinear behavior in damage scenarios, particularly in long-span truss bridges that are vulnerable to progressive failure modes.



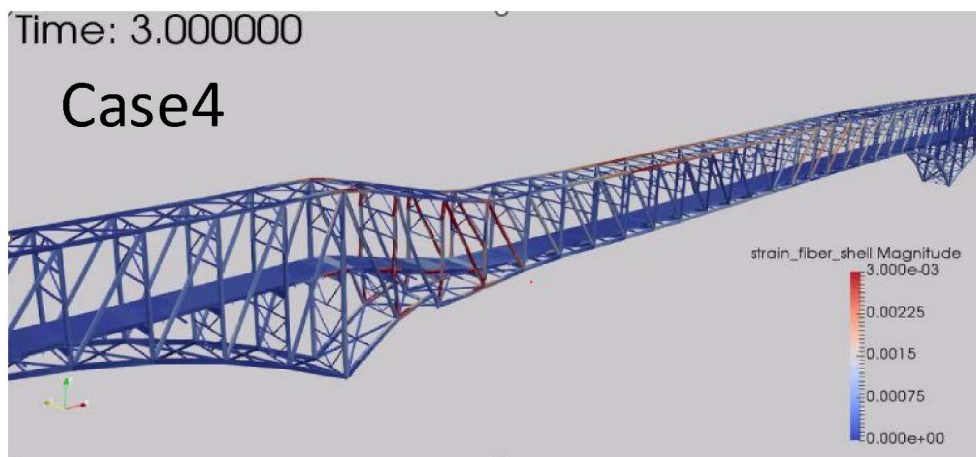
(a) Case 1



(b) Case 2



(c) Case 3



(d) Case 4

Figure 6. 12 Deformation Simulation

▪ GNSS-Based Displacement Monitoring and Model Validation

To verify the accuracy of the digital twin, GNSS-based field displacement data was collected during a continuous monitoring period from November 14, 2018, to November 3, 2020. At key points of the bridge structure, both real-time kinematic (RTK) and static positioning methods were used to obtain 3D displacement measurements in the longitudinal, transverse, and vertical directions. GNSS observation results showed high displacement at G3(at the center of P3 and P4) collision site, with significant deformation observed in the vertical direction. These results were consistent with the finite element analysis (FEA) predictions of Scenario 4, which simulated extensive component damage in the same area. The agreement between the measured and simulated displacements (in terms of magnitude and directional trends)

confirmed the consistency of the structural model and supported the effectiveness of near-real-time performance evaluation using a GNSS-integrated digital twin.

While the correlation between FEA and GNSS data validates the current model’s predictive capability, key limitations persist. Notably, the absence of direct physical verification, such as material property testing, residual stress evaluation, or on-site inspection of damaged elements, limits the ability to fully confirm the damage assumptions used in simulation scenarios. Therefore, Future work will focus on enhancing the calibration accuracy of the digital twin through

- (1) Material and structural sampling to validate mechanical properties and corrosion effect
- (2) Non-destructive evaluation (NDE) techniques, such as ultrasonic testing for internal damage detection
- (3) Scheduled visual inspections to track progressive deterioration and compare with simulated forecasts.

6.5. Comparison between traditional Inspection and the Digital Twin-based approach

Compared to traditional bridge inspection methods in Japan (which are typically visual inspections conducted every five years and are labor-intensive), the proposed framework offers several operational advantages. These include continuous structural monitoring, remote access, and high-resolution 3D visualization, all of which support more proactive, data-driven decision-making. Table 6.1 summarizes the key differences between conventional inspection methods and the proposed digital twin-based approach. The DT-based workflow demonstrates significant advantages over traditional post-accident inspection by enabling real-time deformation monitoring and simulation-based verification.

Table 6. 1 Comparison Between Traditional Inspection and the Proposed Digital Twin-Based Approach

Aspect	Traditional Inspection (Japan)	Digital Twin-Based Approach
Frequency	Periodic (every 5 years)	Continuous (daily or real-time)
Method	Visual/manual	Automated
Data Quality	Subjective	Quantitative
Coverage	Localized (inspection points only)	Full-structure coverage
Accessibility	On-site required	Remote monitoring available

6.6. Conclusion and Limitation

This study presents an integrated BIM-GNSS digital twin framework for lifecycle bridge management, demonstrated through a real-world application to the Oshima Bridge. The framework enables near-real-time displacement monitoring, FEA correlation, and immersive VR visualization. However, limitations include the absence of bidirectional model updating, lack of embedded AI analytics, and limited validation beyond

GNSS data. Future work will focus on incorporating edge computing for real-time data streaming, AI-based anomaly detection, physical degradation testing, and broader applications across infrastructure typologies.

6.7. Reference

1. H. Wenzel, *Health Monitoring of Bridges*, John Wiley & Sons, 2009
2. World Bank, *Infrastructure at the Crossroads: Lessons from 20 Years of World Bank Experience*, Washington, DC, 2006. <http://documents.worldbank.org/curated/en/263111468139507126>
3. Ministry of Land, Infrastructure, Transport and Tourism (MLIT), *Infrastructure Maintenance Yearbook*, Tokyo, Japan, 2018
4. C. R. Farrar and K. Worden, *Structural Health Monitoring: A Machine Learning Perspective*. Chichester, UK: John Wiley & Sons, 201
5. C. Eastman, P. Teicholz, R. Sacks, and K. Liston, *BIM Handbook: A Guide to Building Information Modeling for Owners, Managers, Designers, Engineers and Contractors*, 2nd ed. Hoboken, NJ: Wiley, 2011
6. B. Succar, "Building information modeling framework: A research and delivery foundation for industry stakeholders," *Automation in Construction*, vol. 18, no. 3, pp. 357–375, May 200
7. E. E. Tita, G. Watanabe, P. Shao, and K. Arai, "Development and application of Digital Twin–BIM technology for bridge management," *Applied Sciences*, vol. 13, no. 13, p. 7435, 2023. doi: 10.3390/app131374
8. E. E. Tita, G. Watanabe, H. da C. Ximenes, and H. M. S. Viegas, "Initiatives in Dili of Timor-Leste for implementing traffic management using digital twin-BIM technology," *Journal of Smart Cities and Environmental Infrastructure and AI*, vol. 5, no. 1, pp. 42–56, 2024. doi: 10.11532/jsceiia.5.1_4
9. H. Saputra, R. Pratama, E. E. Tita, and M. Yusa, "Comparative analysis of quantity take-off material between conventional method & BIM Nemetschek All plan method on bridge," *Civil Engineering and Architecture*, vol. 12, no. 4, pp. 2622–2633, 2024. doi: 10.13189/cea.2024.12041
10. M. Grieves and J. Vickers, "Digital Twin: Mitigating unpredictable, undesirable emergent behavior in complex systems," in *Transdisciplinary Perspectives on Complex Systems*, F.-J. Kahlen, S. Flumerfelt, and A. Alves, Eds. Cham: Springer, 2017, pp. 85–11
11. C. Boje, A. Guerriero, S. Kubicki, and Y. Rezgui, "Towards a semantic construction digital twin: Directions for future research," *Automation in Construction*, vol. 114, p. 103179, 20
12. F. Moschas and S. Stiros, "Measurement of the dynamic displacements and of the modal frequencies of a short-span pedestrian bridge using GPS and an accelerometer," *Engineering Structures*, vol. 33, no. 1, pp. 10–17, Jan. 2011.
13. R. Xi, Q. He, and X. Meng, "Bridge monitoring using multi-GNSS observations with high cutoff elevations: A case study," *Measurement*, vol. 168, p. 108303, 2021. doi: 10.1016/j.measurement.2020.108303.
14. Ministry of Land, Infrastructure, Transport and Tourism (MLIT), *i-Construction and National Resilience Initiatives*, 2020. <https://www.mlit.go.jp>.
15. Honshu-Shikoku Bridge Authority. (2019). *Technical Overview of Major Bridges in Japan*.
16. Japan Transport Safety Board (JTSB). (2019). *Marine Accident Investigation Report – Collision of Cargo Vessel with Oshima Bridge*.

7. Data Assimilation and Machine Learning for Bridge Displacement Estimation Using RTK-GNSS: A Perspective on Robust Prediction and Uncertainty Quantification

Overview

As demonstrated in Chapter 6, reliable structural assessment under abnormal and emergency conditions requires more than direct interpretation of monitoring data, as observations are often noisy, incomplete, and influenced by environmental disturbances. This chapter addresses this challenge by focusing on robust state estimation methodologies that enable an operational digital twin to infer the underlying structural behavior from uncertain measurements. Specifically, probabilistic data assimilation and machine learning techniques are introduced to process GNSS-based displacement observations and to estimate the structural state in a stable and uncertainty-aware manner. By transforming raw monitoring data into physically interpretable state variables, this chapter establishes a critical analytical layer that allows the digital twin to function as a reliable engineering decision-support system rather than a descriptive monitoring platform.

7.1. Introduction

(1) Research Background and Objectives

In many countries, numerous bridges constructed during the rapid economic growth era have now exceeded 50 years of service life, creating an urgent need for enhanced inspection and repair activities. This situation is particularly pronounced in Japan, where a large proportion of bridges were constructed in the 1960s and 1970s. The growing demand for maintenance is further exacerbated by increasing labor demands, rising inspection costs, and a shortage of experienced engineers. These challenges underscore the necessity for innovative technologies capable of conducting efficient and high-precision assessments of the long-term structural health of infrastructure.

Against this backdrop, three-dimensional displacement monitoring using the Global Navigation Satellite System (GNSS), including the Global Positioning System (GPS) [1,2], has gained attention as a technology that provides non-contact, high-frequency, and high-precision capabilities for continuous observation of structural displacements and dynamic responses. Although originally developed for military applications, GNSS was adapted for geodetic and surveying purposes in the 1990s, with its application to infrastructure monitoring accelerating following the discontinuation of Selective Availability (SA) in 2000. In Japan, early implementations targeted slopes and dams to mitigate disaster risks [3,4], followed by research on enhancing RTK-GPS reliability in urban environments [5] and developing continuous monitoring methods in landslide-prone regions [6].

In the bridge engineering field, GNSS applications began with evaluating wind-induced deformations in suspension bridge stiffening girders [7] and have since expanded to encompass the identification of

vibration and dynamic characteristics, such as natural frequencies [8,9]. More recently, diverse applications for maintenance and construction monitoring have been actively developed [10–13]. In addition, the integration of GNSS with IoT sensors and SAR imagery [14], time-series prediction of structural behavior [15], and fusion with artificial intelligence (AI) and digital twin technologies [16] have been advancing bridge monitoring toward higher accuracy and real-time performance.

Building on these technological advancements, this study aims to quantify structural responses to temperature and other environmental factors and detect early signs of anomalies through continuous, automated three-dimensional GNSS-based displacement monitoring of bridges. Ultimately, the goal is to develop advanced maintenance strategies by integrating AI-driven analytics with digital twin frameworks, thereby contributing to more efficient and data-driven bridge management.

(2) Related Work and Contribution of this study

In GNSS-based bridge monitoring, it is essential to accurately and reliably estimate structural behavior from observation data affected by environmental variations and non-stationary noise. Traditionally, sequential data assimilation methods, such as the Kalman Filter and its ensemble-based variant, the Ensemble Kalman Filter (EnKF), have been widely applied in this context [9]. In recent years, there has been a growing interest in machine learning techniques, which can capture nonlinear effects in predicting structural behavior. Among these, decision tree-based approaches, such as the Random Forest (RF), have shown promising performance [15].

Furthermore, research has advanced in processing multivariate data and integrative analysis of asynchronous datasets by combining Kalman filtering with AI and sensing technologies. For example, Ma et al. [17] proposed an application of the Kalman Filter that addresses the issue of asynchrony in structural displacement estimation using visual information and accelerometer sensors, achieving a balance between real-time performance and accuracy. Similarly, Forootan et al. [18] demonstrated improved displacement prediction accuracy of GNSS data by integrating Kalman filtering with neural networks in bridge monitoring, highlighting the potential of advanced methods based on sensor data fusion. In addition, Shen et al. [19] conducted a comprehensive review of GNSS-based structural monitoring technologies, summarizing their diverse applications in the field of dynamic monitoring. These studies collectively indicate that displacement estimation technologies are evolving toward higher accuracy, taking into account the characteristics of sensor data and the consistency of time-series information.

However, systematic comparative evaluations of fundamentally different approaches – such as EnKF and RF – applied to the same bridge and identical GNSS datasets remain scarce, and empirical studies that organize their estimation performance and applicable conditions are limited [9, 16, 17]. In this study, it is demonstrated that both EnKF and RF, despite their differing methodologies, can accurately reproduce displacements and thereby contribute to the effective utilization of RTK-GNSS data. Notably, EnKF can provide not only predictions but also quantitative assessments of uncertainty. A better understanding of the characteristics of both approaches offers practical guidance for selecting estimation techniques in GNSS displacement monitoring and contributes to the provision of foundational data for bridge health assessment.

7.2. Case Study Bridge and GNSS Data Characteristics

(1) Case Study: Bridge Monitoring System

This study focused on the Shin-Yahata River Bridge, a five-span continuous curved steel box girder bridge located in Hiroshima City. By selecting a girder bridge type widely used in Japan, the applicability of GNSS monitoring to general-purpose bridges was evaluated. **Figure 7.1** presents an overview of the target bridge and the installation layout of the measurement devices. A reference station was installed at a park adjacent to the A2 abutment, while four rover stations (MG-300, Furuno Electric Co., Ltd.)—R1 through R4—were mounted on the bridge deck. These observation points were strategically located at either midspans or near supports of each span to capture the global behavior of the bridge, focusing on positions with large expected structural displacements and representative of overall structural behavior. This configuration enables characterization of span-by-span displacement distributions and time-series variations in the relative displacements of the bridge.

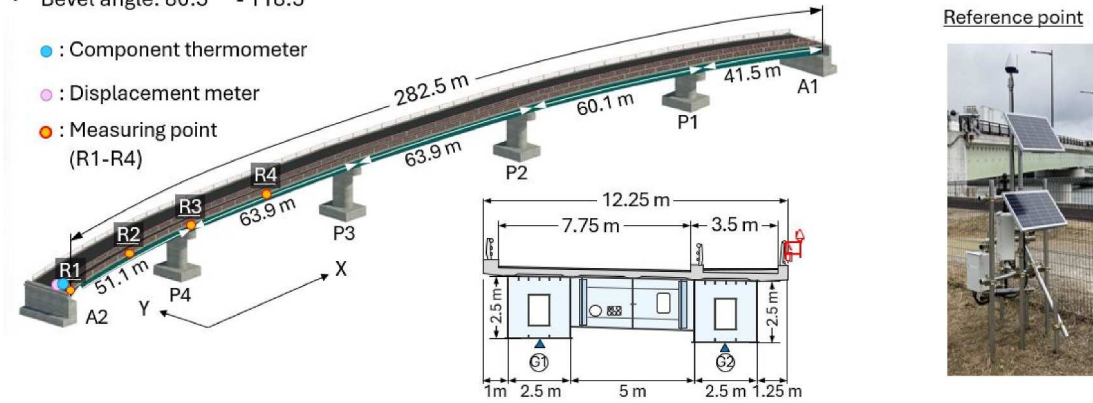
Both static measurements and RTK-GNSS positioning were employed, leveraging their respective advantages. Static measurements provided high-precision displacement data at hourly intervals, suitable for identifying long-term displacement trends. In contrast, RTK-GNSS positioning acquired measurements every 5 min, enabling high real-time detectability of displacements. The monitoring campaign was conducted for approximately 14 months, from January 2022 to March 2023.

To validate the accuracy of GNSS displacement measurements, a contact-type displacement transducer (SDP-300E, Tokyo Measuring Instruments Laboratory Co., Ltd.) was installed at the downstream bearing of the A2 abutment to measure the X-axis relative displacement between the superstructure and the abutment parapet. Furthermore, to assess the influence of environmental factors on superstructure deformation, a structural temperature sensor was mounted inside the box girder near the R1 observation point to record the time-series temperature of the superstructure, which is closely associated with longitudinal deformation.

By employing GNSS, displacement behavior caused by temperature variations and other factors can be monitored with a precision on the order of millimeters, enabling real-time acquisition of essential information for health condition assessment, early anomaly detection, and decision-making regarding traffic closures during disasters. **Figure 7.2** presents an overview of the monitoring system. Displacement data obtained from GNSS sensors are transmitted to a cloud server, where results are visualized for remote monitoring via the Internet.

5-span continuous steel box girder curved bridge + RC abutment, RC pier.

- Bridge Length: 282.5m (51.1+63.9+63.9+60.1+41.5)
- Width: 12.25m (roadway section 7.7m, sidewalk section 3.5m)
- Bevel angle: 80.5° - 118.5°



(a) Entire bridge overview

(b) GNSS reference station



(c) GNSS rover station (d) Contact-type Displ. Gauge (e) Member Temperature Sensor

Figure 7. 1 Overview of the target bridge and installation of measurement instruments

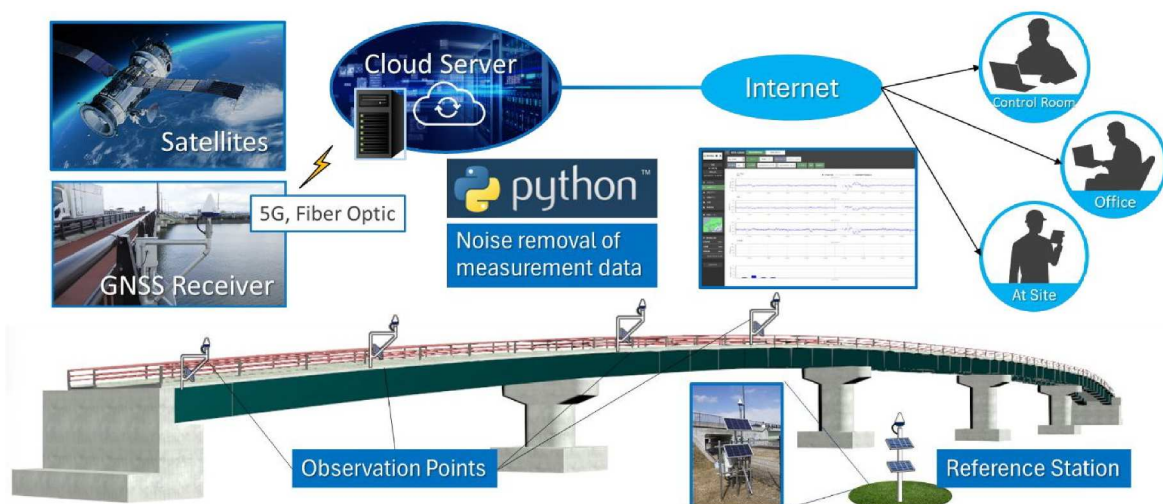


Figure 7. 2 GNSS real-time monitoring system

(2) Case Study: Bridge Monitoring System

The RTK-GNSS measurement data used in this study, while offering excellent real-time capability, are highly sensitive to satellite reception conditions and weather, and thus tend to contain significant noise. As shown in **Figure 7.3**, sporadic outliers were observed in the RTK-GNSS displacement measurements. A comparison with static GNSS measurements and contact-type displacement sensor data confirmed that, although RTK-GNSS performs well in terms of immediacy, its measurement reliability can deteriorate under certain conditions.

To mitigate the influence of such noise and improve the reliability of displacement estimation, an outlier removal process was first implemented using a sliding-window k-nearest neighbor method. In this approach, values deviating substantially from recent displacement trends are regarded as outliers, with determinations made based on consistency with surrounding data. Outlier detection focuses on the relative difference from preceding observations, identifying data points that significantly diverge from neighboring values.

Subsequently, displacement smoothing was attempted using a conventional linear Kalman filter. However, as shown in **Figure 7.4**, although some outliers were eliminated, the smoothing effect was insufficient due to the linearity constraints of the filter.

Therefore, two advanced estimation methods were applied: the model-based data assimilation approach, the Ensemble Kalman Filter (EnKF), which enables flexible state estimation, and the data-driven machine learning method, Random Forest (RF), which can capture nonlinear relationships. Their estimation performances were systematically compared.

It is noteworthy that, as shown in **Figure 7.5**, a clear correlation was observed between the temperature of bridge components and the measured displacements. This relationship provides the basis for incorporating temperature as an explanatory variable in displacement estimation, as discussed later, and is expected to contribute to improved estimation accuracy in this study.

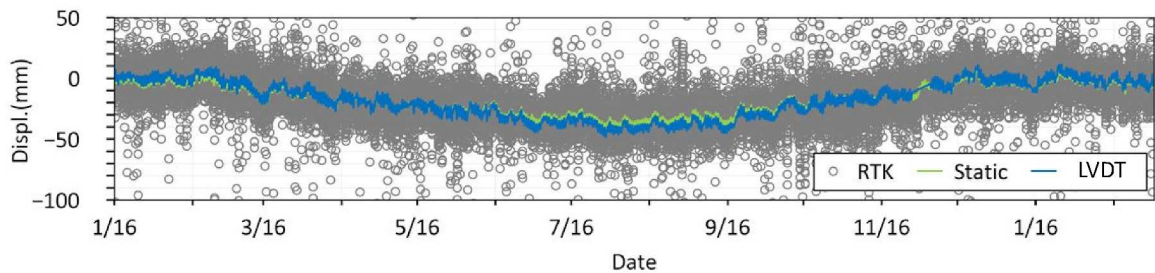


Figure 7. 3 Comparison of displacements at measurement point R1 obtained using different measurement methods (RTK-GNSS, static GNSS, and displacement gauge)

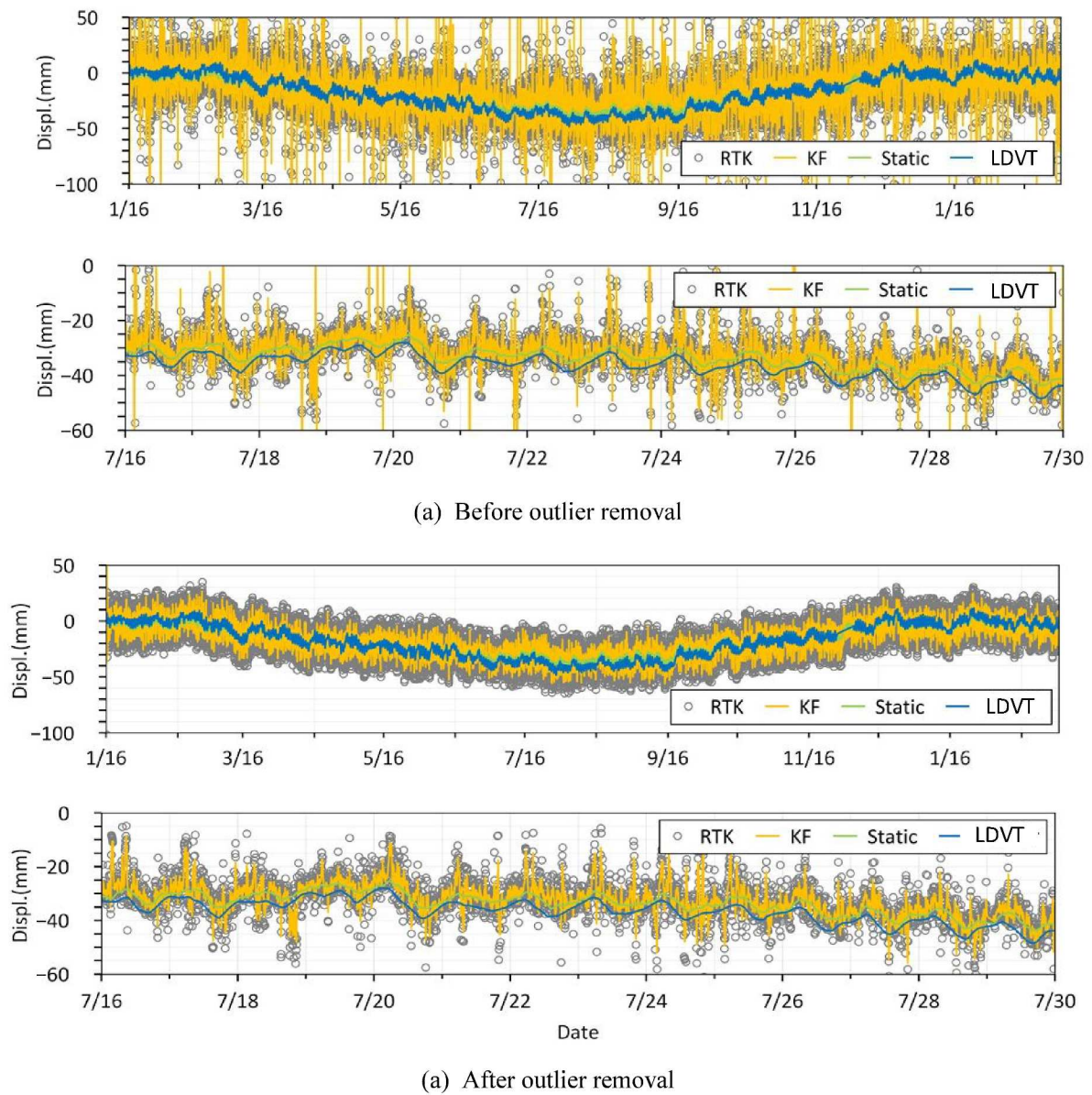


Figure 7.4 Smoothing results using linear least squares estimation

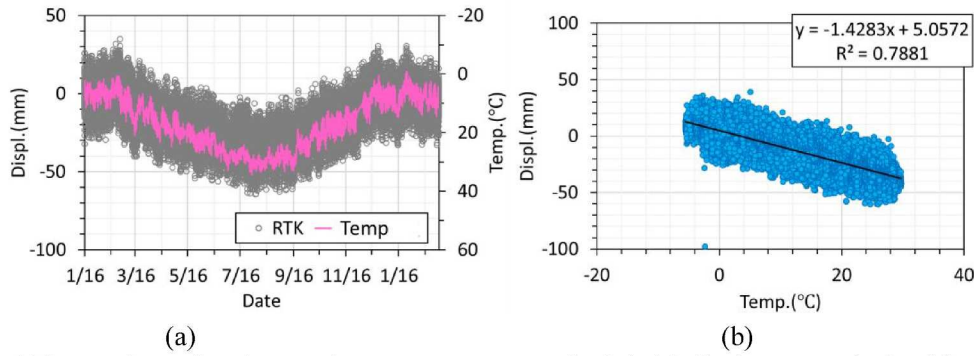


Figure 7. 5 Time-series estimation results at measurement point R1: (a) displacement obtained from RTK-GNSS observations and corresponding member temperature, and (b) their correlation

7.3. Displacement Estimation Methods and Application Results

(1) Displacement Estimation Using EnKF

As noted earlier, when the conventional linear Kalman Filter (KF) was applied, the presence of outliers in the RTK-GNSS observation data, the inherent nonlinearity of the time-series data, and the linearity constraints of the model hindered accurate tracking of the true displacement values. To overcome these limitations, the Ensemble Kalman Filter (EnKF) was employed, offering enhanced capability to accommodate uncertainty and nonlinear system behavior. The EnKF represents the probability distribution of the system state through multiple state estimation samples (ensembles) and enables both state estimation and quantification of the associated uncertainty. The detailed mathematical formulation and processing workflow are illustrated in **Figure 7.6**.

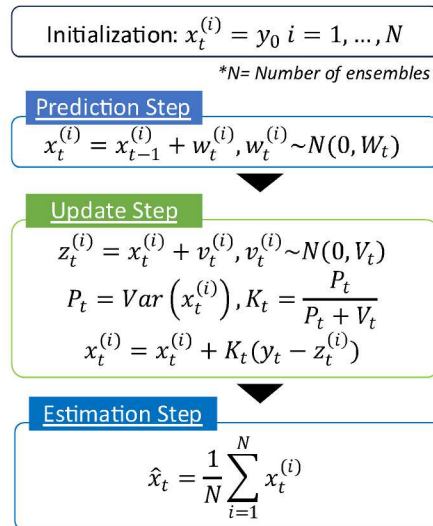


Figure 7. 6 Processing flow and estimation model structure of the Ensemble Kalman Filter (EnKF)

In this study, particular attention was given to the selection of the process noise variance W_t and the observation noise variance V_t , as the EnKF estimation results are highly sensitive to these parameters. The following procedure was adopted: first, a low-pass filter with a time window of 36 samples (equivalent to 3 hours), as expressed in **Equation (7.1)**, was applied to the RTK-GNSS observations. The variance of the first-order differences of the resulting moving-average smoothed values, calculated using **Equation (7.2)**, was then used to estimate W_t . Next, the variance of the differences between the raw GNSS observations and their moving-average smoothed values, determined using **Equation (7.3)**, was used to estimate V_t .

$$\hat{y}_t = \frac{1}{w} \sum_{i=t-w/2}^{t+w/2} y_i \quad (7.1)$$

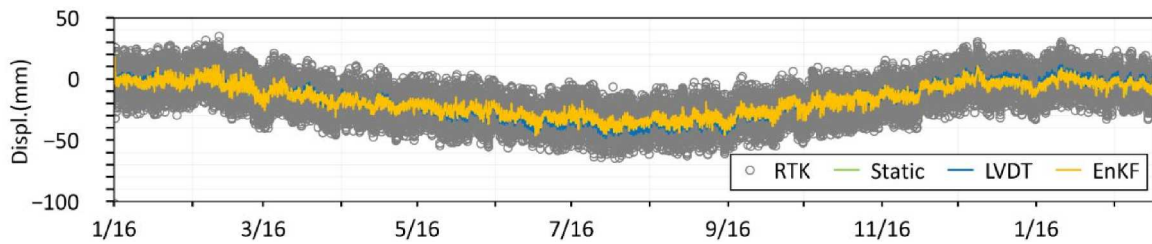
$$W_t = \text{Var}(\hat{y}_t - \hat{y}_{t-1}) \quad (7.2)$$

$$V_t = \text{Var}(y_t - \hat{y}_t) \quad (7.3)$$

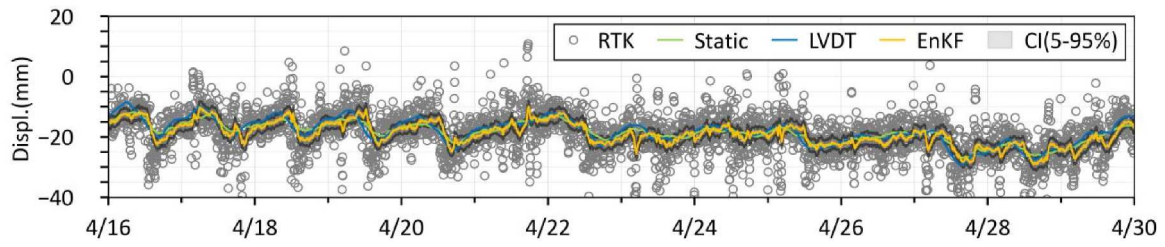
The estimated process and observation noise variances were $W_t = 0.0605$ and $V_t = 33.06$ respectively. These parameters directly influence both the estimated error bounds and the smoothness of the displacement trends. Optimizing their values remains an important task for practical implementation in real-world monitoring environments.

In the comparative analysis conducted in this study, the conventional KF was not applied with a temperature increment term in the smoothing process. This decision was made to ensure fairness, as the fundamental principles of the KF differ from those of the proposed EnKF. Evaluating the performance improvements achievable through such a combination is left for future work.

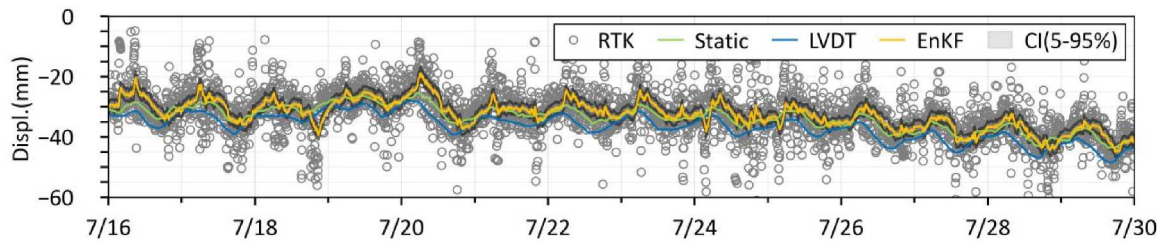
Figure 7.7 presents the displacement estimation results obtained using the EnKF. In both the KF and the EnKF applied here, external explanatory variables such as temperature were not explicitly incorporated into the state or observation equations, and no temperature difference terms were included in the prediction model.



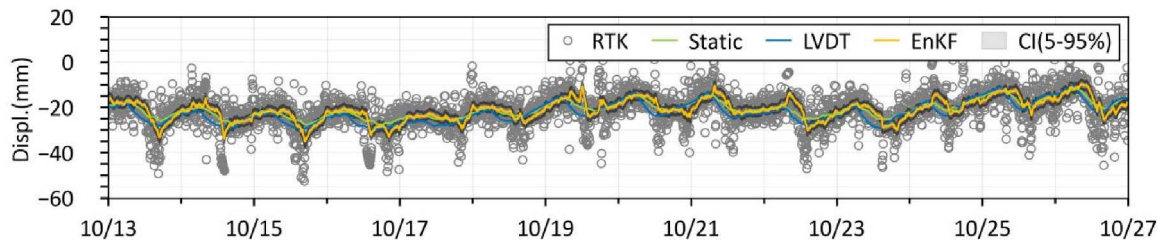
(a) Entire period



(b) April 16 – April 30



(c) July 16 – July 30



(d) October 13 – October 27

Figure 7. 7 Displacement estimation results obtained using the Ensemble Kalman Filter (EnKF), showing the overall observation period and three selected sub-periods in enlarged views. The shaded area represents the 5–95% confidence interval.

- **Panel (a)** illustrates the results for the entire observation period, revealing clear long-term displacement patterns across different seasons. Comparisons with static measurement results and displacement gauge data showed small mean errors and high agreement throughout.
- **Panel (b)** corresponds to a winter period characterized by low temperatures and small diurnal variations, where the influence of temperature fluctuations was minimal. Under these conditions, the results from all three methods nearly overlapped, demonstrating stable estimation performance.
- **Panel (c)** shows a summer period with high temperatures and large diurnal variations, during which the EnKF exhibited strong responsiveness to short-term displacements associated with day–night temperature changes. In this case, the displacement gauge recorded slightly larger amplitudes than both the static measurements and the EnKF estimates.

- **Panel (d)** represents an autumn period with intermediate meteorological conditions. The three methods again exhibited high agreement, with consistent performance in both short-term fluctuations and long-term trends.

The shaded gray areas in Figure 7 indicate the 5% confidence intervals, calculated from the 2.5th and 97.5th percentiles of the ensemble distribution at each time step. These intervals allow for a statistical assessment of both the central tendency of the estimates and their associated uncertainty.

Overall, the results confirm that the EnKF maintains both high responsiveness and stability under varying short-term temperature fluctuations and external disturbances, providing consistent displacement estimates across diverse seasonal and meteorological conditions. While the parameter values were determined from approximately one year of RTK-GNSS data, the estimation process itself operates sequentially at 5-minute intervals, enabling near real-time displacement monitoring

(2) Machine Learning (Random Forest)

- As an alternative displacement estimation approach, the Random Forest (RF) method was employed. RF is a representative ensemble learning technique that constructs multiple decision trees and averages their predictions, thereby reducing overfitting while achieving high predictive accuracy. The Random Forest model does not function merely as a black-box estimator; rather, it extracts physically interpretable decision rules that reflect the thermo-mechanical behavior of the bridge. Analysis of the trained RF model revealed several dominant rule patterns consistent with engineering expectations.

(a) Temperature-driven deformation rules: higher member temperatures and elevated smoothed temperature values consistently led to predictions of positive (expansion) displacement, whereas lower temperatures corresponded to contraction.

(b) Heating–cooling rate rules: rapid temperature increases produced rules associated with short-term expansion, while rapid cooling generated contraction-oriented predictions.

(c) Solar-radiation rules: larger cumulative sunshine duration increased predicted expansion due to greater thermal loading, whereas low sunshine reduced the effect.

(d) Wind-adjustment rules: higher wind speeds introduced cooling effects, with decision trees applying small corrective reductions to displacement predictions.

(e) Multi-variable combination rules: decision paths frequently combined variables—for example, high smoothed temperature *and* high sunshine *and* low wind tended to produce maximum-expansion predictions, while low temperature *and* rapid cooling *and* zero sunshine led to contraction.

Together, these rule structures demonstrate that the RF model captures meaningful nonlinear thermo-mechanical behavior rather than fitting statistical noise, reinforcing the justification for applying RF in displacement estimation. Its underlying mechanism is illustrated in **Figure 7.8**.

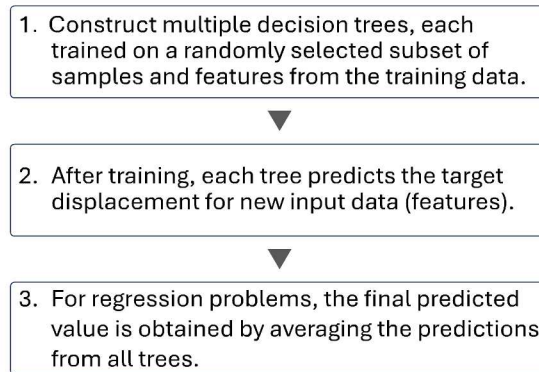


Figure 7. 8 Estimation mechanism of the Random Forest (RF) method

The feature set used for RF included RTK-GNSS displacement data along with meteorological variables such as member temperature, air temperature, wind speed, and sunshine duration. These environmental factors were selected for their potential influence on bridge displacement, with the aim of improving estimation accuracy.

Detailed feature descriptions are provided in **Table 7.1**. One key feature, the *Temperature Moving Average*, was generated by applying a moving average with a six-step time window (equivalent to 30 minutes) to smooth short-term fluctuations and capture underlying temperature trends.

Table 7. 1 List of features used for displacement estimation with the Random Forest (RF) method

Feature	Purpose
Member temperature	Captures basic thermal effects
Temperature difference	Detects abrupt changes
Average temperature shift	Removes short-period noise
Cumulative sunshine duration	Accounts for thermal accumulation effects
Square of wind speed	Represents cooling effects and vibration influences
Air temperature $\times$ sunshine duration	Expresses the interaction effect of thermal expansion

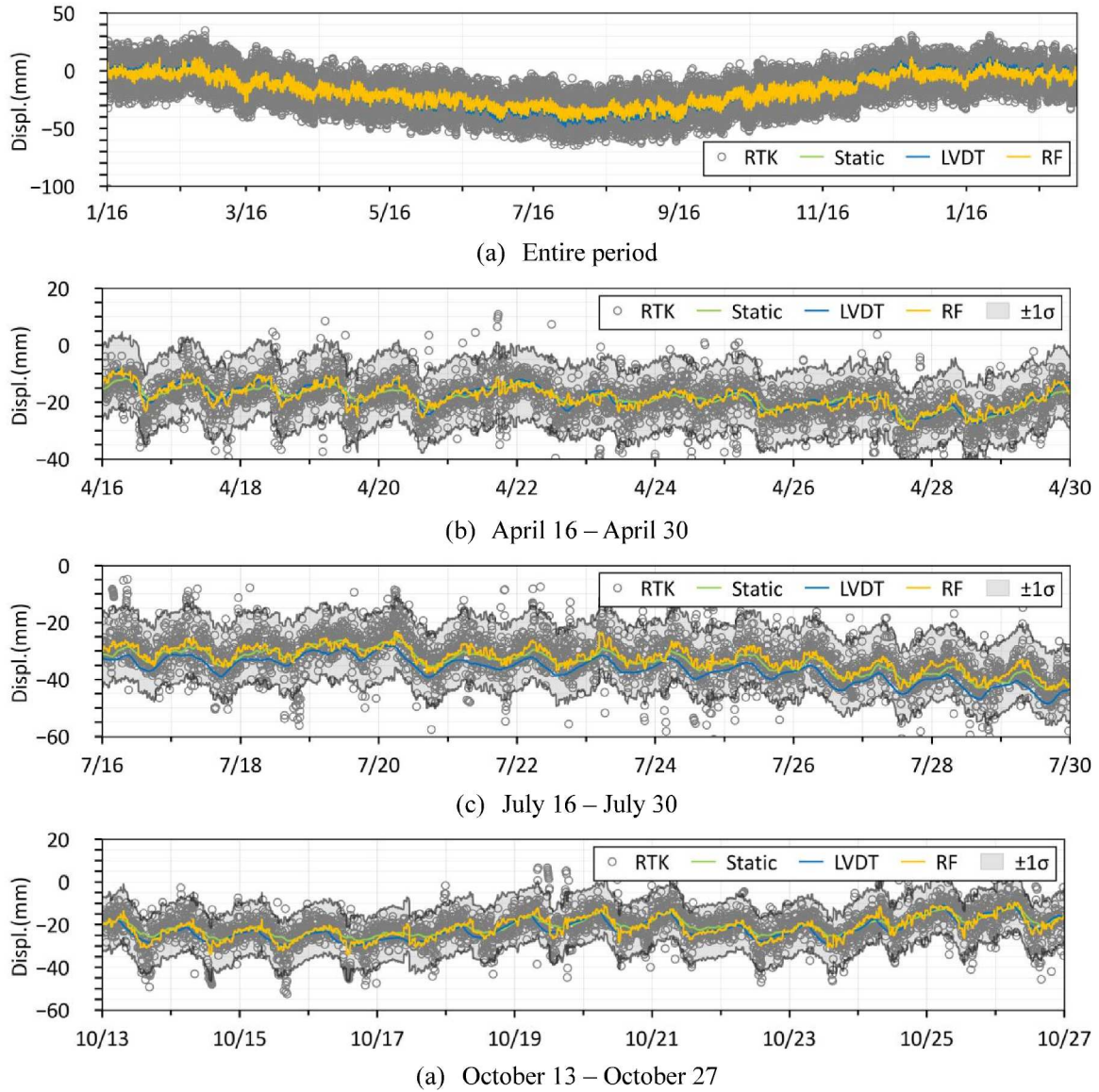


Figure 7.9 Displacement estimation results obtained using the Random Forest (RF) method (overall and enlarged views).

So, the explanation of the figures is as follows:

- Panel (a) shows the results for the entire observation period, clearly capturing overall trends and long-term seasonal patterns. Comparisons with static measurements and displacement gauge data revealed high agreement, particularly in reproducing long-term displacement trends.
- Panel (b) corresponds to a winter period with low temperatures and small diurnal temperature ranges. Under these conditions, the results from all three methods nearly overlapped, indicating stable estimation performance with minimal influence from temperature variation.

- Panel (c) represents a summer period with high temperatures and large diurnal ranges. Here, RF demonstrated responsiveness to short-term displacements driven by daily temperature cycles, although the displacement gauge recorded slightly larger amplitudes than both static measurements and RF estimates.
- Panel (d) shows an autumn period with intermediate meteorological conditions, during which agreement among all three methods was again high, with consistency observed in both short-term fluctuations and long-term displacement trends.

The shaded gray bands in Figure 7.9 indicate $\pm 1\sigma$ confidence bounds, calculated from the 2.5th and 97.5th percentiles of the ensemble distribution at each time step. These intervals allow quantitative evaluation of both variability and stability in the RF estimates.

In post-training operation, RF predicts displacement instantaneously based on feature values at each observation time, enabling near real-time estimation. However, as a pre-trained model, RF requires retraining if substantial changes occur in ground behavior or environmental conditions. Overall, the results demonstrate that RF maintains consistent accuracy across varying environmental conditions, successfully reproducing both long-term trends and short-term variations in bridge displacement.

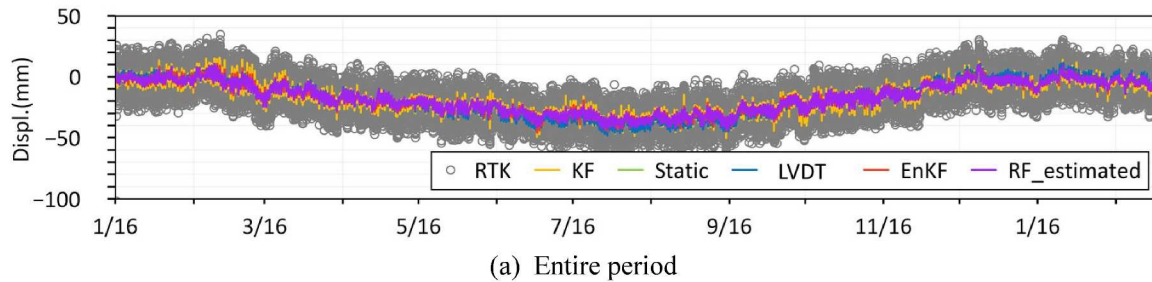
7.4. Performance Comparison and Discussion

(1) Comparison of Estimation Performance of Each Method

The RTK-GNSS observation data and their corresponding displacement estimates contain numerous short-period fluctuations arising from environmental noise and measurement errors. These fluctuations are unrelated to the actual structural displacement behavior, and their direct use in analysis can reduce estimation accuracy or lead to misinterpretation.

To mitigate such effects, a smoothing process using a moving average with a time window of 20 steps (equivalent to 100 minutes) was applied to the estimation results. This filtering clarified the underlying displacement trends, facilitated the identification of structural tendencies, and produced more stable estimates. In the following performance evaluation, these smoothed results are referred to as KF smooth, EnKF smooth, and RF smooth. The conventional KF smooth method served as a benchmark, while the effectiveness of the proposed EnKF smooth and RF smooth methods was assessed.

First, the estimation results from each method were plotted alongside RTK-GNSS data, static GNSS measurements, and displacement gauge readings for visual comparison (**Figure 7.10**).



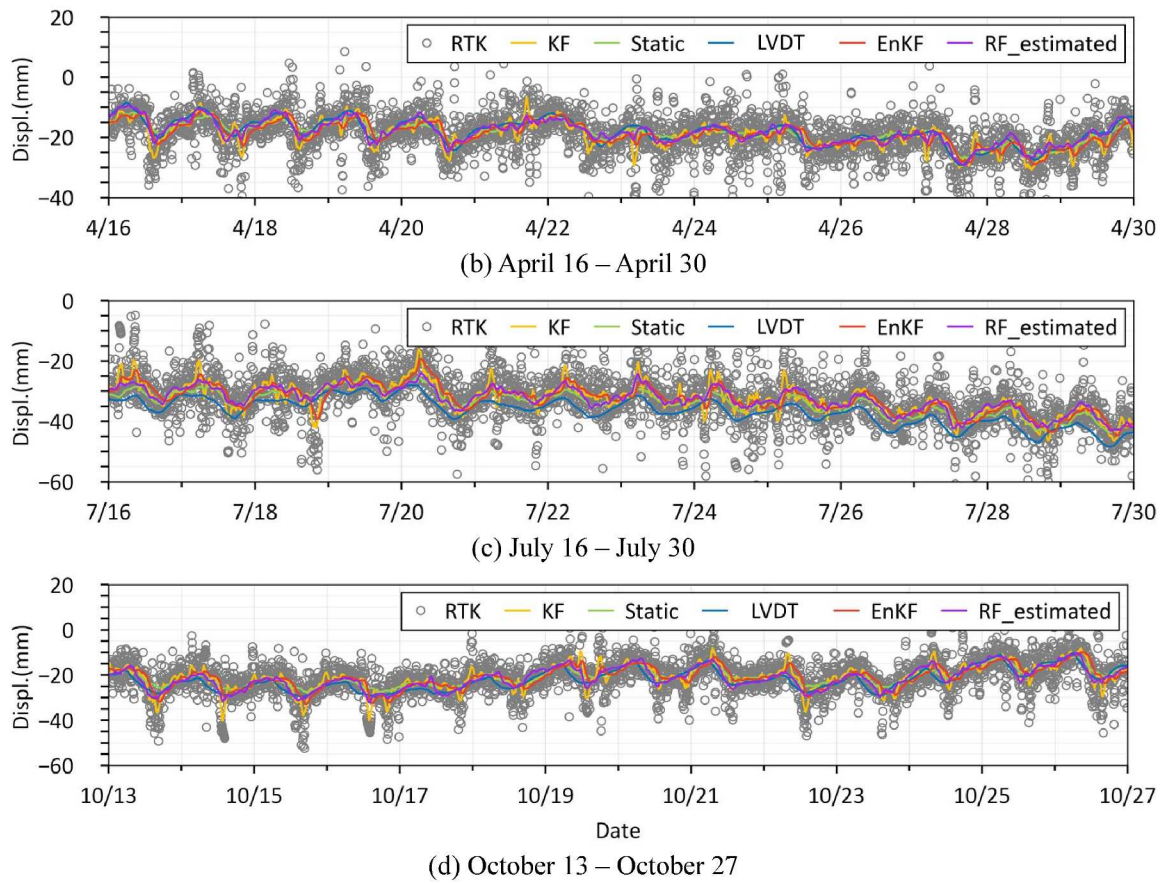


Figure 7. 10 Accuracy comparison among different estimation methods (overall and enlarged views).

Subsequently, estimation accuracy was evaluated based on residuals relative to the displacement gauge and static GNSS data. Four key statistical indicators – Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), maximum error (Max Error), and correlation coefficient (r) – were calculated. A summary of these results is provided in **Table 7.2**.

Table 7. 2 Evaluation metrics for displacement estimation accuracy among different estimation methods.

Estimate Method	Comparison Target	RMSE (mm)	MAE (mm)	Max Error (mm)	Correlation Coefficient r
KF	Displacement meter	3.672	2.887	19.932	0.975
KF	Static	2.747	1.950	18.619	0.977
EnKF	Displacement meter	3.406	2.720	13.225	0.982

EnKF	Static	1.973	1.505	10.467	0.988
RF	Displacement meter	2.807	2.254	9.093	0.993
RF	Static	1.677	1.309	9.093	0.991

The findings confirm that all methods effectively reduced noise present in the GNSS data and produced high-accuracy displacement estimates. Notably, the EnKF smooth, based on model-driven data assimilation, and the RF smooth, based on data-driven machine learning, achieved small maximum errors of 13 mm and 9 mm, respectively. These results demonstrate that both approaches provide sufficient accuracy for quantifying structural responses and detecting early signs of anomalies under real-world conditions. Despite their fundamentally different methodologies, the two advanced methods exhibited comparably high estimation performance – an important and practically relevant finding of this study.

(2) Discussion and Implications for Application

A key factor underlying the comparable displacement estimation accuracy achieved by both the EnKF and RF methods is their inherent flexibility in handling the nonlinearity and uncertainty present in GNSS observation data. The EnKF probabilistically represents uncertainty in the state space through an ensemble of realizations, enabling robust state estimation under stochastic disturbances. In contrast, the RF captures complex and nonlinear patterns in displacement fluctuations by aggregating predictions from multiple decision trees, thereby reducing variance and enhancing predictive stability. Despite being based on fundamentally different principles – model-driven data assimilation versus data-driven machine learning – both methods share essential characteristics for addressing the complexity of bridge displacement behavior, which likely accounts for their similar estimation performance.

From a practical perspective, the EnKF offers the advantage of incorporating physical knowledge through model formulation and error covariance settings and is inherently well-suited for real-time sequential processing. However, its high configurability necessitates careful parameter tuning to achieve optimal performance. Conversely, the RF is highly versatile and can provide accurate predictions immediately after training, but it requires a sufficiently large and representative training dataset for model construction, and its predictive performance tends to degrade in extrapolation scenarios.

These comparative insights provide practical guidelines for selecting or combining estimation techniques based on the characteristics of GNSS monitoring data and operational constraints. They also highlight promising directions for integrating model-based and data-driven approaches, contributing to the continued advancement of bridge health monitoring technologies.

7.5. Conclusions

This study applied and comparatively evaluated two displacement estimation approaches – data assimilation using the Ensemble Kalman Filter (EnKF) and machine learning using the Random Forest (RF) – for GNSS-based bridge monitoring. The main findings are as follows:

- **EnKF performance** – By accounting for nonlinearity and uncertainty, the EnKF successfully overcame the limitations of the conventional linear Kalman Filter (KF) in tracking true displacement values. It achieved estimates that closely matched those from displacement meters and static GNSS measurements.
- **RF performance** – The RF-based machine learning approach, when provided with relevant features such as member temperature and meteorological conditions, reproduced displacement behavior consistent with reference measurements, demonstrating estimation accuracy comparable to the EnKF.
- **Complementary methods** – The similar performance achieved by these fundamentally different approaches suggests the feasibility of flexible method selection for high-accuracy displacement estimation from noisy real-time GNSS data.

These results promote the utilization of GNSS data for bridge monitoring, showing that accurate displacement estimation is achievable even under real-world noise conditions. Future work will include extending these methods to dynamic displacement estimation, verifying generalizability across various bridge types and environments, integrating multi-sensor data for redundancy and improved accuracy, implementing real-time processing, and applying the approaches to long-term health assessment and anomaly detection.

It should be noted that this study did not evaluate the performance of the conventional KF with an added member temperature increment term; this will be investigated in future work.

Each method also has inherent limitations. The EnKF updates sequentially based on a system model, making it less suited to extrapolation beyond the modeled phenomena, and its accuracy is sensitive to the model structure and error covariance settings. The RF excels at nonlinear predictions from observed data but suffers from reduced accuracy in extrapolation beyond the range of training data, with additional challenges related to limited interpretability and the need for periodic retraining in long-term monitoring.

From an operational perspective, further evaluations under realistic field conditions are needed to assess the impact of changes in GNSS observation environments (e.g., signal obstruction, multipath effects), sensor failures, and sudden weather changes on estimation accuracy. Addressing these challenges will require the development of hybrid approaches, integration with multiple sensors, and the incorporation of anomaly detection and retraining mechanisms into operational frameworks.

Overall, both the EnKF and RF demonstrated high agreement with displacement measurements across different seasonal and meteorological conditions, capturing both short-term variations and long-term trends. While the EnKF offers immediacy and uncertainty quantification through sequential processing, the RF enables rapid estimation via a trained model, though retraining is necessary when environmental conditions change significantly. The balance between real-time capability and accuracy achieved in this study provides a solid foundation for the practical implementation of continuous GNSS-based bridge monitoring systems, contributing to early anomaly detection and long-term structural health management.

7.6. References

- 1) Misa, P., and Enge, P. (2010). *Understanding GPS: Principles and Applications* (2nd ed.). Trans. by The Institute of Positioning, Navigation, and Timing of Japan. Tokyo: The Institute of Positioning, Navigation, and Timing of Japan.
- 2) Hofmann Wellenhof, B., et al. (2005). *GPS: Theory and Practice* (5th ed.). Trans. by Nishi, S. Tokyo: Springer-Verlag Tokyo.
- 3) Soda, H., and Sato, N. (2018). Approximation method for long-term horizontal displacement behavior of fill dams using GPS measurements. *Journal of Japan Society of Civil Engineers, Ser. C (Geosphere Engineering)*, 74(3), pp. 248-258. (in Japanese)
- 4) Nakajima, S., Furuyama, Y., Hayashi, Y., Nguyen, T. K., Shimizu, N., and Hirokawa, S. (2018). Effect of error correction and long-term continuous monitoring results for 3D displacement measurement of steep long slopes using GPS. *Journal of the Japan Landslide Society*, 55(1), pp.13-24. (in Japanese)
- 5) Shirai, T., and Kubo, N. (2012). Improving RTK-GPS reliability in urban areas. *Journal of the Japan Society for Aeronautical and Space Sciences*, 60(1), pp. 40-47. (in Japanese)
- 6) Kokusai Kogyo Co., Ltd. (n.d.). NETIS registered technology: KT-190078-A, Shamen-net measurement information service.
<https://www.shamen-net.com/index.html> (Accessed: 2025-08-11).
- 7) Nakamura, S. (2000). Measurement of wind-induced deformation of suspension bridge stiffening girder using GPS. *Journal of Japan Society of Civil Engineers*, 658/VI-48, pp. 231-243. (in Japanese)
- 8) Yang, J., Ma, X., Yuan, B., Xu, B., Fu, Q., and Xu, Y. (2020). Global Navigation Satellite System-based positioning technology for structural health monitoring: A review. *Structural Control and Health Monitoring*, 27(1), e2467.
- 9) Wang, X., Zhao, Q., Xu, R., Liu, C., Liu, G., and Liu, L. (2021). Review of bridge structural health monitoring based on GNSS: From displacement monitoring to dynamic characteristic identification. *IEEE Access*, 9, pp.80043–80065
- 10) Arii, K., Tanaka, T., Sato, W., Fukuba, T., Egawa, M., and Shimizu, N. (2023). Automatic continuous three-dimensional displacement monitoring of bridges using GNSS static positioning. *Journal of Japan Society of Civil Engineers*, 79(6), 23-00002. (in Japanese)
- 11) Wada, R., Ohno, T., Yoshida, I., Sekiya, H., Yasuda, A., and Yoshiura, N. (2025). Interpretation of 3D deformation behavior of bridges during construction using GNSS. **AI and Data Science Transactions**, 6(1), pp. 217-223. (in Japanese)
- 12) Wada, R., Ohno, T., Yoshida, I., Sekiya, H., Morichika, S., Yasuda, A., and Yoshiura, N. (2025). Estimation of bridge displacement based on inverse analysis of virtual loads applied to a 3D finite element model. *Journal of Japan Society of Civil Engineers*, 81(15), 24-15020. (in Japanese)

- 13) Hotta, K., Maruyama, K., Yoshida, I., Sekiya, H., Yasuda, A., and Yoshiura, N. (2024). Feasibility study on understanding deformation during bridge construction using GNSS. *Journal of Structural Engineering A*, 70A, pp. 155-163. (in Japanese)
- 14) Sato, W., and Imai, Y. (2024). Efforts to streamline and improve infrastructure inspections by integrating GNSS, IoT sensors, and satellite SAR. *Construction Machinery*, p. 111. (in Japanese)
- 15) Xin, J., Zhou, J., Yang, S., Li, X., and Wang, Y. (2018). Bridge structure deformation prediction based on GNSS data using Kalman-ARIMA-GARCH model. *Sensors*, 18(298).
- 16) Tomoe, Y., Watanabe, G., Tita, E. E., and Nishino, S. (2025). Basic study on anomaly detection of continuous curved steel box girder bridges using GNSS displacement monitoring and digital twin. *AI and Data Science Transactions*, Vol.6, No.2, pp.237-246. (in Japanese)
https://doi.org/10.11532/jsceiii.6.2_237
- 17) Ma, Y., Zeng, L., Xu, M., Wang, L., and Zhang, L. (2022). Structural displacement estimation by fusing vision and acceleration using Kalman filter: dealing with nonsynchronization. *Automation in Construction*, 138, 104274.
- 18) Forootan, E., Farzaneh, S., Naderi, K., and Cederholm, J. P. (2021). Analyzing GNSS measurements to detect and predict bridge movements using the Kalman filter (KF) and neural network (NN) techniques. *Geomatics*, 1(1), pp. 65-80. doi:10.3390/geomatics1010006
- 19) Shen, N., Chen, L., Liu, J., Wang, L., Tao, T., Wu, D., and Chen, R. (2019). A review of Global Navigation Satellite System (GNSS) based dynamic monitoring technologies for structural health monitoring. *Remote Sensing*, 11(9), 1001. doi:10.3390/rs11091001

8. Digital Twin for bridge anomaly detection and validation based on GNSS and FEA

Overview

This chapter focuses on the physical verification of the proposed Operational Digital Twin framework through finite element analysis (FEA), addressing a critical requirement for reliable engineering decision-making. While the preceding chapter established robust displacement estimation under uncertainty using GNSS observations and data-driven methods, estimation results alone are insufficient unless their physical plausibility is rigorously examined. Accordingly, this chapter introduces a physics-based validation layer that evaluates whether the estimated structural responses are consistent with fundamental principles of structural mechanics.

To this end, a high-fidelity finite element model of the target bridge is developed through seamless interoperability with the BIM-based digital representation. The numerical model incorporates realistic geometry, material properties, boundary conditions, and temperature effects, enabling detailed simulation of structural behavior under operational loading conditions. By systematically comparing GNSS-observed displacements with FEA-predicted responses, the proposed framework verifies the consistency between measured behavior and mechanically admissible structural states.

Through this integration of monitoring data, uncertainty-aware estimation, and physics-based verification, this chapter demonstrates how the digital twin evolves from a data-driven interpretation tool into a reliable operational system. The results presented herein establish the final component required for the proposed framework to function as an Operational Digital Twin, capable of supporting engineering judgment and decision-making for complex bridge structures under real-world conditions.

8.1. Introduction

The digital twin (DT) is a dynamic and virtual representation of physical assets, systems, and processes that are continuously synchronized with those in the real world through data integration. This technology is emerging as a transformative approach in many fields, including product design, manufacturing, operations, asset management, and especially in the development of smart cities and intelligent infrastructure systems. In the context of civil and infrastructure engineering, a digital twin enables real-time monitoring, predictive maintenance, and performance optimization of complex assets such as bridges, tunnels, and transportation networks. The evolution of Construction 4.0, which integrates advanced technologies such as Building Information Modeling (BIM), Internet of Things (IoT), artificial intelligence (AI), and digital twin frameworks, is significantly accelerating the digital transformation of the construction and infrastructure sectors. This paradigm shift will not only redefine how infrastructure is designed and maintained but also facilitate data-driven decision-making throughout the lifecycle [1-5].

In the Architecture, Engineering, and Construction (AEC) industry, the most widely adopted concept of Digital twin is Building Information Modeling/Management (BIM). This technology enables the creation of a comprehensive virtual representation of buildings and infrastructure such as bridges, tunnels, road networks, and more. BIM offers substantial benefits throughout the entire project lifecycle, encompassing planning, conceptual and detailed design, construction, operation, and maintenance. Furthermore, it significantly enhances collaboration among stakeholders, thereby improving productivity and project outcomes[4,6,7].

Bridges are vital infrastructures that enhance connectivity, enabling the efficient transport of people and goods, and fostering socio-economic development [8]. The strength and durability of bridges are crucial for the safe functioning of modern transportation systems [9,10]. These structures frequently experience complex loading conditions, such as vehicle traffic, fluctuations in temperature, and environmental impacts, which can lead to time-dependent displacements and deformations [11,12]. Accurate and continuous monitoring of such displacements is essential for effective bridge maintenance, early anomaly detection, and overall infrastructure resilience [13].

In bridge engineering, Digital twin technology enables the seamless integration of geometric models, sensor data, and analytical simulations to support condition assessment and data-driven decision-making. The implementation of DT in bridge infrastructure, particularly when combined with Global Navigation Satellite System (GNSS) and Finite Element Analysis (FEA), provides a robust framework for continuous displacement monitoring and performance numerical validation throughout the structure's lifecycle [10,14].

GNSS has emerged as a reliable, non-contact displacement monitoring technology capable of capturing long-term structural movements with millimeter-level accuracy. Its effectiveness is particularly notable in long-span or curved bridges, where traditional tools such as accelerometers or strain gauges may be constrained by limited spatial coverage or increased sensitivity to noise [9,11]. In parallel, FEA serves as a powerful numerical approach for simulating structural responses under various loading and boundary conditions, enabling the calibration and numerical validation of the DT model against field measurements [12]. Therefore, the integration of DT with high-precision monitoring tools like GNSS and FEA offers a transformative and scalable solution for Structural Health Monitoring (SHM), enhancing both predictive maintenance and lifecycle management of bridge infrastructure [4,5,8,14].

In recent years, the importance of proactive bridge maintenance has been underscored in Japan due to the aging of a large portion of its infrastructure. More than 40% of Japan's approximately 730,000 bridges are over 50 years old, with projections indicating this will exceed 60% by 2030 [15]. In response to this critical situation, the Ministry of Land, Infrastructure, Transport and Tourism (MLIT) has adopted a strategic shift from reactive to preventive maintenance, introducing a nationwide inspection cycle of once every five years for all bridges under public management since 2014 [16]. Moreover, MLIT emphasizes the utilization of advanced technologies such as sensor-based monitoring, digital twins, and artificial intelligence to support condition-based maintenance and lifecycle extension strategies. The growing complexity of maintaining long-span and uniquely shaped bridges, such as curved steel bridges, demands the integration of high-resolution monitoring tools and predictive modeling to support early intervention and optimize maintenance costs.

Recent studies have explored GNSS observation, FEA models to monitor bridge displacements, and detect structural anomalies. For example, Niu et al. (2023) presents a method that combines multi-GNSS and

acceleration data to estimate dynamic displacements and perform modal analysis of long-span bridges. The integration enhances the accuracy of displacement measurements and provides valuable insights into the structural behavior under dynamic loads[17]. Xue et al.2023, explore the feasibility of using low-cost GNSS receivers to monitor the dynamic response of a pedestrian bridge.[18]. Li et al(2023) introduce a predictive model combining Kalman filter, ARIMA, and GARCH techniques to forecast bridge deformations using GNSS data. The approach enhances the ability to predict structural responses, contributing to proactive maintenance strategies[19]. Wang et al (2024) propose a data-driven method to quantify the impact of various loading factors on bridge displacements measured by GNSS. The approach aids in distinguishing between different sources of structural movement, enhancing the interpretation of monitoring data[20]. However, limited research has been conducted on the application of such integrated DT frameworks to continuous curved steel bridges, which present additional challenges due to their asymmetric geometries and complex boundary conditions.

This study aims to address this research gap by developing a comprehensive DT model for a continuous curved steel bridge using Building Information Modeling (BIM) as the base geometry, coupled with GNSS-based displacement monitoring and FEA-based numerical validation. The primary objectives are to (1) implement a real-time GNSS monitoring system at critical bridge points, (2) simulate displacement responses under real-world loading conditions using FEA, and (3) validate and update the digital twin through comparative analysis. However, the FEA conducted in this chapter is linear elastic, appropriate for validating displacement and deformation shapes, but insufficient for modeling cracking or progressive slab deterioration. The findings of this research are expected to contribute toward a more intelligent and data-driven approach to structural health monitoring, offering practical insights for bridge asset management and future digital twin implementations in civil infrastructure.

8.2. Research strategy

The bridge maintenance management strategy adopted in this study is shown schematically in **Figure 8.1**. A high-fidelity digital twin of the bridge is built using Building Information Modeling (BIM), accurately replicating the geometry and attributes of the physical structure. Continuous displacement data is acquired from observation points strategically positioned along the bridge, using the Global Navigation Satellite System (GNSS). To ensure the reliability of the GNSS-derived measurements, a numerical validation procedure is carried out using Finite Element Analysis (FEA), allowing a direct comparison between the observed and simulated structural responses. This comparative validation increases the credibility of the monitoring framework and allows for a comprehensive understanding of the bridge's structural performance. The integrated approach ultimately supports the development of a robust, data-driven Structural State Monitoring (SHM) system designed for long-term bridge maintenance.

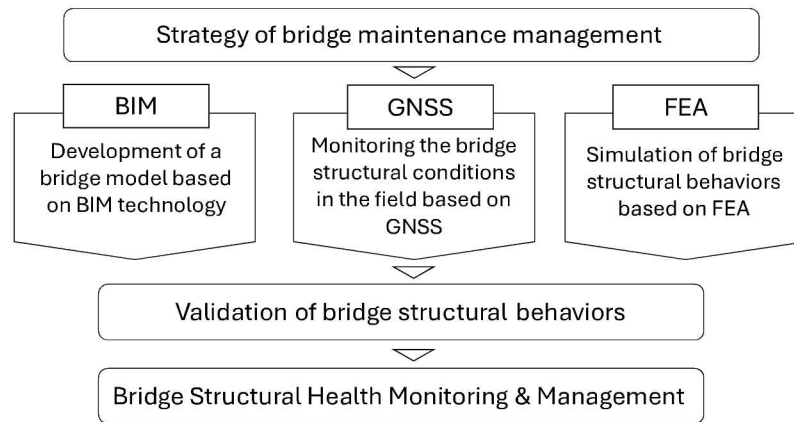


Figure 8. 1 Research Strategy

(1) Digital Twin Frameworks for this research

Digital twin technology is increasingly gaining attention across various engineering domains, including bridge engineering. In this study, we apply DT technology to bridge structural health monitoring (SHM) to assess the condition and performance of the structure over time. Accordingly, we propose the development of a DT framework, as illustrated in **Figure 8.2**. The development process comprises the following six stages:

1. **Physical Model:** This stage involves conducting a site investigation of the bridge and collecting relevant data from the bridge owner, including as-built drawings, photographs, and inspection reports. These materials form the foundational knowledge base of the bridge's physical condition and geometry.
2. **Cyberspace Model:** Based on the collected data, a digital model of the bridge is created using Building Information Modeling (BIM) software, specifically Autodesk Revit. This step involves accurately replicating the geometry and configuration of the actual bridge to create a detailed digital representation.
3. **Structural Model:** A 3D structural model is developed for numerical analysis. The BIM model is exported as an Industry Foundation Classes (IFC) file to enable interoperability between Revit and the Finite Element Analysis (FEA) software DIANA. The structural model in DIANA is used to simulate the bridge's behavior under various loading conditions and later serves as the basis for validating the deformation behavior observed from the monitoring system.
4. **GNSS Monitoring System:** To capture real-time displacement behavior, a Global Navigation Satellite System (GNSS) monitoring system is installed on the bridge. GNSS sensors are strategically placed at critical locations, including Abutment 2 (A2), the mid-span between A2 and Pier 4 (P4), at P4 itself, and the mid-span between P4 and Pier 3 (P3). The sensors continuously collect displacement data, which is transmitted to a cloud server. These data are then made accessible to stakeholders for real-time monitoring and structural assessment.

5. **Observation Data:** After data preprocessing, the GNSS observations are analyzed to evaluate the 3D displacement behavior of the bridge, including longitudinal, transverse, and vertical displacements. This step provides valuable insights into the bridge's structural response over time.
6. **Numerical Validation:** Finally, the numerical results from FEA are compared with the GNSS observation data to validate the simulated deformation. This comparison ensures the reliability of the DT framework in capturing actual bridge behavior and enhances confidence in the monitoring system.

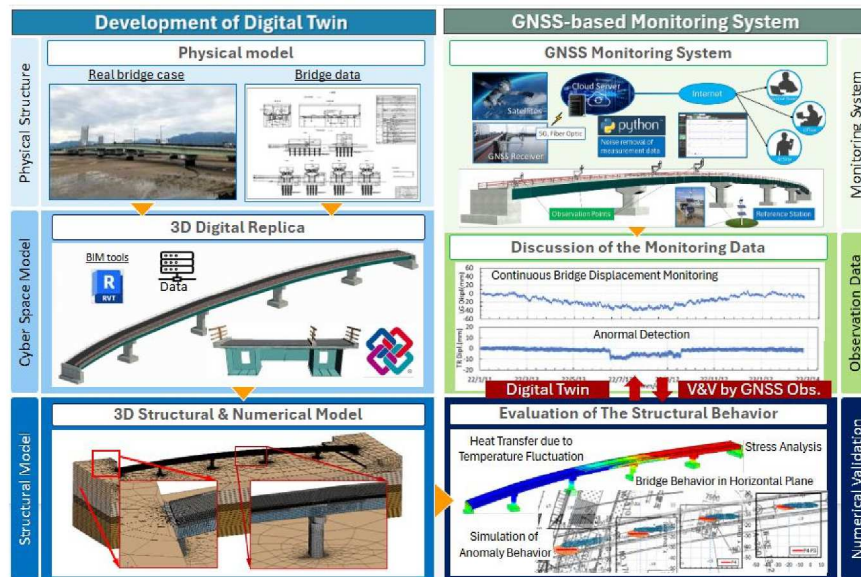


Figure 8. 2 Conceptual Framework of Digital Twin (DT) for this research.

(2) BIM Concept and Application in Bridge Management and Maintenance

Building Information Modeling (BIM) has evolved into a comprehensive digital process that facilitates the generation and management of structured, interoperable information throughout the life cycle of infrastructure assets. It integrates geometric, semantic, and temporal data into a centralized digital environment, supporting informed decision-making from initial design through construction, operation, maintenance, and eventual decommissioning phases, as shown in **Figure 8.3**.

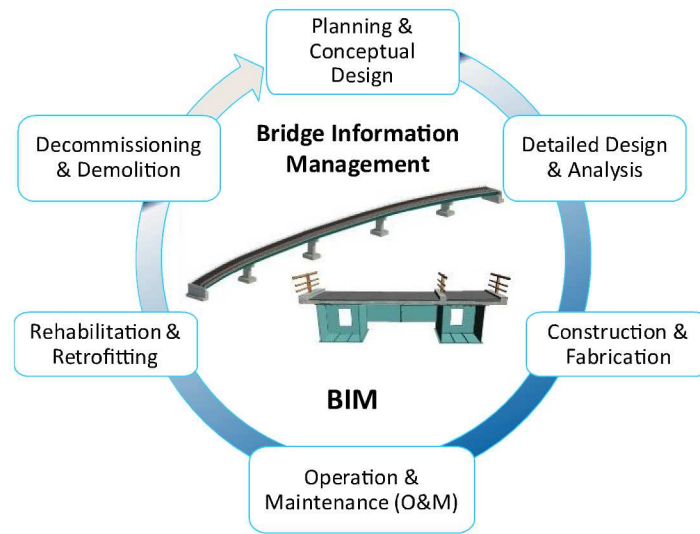


Figure 8. 3 Building Information Modeling/ Management

BIM was initially developed for the building sector; its adoption has expanded significantly to include civil infrastructure, particularly bridge engineering [21,24]. In the bridge engineering field, particularly in the context of bridge management and maintenance, BIM serves as a powerful enabler for developing a digital, data-rich representation of bridge assets. These models encapsulate not only the physical characteristics of structural components but also metadata related to materials, construction history, inspection records, and performance attributes. This integration enables infrastructure entities to move from a reactive to a proactive asset management strategy, enhancing lifecycle performance and sustainability [4,5,22,23].

(3) Target Bridge

In this study, a five-span continuous curved steel girder bridge over the Shin-Yawata River in Hiroshima, as shown in **Figure 8.4**, was selected as the target for displacement monitoring using GNSS. This bridge is an ideal example of modern urban infrastructure in a dynamic seismic and hydrologic environment for long-term structural health monitoring. The bridge is 282.5 meters long with an overall deck width of 12.25 meters. The cross section consists of a 7.7-meter-wide roadway and a 3.5-meter-wide sidewalk, designed to accommodate both traffic and pedestrian flows.

The bridge geometry includes significant plane curvatures with bevel angles of 80.8° and -118.5° , which are essential to the analysis because they result in complex torsional behavior and lateral force effects. The superstructure consists of a reinforced concrete (RC) slab deck with asphalt pavement, supported by two parallel steel box girders. This structural configuration provides an efficient balance of flexural capacity, torsional stiffness, and durability, which is often required for medium- and long-span urban bridges.

The substructure consists of reinforced concrete piers and columns and is founded on concrete piles to ensure stability against riverbed erosion and seismic loading. To accommodate thermal expansion and structural movement, a combination of pinned bearings for the abutments and roller (movable) bearings for the intermediate piers is used. This bearing system allows for longitudinal displacement while maintaining structural continuity. The bridge was chosen for GNSS-based displacement monitoring due to its geometric

complexity, mixed material system, and susceptibility to thermal and dynamic effects. Such monitoring provides highly accurate real-time data essential for validating numerical models, assessing structural performance under operational loads, and developing DTs for bridge life cycle management.

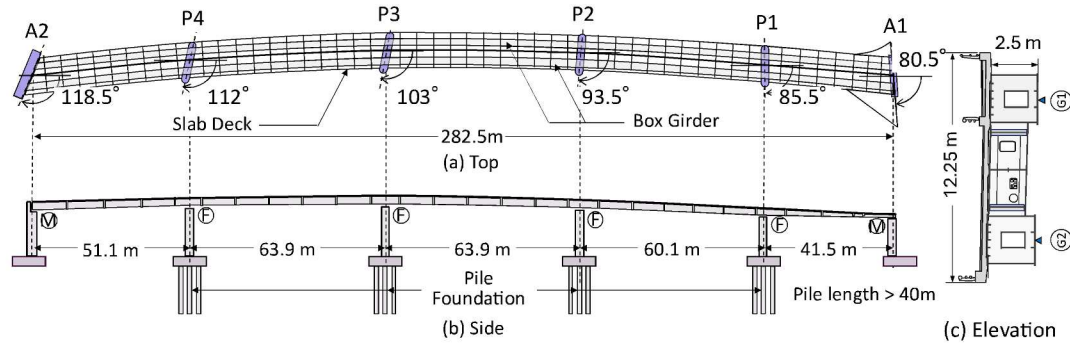
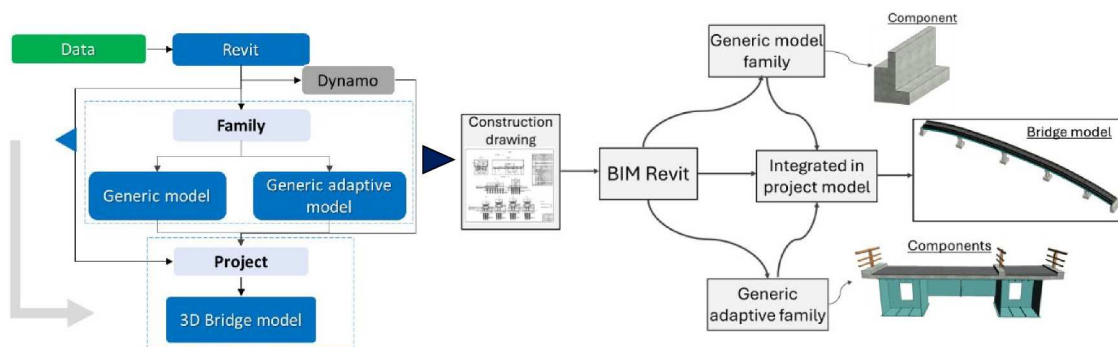


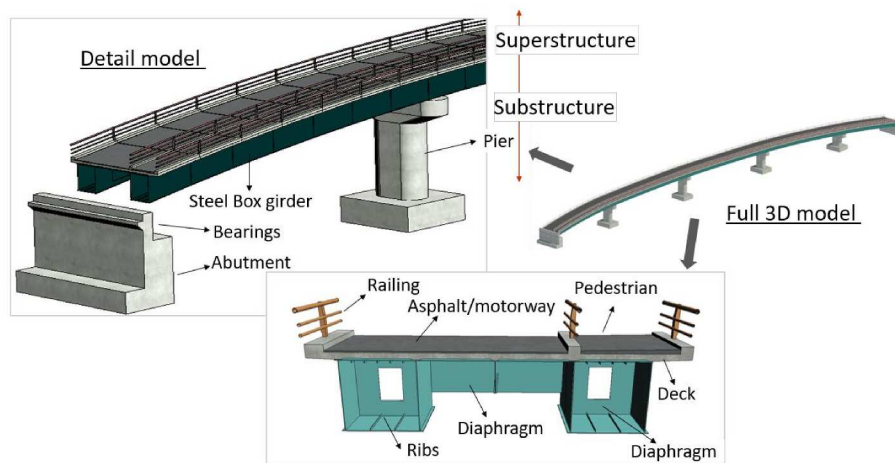
Figure 8. 4 Top, Side, and Elevation of a Target Bridge of the Digital Twin BrSHM Research Project (5 Span Continuous Bridge with Steel Two Box Girders and RC Slab).

(4) BIM-Based Parametric Modeling of a Continuous Curved Steel Bridge

The digital twin of the continuous curved steel bridge in this study was developed using BIM-based parametric modeling, as shown in **Figure 8.5(a)**. Based on bridge-related information such as built drawings, construction documents, and engineering reports, BIM tools were utilized to construct an accurate and data-rich digital twin model was constructed. In developing a comprehensive Building Information Modeling (BIM) representation of the continuous curved steel bridge, Autodesk Revit was employed to build both substructure and superstructure components using an object-oriented and parametric modeling approach. Two different Revit family types were utilized to address the various geometric and structural complexities inherent in the bridge system: the generic model family and the adaptive component family were selected based on their modeling capabilities and flexibility.



(a) Develop a BIM bridge model



(b) Detail BIM bridge Model

Figure 8. 5 Development of the Digital Twin of the Bridge

(a) Generic Model Families for Substructure Elements:

For the bridge substructure, including abutments, piers, and foundation piles, Generic Model Families were utilized. These families are particularly well-suited for components with relatively standardized and prismatic geometries, allowing for efficient parametric control over dimensions, materials, and placement within the project environment. Generic Model Families support native Revit parameters, which enable the customization of structural dimensions such as pier height, pile diameter, and abutment geometry, facilitating consistency across instances and ease of modification. The use of this family type ensured that substructure elements were modeled with the required geometric fidelity while maintaining interoperability with the overall Revit project model.

(b) Adaptive Component Families for Superstructure Modeling:

The superstructure of the bridge, comprising the curved alignment of steel box girders, the RC slab deck, and the asphalt surfacing, presented significant geometric complexity due to the bridge's plan curvature and variable cross-sectional profiles along its span. To accurately capture these variations, Adaptive Component Families were employed. Adaptive components offer a higher degree of flexibility and are specifically designed to respond to multiple adaptive points placed in 3D space. These points can be positioned along a reference curve or surface, allowing the modeled element to adapt its shape and orientation dynamically based on control geometry. This approach was particularly effective in representing the continuous curvature of the steel girders, as well as the alignment of the bridge deck in both the longitudinal and transverse directions. The Adaptive Family method allowed for seamless alignment with reference paths derived from civil alignment data, ensuring both geometric accuracy and consistency with roadway design intent.

(c) Integration with Dynamo for Parametric Control:

To further enhance the automation and parametric adaptability of the superstructure model, Dynamo for Revit, a visual programming interface, was integrated into the modeling workflow. Dynamo scripts were

developed to place adaptive components along the bridge alignment was automated to control variables such as span length, deck width, girder spacing, and cross-sectional orientation. This parametric integration enabled the generation of a data-rich, geometrically accurate bridge model that can dynamically respond to changes in design parameters and alignment profiles.

(d) Model Integration in Revit Project Environment:

Once the modeling of individual components was completed, both substructure and superstructure elements were integrated within the unified Revit project model as shown in **Figure 8.5(b)**. This integration facilitated spatial coordination, clash detection, and documentation generation within a single BIM environment. The integrated model serves as the foundation element of the bridge's digital twin and allows for future enhancements such as structural analysis, construction sequencing, and GNSS-based displacement data integration.

(5) GNSS-based Monitoring System

In this study, a GNSS-based monitoring system was established to capture long-term, real-time deformation of a continuous curved steel bridge, as illustrated in **Figure 8.6**. To ensure comprehensive deformation monitoring across critical structural regions, multiple high-precision GNSS sensors were strategically installed along the bridge. The sensor layout consists of the following: R1 at the A2 abutment, R2 at the mid-span between A2 and pier P4, R3 on pier P4, and R4 on pier P3. This sensor configuration was designed to capture both global and localized displacement behavior across different structural components, particularly in areas expected to exhibit significant dynamic and thermal responses. To complement the GNSS measurements, a displacement gauge and a component temperature sensor were also installed at the A2 location. This setup enables the simultaneous capture of thermal-induced deformation and material responses, thereby facilitating a more holistic interpretation of structural behavior under varying environmental and loading conditions.

The GNSS units were configured to collect position data at five-minute intervals over a 436-day monitoring period, spanning from January 12, 2022, to March 27, 2023. These sensors continuously receive signals from a constellation of GNSS satellites, allowing for the precise detection of three-dimensional displacement over time. The raw data were transmitted and archived in a cloud-based server infrastructure, enabling remote accessibility and facilitating data processing from any internet-connected location. To enhance the signal quality and eliminate noise measurement, a Kalman Filter algorithm was implemented using Python programming tools.

This filtering process significantly improved the reliability of the displacement time series by minimizing stochastic errors inherent in GNSS observations. The refined displacement data were then utilized for evaluating long-term structural deformation, identifying anomalous movement patterns, and assessing the bridge's structural integrity under real-world operational conditions. Ultimately, this monitoring framework contributes to the creation of a data-driven digital twin of the bridge, serving as a foundational tool for structural health monitoring (SHM), predictive maintenance, and lifecycle management.

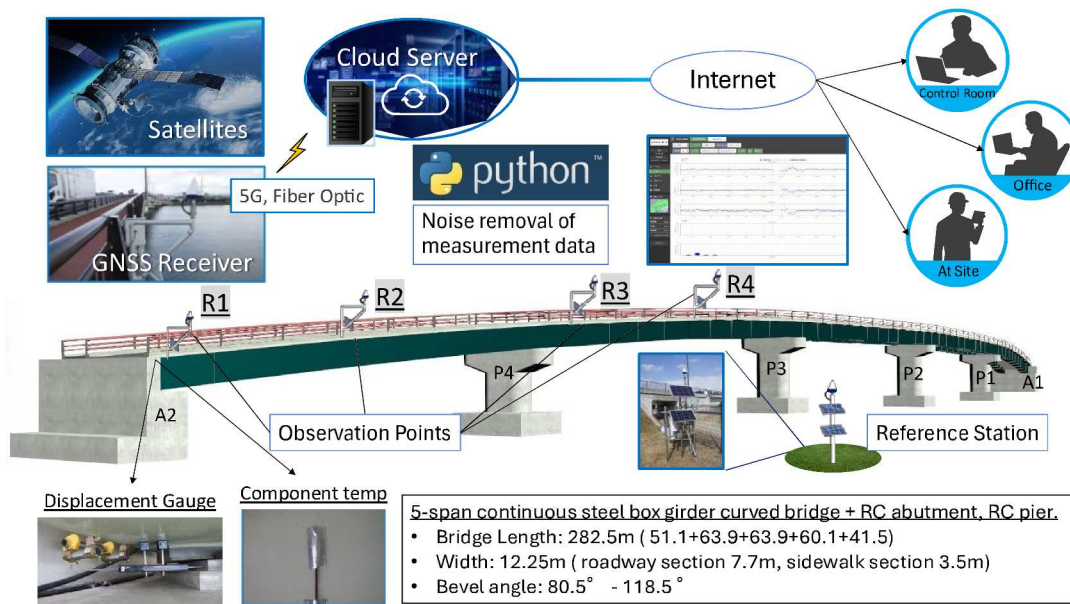


Figure 8. 6 GNSS-based Monitoring System

(6) Temperature observation

To assess the influence of thermal effects on the structural behavior of the bridge during long-term monitoring, component temperature sensors were installed on a steel box girder near abutment A2, as shown in **Figure 8.7**.

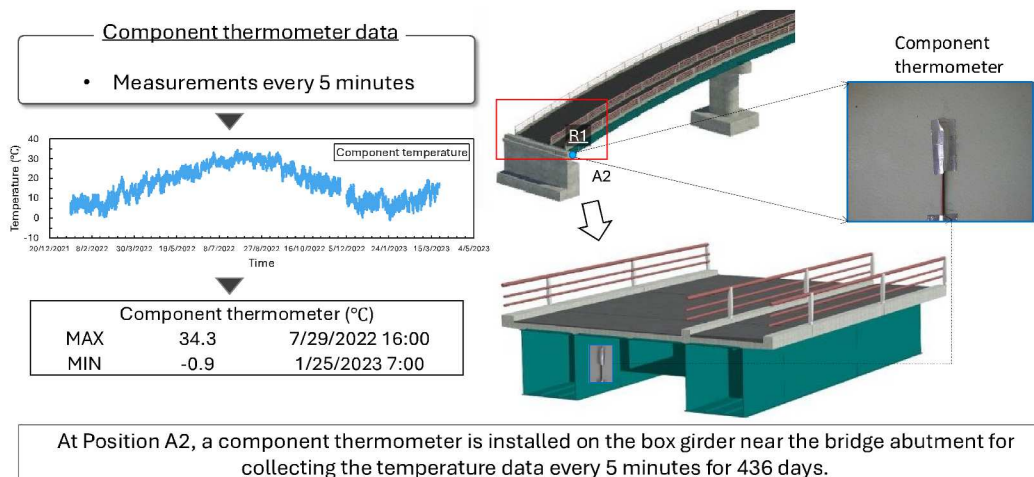


Figure 8. 7 Temperature observation

This location was strategically chosen due to its sensitivity to thermal boundary conditions and its proximity to both substructure and superstructure interfaces, where thermal gradients are expected to cause significant deformation. The temperature sensors were set to record data at five-minute intervals and

continuously captured diurnal and seasonal temperature changes throughout the 436-day observation period. This monitoring period spanned the four seasons of Japan, in particular Hiroshima city, covering the entire thermal cycle from the coldest days of winter to the hottest days of summer.

During this period, the highest temperature was recorded on July 29, 2022, at 34.3°C, and the lowest temperature dropped to -0.9°C on January 25, 2023. This high-resolution temperature data plays an important role in understanding the thermal behavior of steel bridge structures, particularly the longitudinal displacements, stress distribution, and expansion and contraction phenomena that affect the overall performance of the structure. In continuous curved steel bridges, temperature-induced deformation not only affects linear expansion but can also lead to secondary effects such as torsional response and bearing movement, especially in the vicinity of abutments and piers. By integrating this temperature data set with corresponding GNSS-based displacement measurements, the relationship between temperature and displacement can be quantitatively evaluated.

This analysis is essential to distinguish between load-induced and thermally induced movements, validate numerical models, and improve the accuracy of the digital twin for structural health monitoring (SHM). In addition, the dataset will support the development of predictive models for maintenance scheduling, fatigue assessment, and long-term performance prediction of steel bridge infrastructure under a variety of climatic conditions.

(7) BIM-to-FEA Interoperability for Structural Analysis of the Digital Twin

In this study, a digital twin-based interoperability workflow was implemented to facilitate the structural analysis of a continuous curved steel bridge, as shown in **Figure 8.8**. The objective was to bridge the gap between the BIM (Building Information Modeling) and FEA (Finite Element Analysis) environments, allowing seamless exchange of geometry and structural data between the platforms. The process begins with the creation of a parametric BIM model of the subject bridge using Autodesk Revit to accurately model key structural components such as girders, slabs, abutments, and piers based on construction drawings.

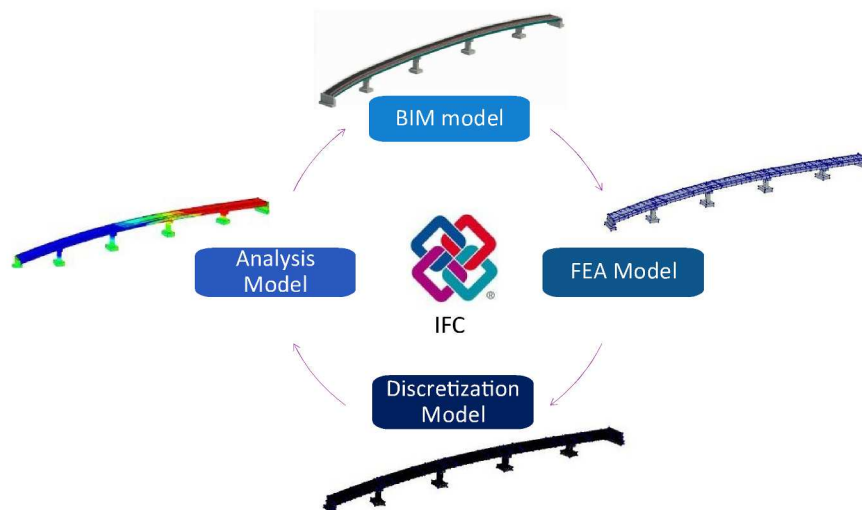


Figure 8. 8 BIM-to-FEA Interoperability for Structural Analysis of the Digital Twin

The model is exported in Industry Foundation Classes (IFC) format, a widely adopted open standard for data interoperability between BIM authoring tools and analysis platforms. The exported IFC files are imported into DIANA FEA, a software environment dedicated to nonlinear and Multiphysics structural analysis. The imported bridge geometry undergoes a data validation and transformation process to interpret and refine the analysis elements.

At this stage, material properties, boundary conditions, and load cases (including dead weight, live loads, and thermal loads) are assigned based on engineering specifications and design codes. Following data assignment, finite element mesh generation techniques are used to discretize the geometry and convert the continuous structural model into an interconnected element-node system. Selecting the appropriate element type (in this case, Shell element and Solid element are used) and mesh density is critical to obtaining accurate simulation results while maintaining computational efficiency.

After the discretization is complete, a structural analysis is performed. DIANA FEA calculates stress distributions, deformation patterns, and structural response under a variety of loading scenarios. The results are interpreted to evaluate the structural performance of the bridge and its behavior under complex operational and environmental conditions.

This BIM-FEA interoperability framework enhances the analysis capabilities of the digital twin, allowing engineers to perform predictive simulations and validate real-time sensor data within a unified modeling environment. In addition, the process improves consistency, reduces manual rework, and provides a scalable pathway for integrating design, monitoring, and analysis workflows in bridge lifecycle management.

(8) Validation using FE analysis

In this phase of the study, the deformation behavior of the bridge structure obtained from Global Navigation Satellite System (GNSS) observations is subjected to numerical validation using Finite Element (FE) Analysis that specifically considers the effects of loading due to temperature. The numerical validation process compares the observed GNSS displacement time series with the simulated displacements obtained from the FE model under identical temperature and boundary conditions. This step ensures that the numerical model accurately represents the physical behavior of the bridge relative to real-world environmental influences.

The numerical validation work focuses on ensuring that the FE model, including material properties, boundary conditions, and thermal loading conditions, can reproduce the measured structural response within acceptable limits. Special attention is paid to the effects of thermal expansion. The effect of thermal expansion is particularly significant for steel bridges due to the high coefficient of thermal expansion of the material; incorporating temperature data measured simultaneously with GNSS displacements allows for a coupled thermal-mechanical analysis and increases the fidelity of the numerical validation.

Through this integrated verification and numerical validation process, the accuracy and reliability of the Digital Twin-based Bridge Structural Health Monitoring (BrSHM) system were established. This allows the digital twin to function not only as a real-time monitoring tool but also as a predictive analytical model capable of simulating structural response under a variety of operational and environmental conditions. This dual capability is an important advance in the implementation of data-driven SHM strategies for complex bridge structures.

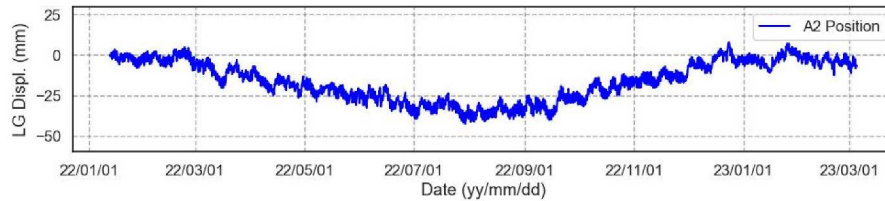
8.3. Bridge deformation based on GNSS observation data

After collecting long-term deformation data of the target bridge using GNSS observation sensors, the data is thoroughly processed and evaluated to reduce noise. Then, the displacement results of Longitudinal, transversal, and vertical are presented as follows

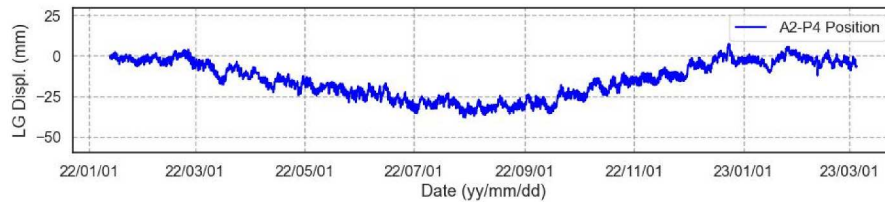
(1) Longitudinal Deformation of the Bridge Based on GNSS Observation Points

The longitudinal deformation behavior of the bridge was evaluated using GNSS-based monitoring data, as shown in **Figure 8.9**. The results show a clear spatial gradient in displacement along the longitudinal axis of the bridge, highlighting that the deformation response varies depending on the location of the structure. The R1 GNSS sensor located near abutment A2 recorded a maximum longitudinal displacement of 43.6 mm. This displacement gradually decreased at R2, located at the midpoint between Abutment A2 and pier P4, where a displacement of 38.5 mm was observed; at R3 (on pier P4), the displacement decreased further to 30.5 mm, and the minimum displacement was 22.3 mm at R4, located between P4 and P3.

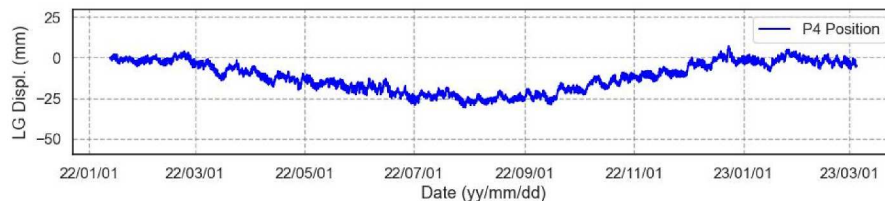
This deformation trend is mainly due to the temperature-induced expansion and contraction of the steel superstructure. Steel has a relatively high coefficient of thermal expansion of about $12 \times 10^{-6} / ^\circ\text{C}$ and is particularly sensitive to changes in temperature. During periods of higher temperatures, such as the summer months, the bridge superstructure expands, especially in the longitudinal direction. The expansion is more pronounced near the abutment (R1), where longitudinal restraint is relatively limited due to the continuous, horizontal curvature of the bridge and the presence of pinned bearings at the abutments and roller bearings at the intermediate piers.



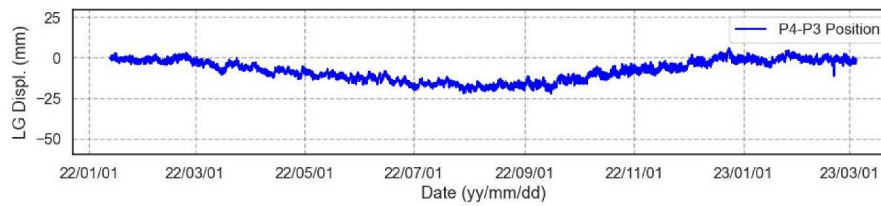
(a) R1 (at A2)



(b) R2 (at the center of A2 and P4)



(c) R3 (at P4)



(d) R4 (at the center of P4 and P3)

Figure 8. 9 Bridge deformation in the longitudinal direction at the GNSS observation point

Conversely, in cold weather, the decrease in temperature leads to thermal contraction, which reverses the direction of displacement. The magnitude of longitudinal deformation at each GNSS observation point is strongly influenced by its proximity to structural restraints such as fixed piers or movable supports. Observation points close to expansion joints or roller bearings (e.g., R1 and R2) exhibit larger displacements because the structure can accommodate thermal movement. In contrast, observation points close to fixed or rotationally constrained supports (e.g., R3 and R4) show less movement due to the stiffness provided by the restraints. A 436-day-long-term monitoring of the bridge and data acquisition during all four seasons provided comprehensive knowledge of the bridge's thermo-mechanical performance. These findings are essential for evaluating thermal fatigue behavior, expansion joint serviceability, and stress redistribution mechanisms in continuous steel bridges with curved geometries. In addition, the deformation data obtained from GNSS serves as a benchmark data set for validating finite element (FE) models within the digital twin framework, ensuring consistency between simulation and actual structural behavior under environmental loading conditions.

(2) Transverse Deformation of the Bridge Based on GNSS Observation Points.

In addition to longitudinal behavior, lateral deformation of the bridge was also monitored using GNSS sensors, the results of which are shown in **Figure 8.10**. The data revealed that a distinct pattern of lateral movement occurred, especially during periods of hotter temperatures. Lateral displacements of approximately 10.9 mm were observed at R1, located near abutment A2, indicating that significant lateral displacements occurred during the summer period. This behavior is due to the thermal expansion of the steel superstructure, which causes the bridge to move not only longitudinally but also laterally due to its curved shape and associated eccentric load path. As the bridge expands, the superstructure may contact the abutment back wall or bearing seat, causing deflection due to restraint, leading to lateral movement. When axial expansion reaches its limit due to contact and restraint, the superstructure is forced to move laterally downstream, especially on curved bridges where curvature induces out-of-plane effects. A similar, though less significant, lateral displacement was observed at R2 (mid-span between A2 and pier P4), with a displacement of about 4.0 mm. The magnitude of displacement was further reduced at R3 (on pier P4), where approximately 2.0 mm of lateral movement was observed; at R4 (between P4 and P3), the displacement was negligible (close to 0 mm). This suggests that lateral movement is minimal in areas where the structure is highly constrained or where thermal expansion has dissipated along the length of the bridge.

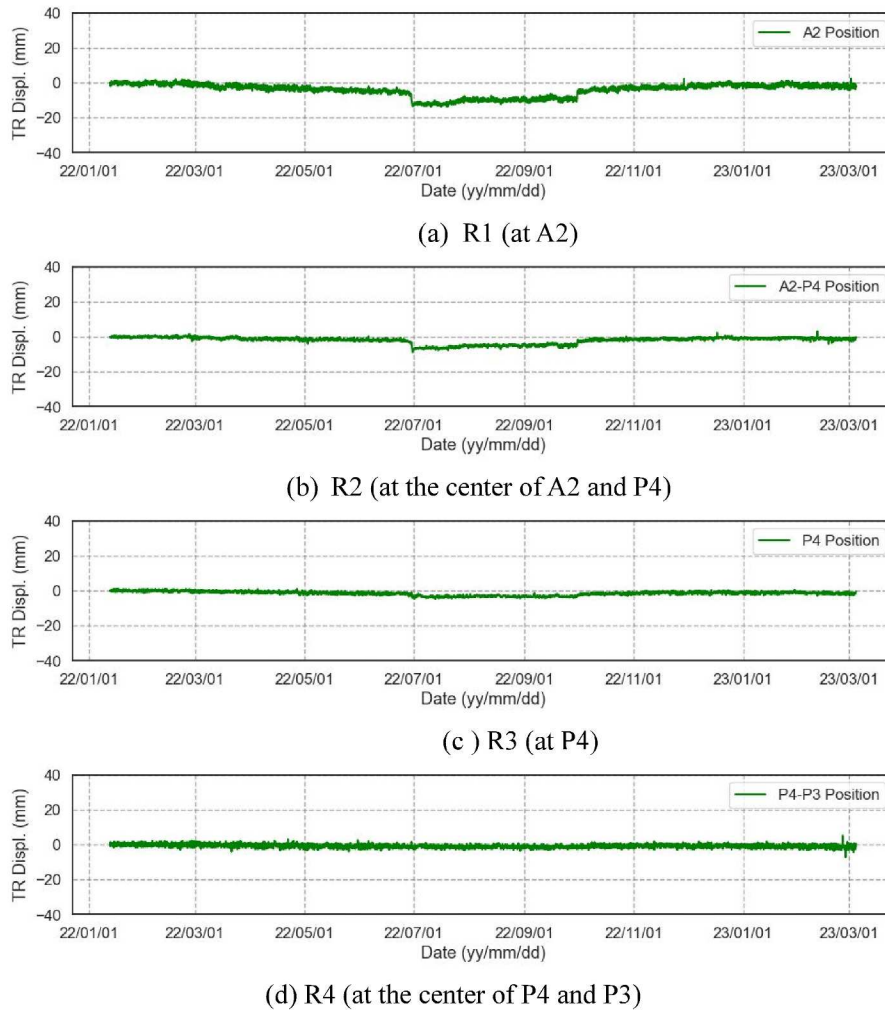


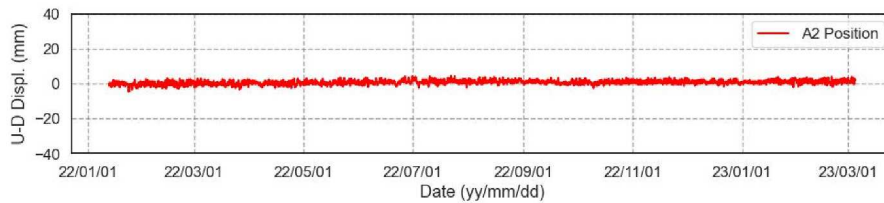
Figure 8.10 Bridge deformation in the transversal direction at the GNSS observation point

This spatial decay of lateral displacement from R1 to R4 emphasizes the combined effects of structural boundary conditions, curvature-induced kinematics, and constrained stiffness. The abutment region (R1) is usually more susceptible to asymmetric thermal forces, especially in bridges with horizontal curvature, leading to more pronounced lateral deformations. Conversely, piers and intermediate support (e.g., R3 and R4) provide greater restraint in the lateral direction, thereby limiting lateral movement.

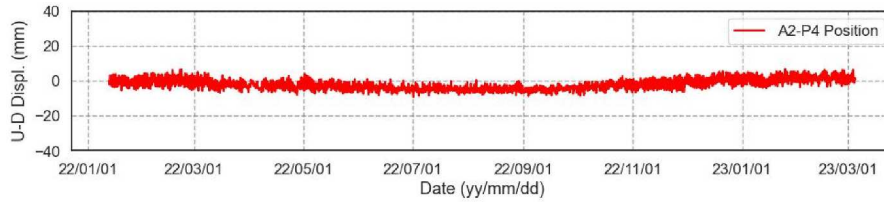
Understanding this behavior is critical, especially as unexpected excessive lateral deformation can affect the structural integrity of bearing alignments, expansion joints, and even the joints between deck segments and supporting elements. The results of this study underscore the importance of continuous lateral monitoring in curved steel bridges, which can reveal potential misalignments and performance issues that cannot be captured by longitudinal monitoring alone. In addition, the dataset supports the calibration and numerical validation of numerical models within the digital twin framework, allowing for more accurate simulation of thermal-mechanical interactions under realistic boundaries and environmental conditions.

(3) Vertical (Up-Down) Deformation of the Bridge Based on GNSS Observation Points

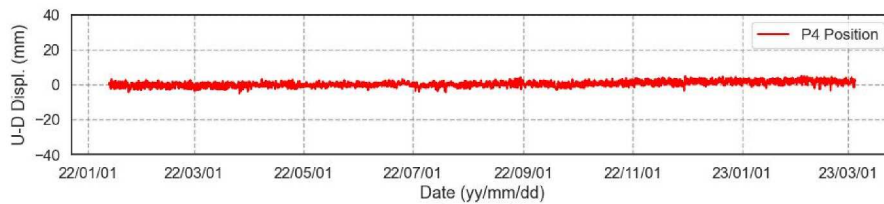
Vertical deformation, which represents the vertical movement of the bridge deck, was also monitored using high-precision GNSS sensors, the results of which are shown in **Figure 8.11**. These observations provide insight into the bending response of the bridge under the combined effects of dead load, thermal effects, and time-dependent behaviors such as creep and settlement. At R1, located near abutment A2, the vertical displacement observed was negligible (approximately 0 mm). This is consistent with expectations, since abutments are usually installed on relatively stiff substructures such as spread footings or pile caps that provide rigid vertical support and limit vertical movement. In contrast, a downward displacement of approximately 9.2 mm was observed at R2, located near the midspan between A2 and P4. This deformation is consistent with deflection of the girder span due to long-term effects such as dead weight, environmental loading, deck system creep, and minor settlement of the supports.



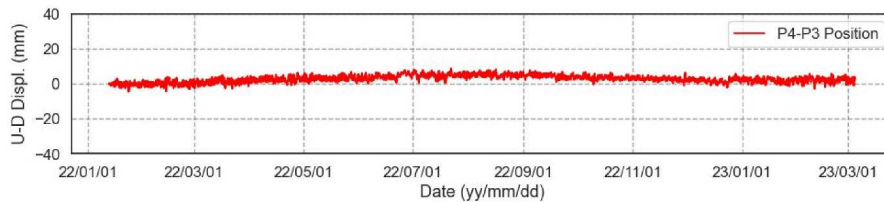
(a) R1 (at A2)



(b) R2 (at the center of A2 and P4)



(c) R3 (at P4)



(d) R4 (at P4 and P3)

Figure 8. 11 Bridge deformation in the up and down direction at the GNSS observation point

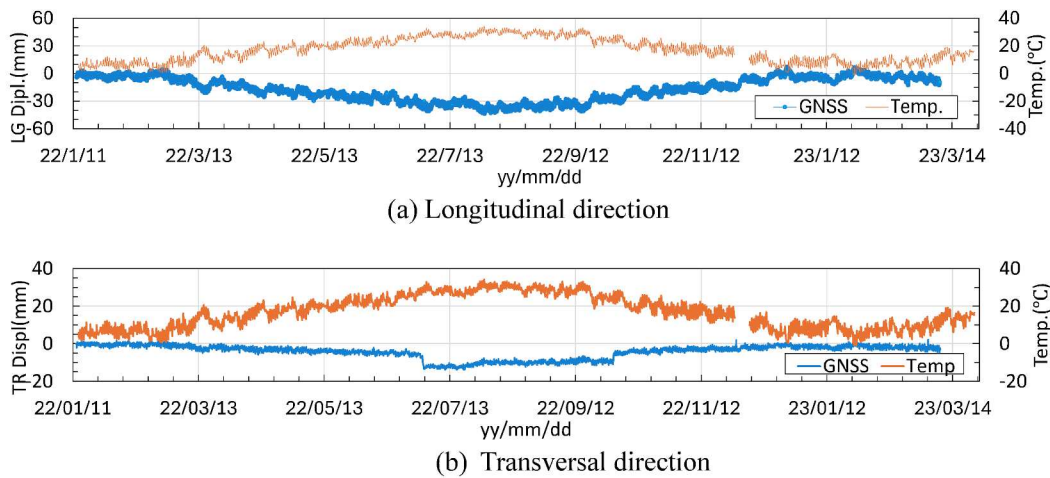
Vertical displacement was almost 0 mm at R3 (location of pier P4), confirming that the piers as intermediate supports generally have high vertical stiffness due to the deep foundation and pile arrangement, which suppressed significant vertical displacement. Interestingly, a positive (upward) displacement of about 8.5 mm was observed at R4, located between P4 and P3 piers. This counterintuitive behavior suggests the influence of thermal gradients and differential expansion in curved steel bridges, possibly causing local uplift effects. In continuous curved girders, warping torsion, thermal warping, and bearing reaction may lead to unexpected vertical displacements. For example, uneven heating of the top and bottom flanges during the day can cause vertical camber due to differences in thermal curvature, especially in lightly restrained segments of the bridge. In addition, the bearing stiffness and thermal restraint of piers can create articulated ridges in adjacent spans under certain boundary and loading conditions.

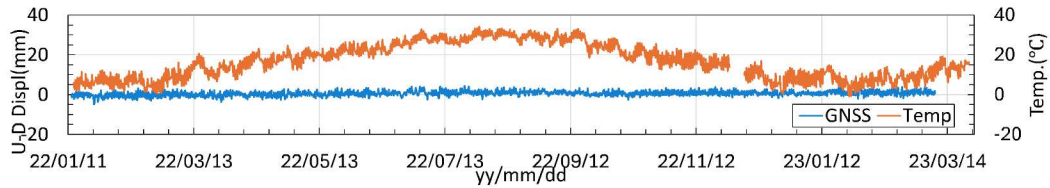
These vertical deformation patterns are critical to understanding the structural health and serviceability of bridges, especially for evaluating span deflections, bearing capacity, and overall curvature behavior. It also serves as an important input for validating the results of finite element analysis (FEA) to ensure that the digital twin model accurately reflects the actual structural response. By capturing both quasi-static vertical deformations and possible dynamic vertical anomalies, this GNSS-based monitoring increases confidence in the long-term structural performance assessment of continuous curve steel bridges.

8.4. Validation of the Digital Twin model based on the GNSS observation data for bridge deformation behavior

(1) Bridge deformation behavior due to the temperature fluctuations

This study uses long-term GNSS displacement data and temperature records to critically examine the relationship between bridge deformation behavior and ambient temperature fluctuations. **Figure 8.12** shows the correlation between temperature fluctuations and the resulting deformation of the structure, focusing in particular on observation point R1, located near abutment A2.





(c) Up and down direction

Figure 8. 12 Bridge deformation and temperature fluctuation

The longitudinal deformation observed at R1 clearly shows a strong seasonal correlation with temperature. As the ambient temperature increases (especially in summer), the bridge superstructure undergoes thermal expansion, resulting in an observed maximum displacement of approximately 43.6 mm. This expansion follows a linear thermal strain relationship given by Equation:

$$\Delta L = \alpha \cdot L \cdot \Delta T \quad (8.1)$$

Where:

- ΔL is the change in length,
- α is the coefficient of thermal expansion of steel (approximately $12 \times 10^{-6}/^{\circ}\text{C}$),
- L is the effective length of the girder segment,
- ΔT is the temperature changing.

This relationship explains the gradual increase in displacement from cold (non-summer) to hot (summer) months and the decrease in displacement as the cooler months return. This response is most pronounced at the free or semi-fixed ends of the bridge, such as the abutments, where the longitudinal restraints are more limited, allowing for more definite heat transfer. The data confirms the expected elastic deformation behavior of steel bridge systems subjected to environmental loading.

(a) Transverse Deformation

In the lateral direction, the displacement pattern exhibits a distinct nonlinear behavior. Initially, as temperatures begin to rise before the summer peak, the lateral displacement remains relatively small. However, once the maximum summer temperature is reached, a drastic lateral displacement of approximately 10.9 mm is observed at R1. This drastic displacement was attributed to the bridge superstructure expanding beyond the capacity of the designed expansion joints. When the expansion reaches the mechanical limit of the joint, the girder applies pressure against the abutment wall, resulting in a forced lateral displacement, often downstream due to geometric asymmetry or support conditions. This behavior emphasizes the importance of detailed design and maintenance of proper expansion joints in steel bridges, especially in regions with extreme temperature fluctuations. Restrained expansion joints can induce unintended lateral forces that can compromise bearing performance and long-term structural integrity.

(b) Vertical deformation

In the vertical (up and down) direction, the observed displacement is negligible at R1, even under peak thermal conditions. This is consistent with engineering expectations. This is because vertical thermal deformation is generally minimal for steel box girders with symmetrical cross-sections and uniform temperature distribution. Furthermore, vertical restraints by abutments and piers minimize significant vertical displacements due solely to temperature changes. This observation confirms that thermal effects on vertical deformation are less significant than in the longitudinal and transverse directions, unless accompanied by differential heating or long-term settlement.

Therefore, the results from this long-term monitoring study highlight the important role of temperature as the dominant environmental load on bridge performance, particularly for continuous curved steel bridges. Longitudinal expansion, lateral shifts due to joint restraints, and minimal longitudinal changes form a comprehensive thermal deformation profile of the bridge. These results are not only essential for calibrating digital twin models and validating finite element simulations, but also for future design improvements of bearings, expansion joints, and bridge connection systems under thermal loading.

(2) Validation of GNSS Observations Using LVDT Measurements at Abutment A2

To further evaluate the accuracy and reliability of GNSS-based displacement monitoring, an independent sensor-based verification approach was employed at abutment A2, where the maximum longitudinal displacement was observed. Specifically, a linear variable differential transformer (LVDT) was installed to acquire highly accurate displacement data at the same location, as shown in **Figure 8.13**. LVDT is widely recognized in structural health monitoring (SHM) due to its high sensitivity and sub-millimeter resolution, making it a suitable benchmark for validating displacements acquired via GNSS. Comparison between displacement time series obtained from GNSS and LVDT measurements have revealed a strong correlation, especially in thermal expansion and contraction cycles, it is clear that there is a strong correlation in terms of both magnitude and temporal response.

The consistency between the two data sets confirms the effectiveness of GNSS systems in capturing real-time bridge deformation with sufficient accuracy, even in the slow-moving thermally induced displacement regime. This agreement is particularly significant given the inherent differences between the two measurement technologies: GNSS provides geospatial positioning in a global coordinate frame, whereas LVDT provides high-frequency, local relative displacement data. The successful cross-validation not only reinforces confidence in the GNSS measurements but also supports its integration into digital twin frameworks for long-term SHM of bridges.

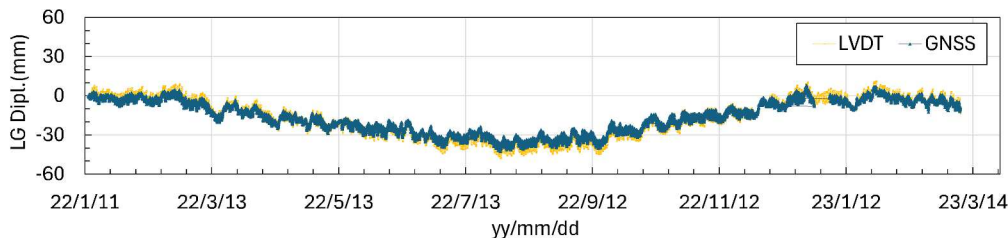


Figure 8. 13 Validation of GNSS Observations Using LVDT Measurements at Abutment A2

(3) Bridge Deformation Trends in the Horizontal Plane at A2

To evaluate and verify the deformation trends of the bridge in the horizontal plane under various temperature conditions, particularly longitudinal and lateral displacements, GNSS displacement data were analyzed over three time periods (pre-summer, summer, and post-summer) with a primary focus on the location of the A2 abutment. As shown in **Figure 8.14**, the pre-summer period extended from January 12 to June 27, 2022. During this period, the ambient temperature increased gradually, and corresponding GNSS measurements showed a gradual expansion of the bridge superstructure in the longitudinal direction. This is consistent with the thermoelastic response of steel, in which the elongation of the structure occurs linearly with increasing temperature. The summer season began on June 28, 2022, and lasted until September 30, 2022.

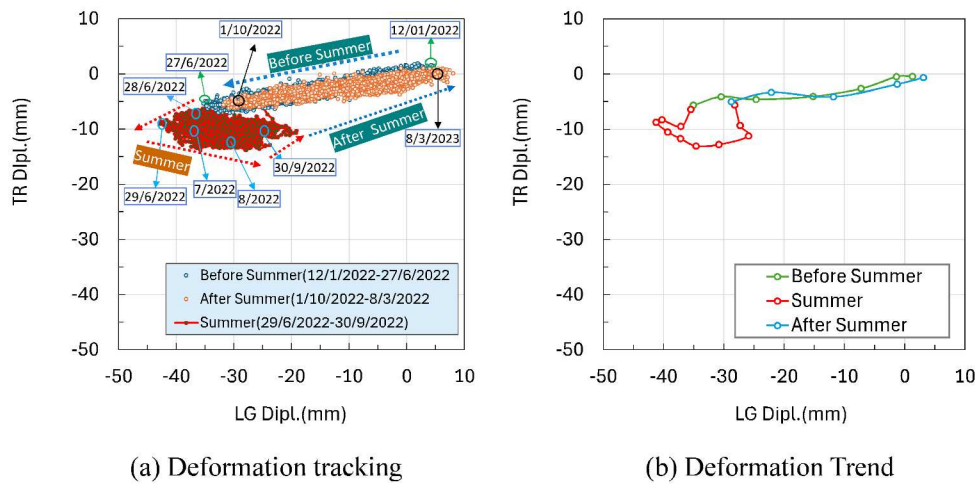


Figure 8. 14 Bridge deformation at the horizontal plane at A2

This period is the peak of the heat load on the structure. As a result:

- Longitudinal displacements in R1 (near A2) reached a maximum of 43.6 mm, reflecting significant axial expansion along the bridge alignment.
- At the same time, a lateral displacement of approximately 10.9 mm was observed downstream, indicating lateral movement of the superstructure.

This combination of horizontal displacements (both longitudinal and lateral) highlights the complex two-dimensional (2D) thermal deformation behavior of continuously curved steel bridges, where geometry, support conditions, and boundary constraints amplify multi-directional expansion.

Following the peak of summer, the ambient temperature gradually decreased after summer ended (October onward). As expected, the bridge contracted, and horizontal displacements gradually decreased. This reversible deformation behavior confirms that the horizontal movement of the structure is primarily elastic and thermally driven, consistent with the principle of linear thermal expansion in homogeneous isotropic

materials such as steel. The horizontal deformation observed at location A2 can be attributed to the following engineering mechanisms:

- Axial movement due to thermal expansion: Due to the continuous and curved geometry of the bridge, expansion is more pronounced at the free or semi-constrained ends (like A2), especially if the structure is supported by rollers or guided bearings.
- Lateral displacement due to abutment restraint: The transverse displacement occurs when the expanding girder reaches the mechanical limit of its expansion joint, causing the structure to bear against the abutment wall, which leads to a forced lateral redirection of the expansion vector.
- Support Configuration and Expansion Path: The deformation path is influenced by the location and type of support. At abutments like A2, roller bearings allow longitudinal movement, but once constrained laterally, this results in non-uniform deformation in the transverse plane.

To provide more context, **Figure 8.15** shows a spatial deformation map across the entire bridge structure, integrating GNSS data from all observation points. This comprehensive view shows gradients in both longitudinal and lateral displacements, highlighting how different segments of the bridge respond in varying ways based on their proximity to expansion joints, piers, and fixed points. Systematic deformation patterns confirm that thermal gradients and structural connections influence the overall horizontal deformation behavior.

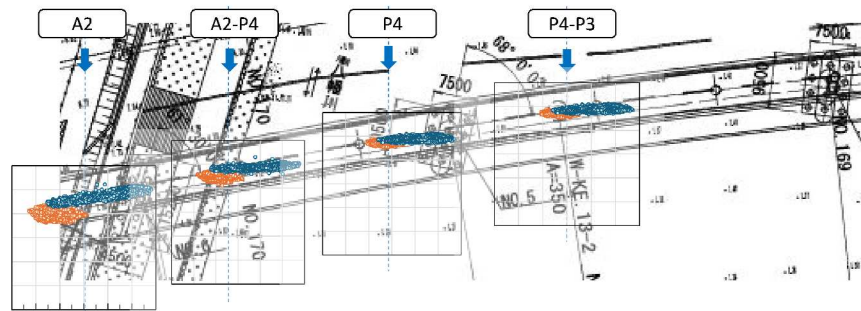


Figure 8. 15 Bridge deformation in the horizontal plane for all measurement points

8.5. Validation of Deformation-Based GNSS Observation by FEA Simulations

In this study, two finite element simulation scenarios were developed and analyzed to assess the reliability of GNSS-based displacement monitoring and to validate the numerical model of the bridge's structural response. This section presents a comparison of the simulation results with observed GNSS deformation data under two different boundary conditions.

(1) Case 1: Fixed-Based Assumption (Without Soil–Foundation Interaction).

In the first scenario, the bridge supports are modeled using a simplified fixed foundation assumption, as shown in **Figure 8.16**. This approach assumes that the foundation system is perfectly rigid and prevents any relative movement between the structure and the ground. While this model is easy to implement and

computationally efficient, it does not account for the flexibility of the ground medium or the actual behavior of the pile foundation system.

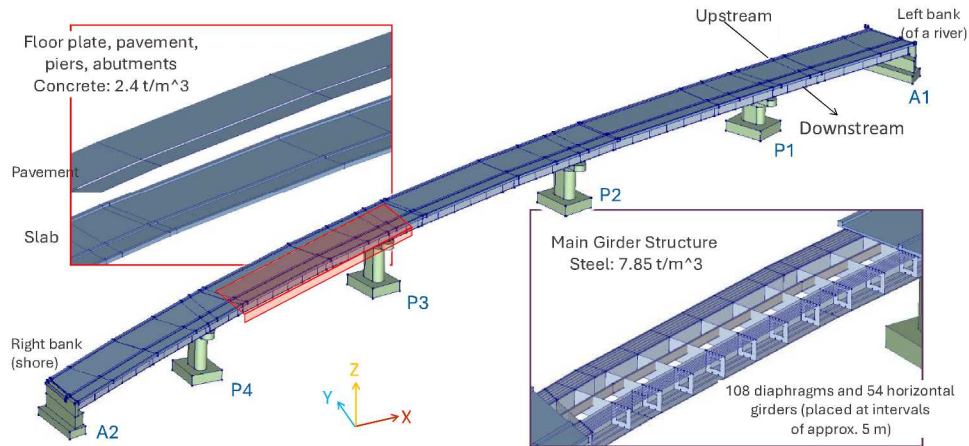


Figure 8. 16 Structural model for the Finite Element Analysis to validate the bridge behavior.

The fixed-base model typically underestimates displacements at the abutments and piers, particularly in curved and continuous bridge structures where temperature-induced movements are significant. Consequently, this assumption often leads to discrepancies between observed GNSS displacements and simulated results, especially in the transverse and longitudinal directions.

(2) Case 1: Full Scale Model of Finite Element Analysis (FEA)

A necessary for conducting detailed and accurate finite element analysis (FEA) of bridges is the creation of a high-fidelity, full-scale, three-dimensional (3D) structural model. In this study, Building Information Modeling (BIM) was employed to build a comprehensive 3D model of the bridge, which was exported in Industry Foundation Class (IFC) format. The IFC format serves as a standardized, interoperable data exchange format. It functions as a standardized, interoperable data exchange format and allows seamless integration with advanced FEA software such as DIANA FEA, as shown in Figure 16. The 3D model captures the basic geometric, material, and structural properties of the bridge, ensuring that all critical components are included in the simulation environment. The structural system of a bridge consists of the following elements. Superstructure like concrete Slab, Twin Steel Box Girders, Diaphragm Bracing system (108 diaphragms), Horizontal Cross (54 cross girders). Substructure components such as Abutments and Piers.

(a) Material Properties for Fixed-Base Assumption Case.

In the fixed-base assumption scenario used in finite element analysis (FEA), the structural response of a bridge is simulated without incorporating the effects of soil-structure interaction. To ensure the fidelity and accuracy of the simulation results, appropriate material properties must be assigned to all structural members in accordance with established engineering standards and actual design specifications.

Table 8. 1 Material properties

Material	Parameters	Symbol	Units	
Concrete	Young's modulus	E	GPa	25
	Poisson's ration	ν		0.2
	Mass density	ρ	Kg/m ³	2400
	Thermal Effect			
	Thermal expansion coefficient	α	/°C	1.0E-5
	Heat flow			
	Conductivity		W/m°C	2.7
	Capacity		J/m ³ °C	2.8+E6
Steel	Young's modulus	E	GPa	210
	Poisson's ration	ν		0.3
	Mass density	ρ	Kg/m ³	7850
	Thermal expansion coefficient	α	/°C	1.2E-6

The main materials considered in the model include reinforced concrete and structural steel, which are commonly used in the construction of steel-concrete composite bridges. The detailed mechanical properties applied to the simulations are shown in **Table 8.1**. These material definitions are crucial for simulation.

(b) Idealization of Boundary Conditions for Pile Caps and Abutments

In finite element modeling of bridge structures, an accurate representation of boundary conditions is fundamental to obtaining realistic simulation results. In this study, the pile caps and the bottom of the abutments were idealized as fixed supports. This modeling assumption is used in Fixed-Based Assumption scenarios, where the interaction between the substructure and the surrounding soils is ignored to simplify the analysis. As shown in **Figure 8.17**, fixed support was implemented by fully constraining the translational degrees of freedom: T1(Longitudinal direction), T2 (Transverse direction), and T3 (Vertical direction). This constraint implies that no displacement occurs in any of the three global coordinate directions at the base of the supports. The rigid connection to the ground effectively treats the abutments and pile caps as being anchored into an infinitely stiff foundation.

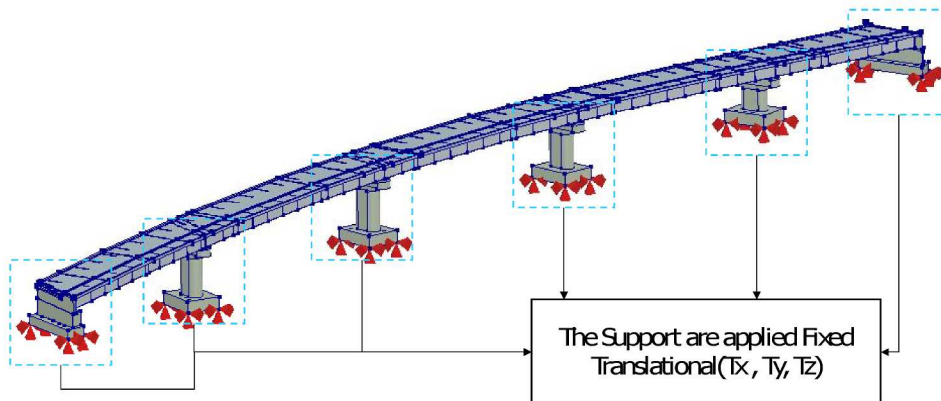


Figure 8. 17 Support

(c) Modeling of Bearings Using Spring Elements

To accurately capture the boundary flexibility and load transfer characteristics at the superstructure and substructure interface, the bridge bearings were modeled using spring elements with directional stiffness characteristics. As shown in **Figure 8.18** and detailed in **Table 8.2**, these spring elements simulate the elastic behavior of the actual bearing system, controlling translational and rotational motion while resisting excessive displacement under operational loads. From a structural engineering perspective, modeling the bearings as spring supports provides a more realistic representation of the behavior of semi-rigid joints, especially in long-span bridges where thermal expansion, creep, contraction, and dynamic loading can significantly affect the structural response. The spring constants assigned in each direction reflect the mechanical stiffness of the bearing system; Longitudinal (x) and Transversal (y) stiffnesses represent lateral resistance to traffic and Seismic loads, Vertical(z) stiffness addresses vertical load bearing capacity, and Rotational Stiffnesses(R_x , R_y , R_z) simulate the flexural and torsional resistance offered by the bearings. Therefore, this modeling approach also enables the simulation of differential displacements across supports, an essential factor in evaluating stress redistribution, bridge deck continuity, and expansion joint behavior.

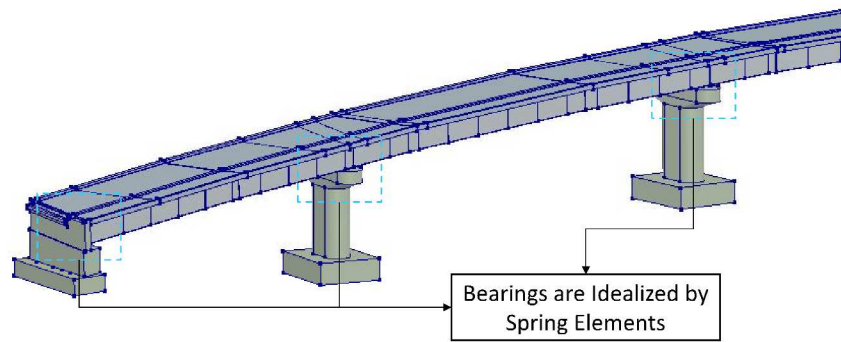


Figure 8. 18 Springs

Table 8. 2 Boundary conditions are idealized as springs.

Support Location	Direction	Stiffness Value	Unit	Engineering Assumption
A2 & A1	X (Vertical)	10^6	MN/m	Fully restrained vertically to simulate support against vertical loads.
	Y (Longitudinal)	1.0	MN/m	Free in longitudinal direction to simulate thermal expansion (expansion bearing).
	Z (Transverse)			Free in transverse direction to accommodate lateral movement.
	Rx (Rotation about X)	10^6	MN/°	Restrained to simulate bending stiffness.
	Ry (Rotation about Y)			Restrained to simulate rotational fixity.
	Rz (Rotation about Z)	1.0	MN/°	Free torsional rotation to allow minor twisting due to thermal effects.
P4 – P1	X (Vertical)	10^6	MN/m	Fully restrained vertically, simulating foundation fixity
	Y (Longitudinal)			Fixed longitudinally to provide axial stability.
	Z (Transverse)			Fixed transversely to resist lateral forces.
	Rx (Rotation about X)	10^6	MN/°	Rotational fixity against lateral bending.
	Ry (Rotation about Y)			Rotational fixity against longitudinal bending.
	Rz (Rotation about Z)	1.0	MN/°	Torsional freedom to accommodate deck warping or thermal-induced twist.

(d) Load Considerations in Finite Element Analysis

The loads considered in this analysis are as follows:

- Self-weight (DL): This load represents the self-weight of all permanent structural components of the bridge, including the concrete deck, steel box girders, diaphragms, and piers. Dead load is automatically calculated within the DIANA FEA software based on the defined material densities and geometries of the modeled components. It forms the baseline gravitational force acting on the bridge and significantly influences the design of both the superstructure and substructure.
- Superimposed dead load (SDL): Superimposed dead loads are additional non-structural permanent loads applied to the bridge after construction of the primary load-carrying system. These include the asphalt concrete pavement, steel railings, parapets, barriers, and safety fences. In this analysis, the total SDL was simplified and applied as a uniformly distributed line load of 50 kN/m along the longitudinal direction of the bridge deck.
- Temperature load effect (Thermal Load Effect): Thermal loads can induce expansion or contraction in the bridge components, leading to additional stresses if restrained. This phenomenon is particularly important in steel bridges due to the high coefficient of thermal expansion of steel.

(e) Discretization (Meshing)

A mesh is a discrete representation of a larger geometric domain using smaller cells. Meshing is dividing continuous geometry into discrete elements in order to solve the structural behavior by FEA. In this study, a full-scale 3D bridge model was meshed in DIANA FEA using the HEX/SQUAD element type and a mesh size of 700 mm. Hexahedral elements were used to capture stress and displacement fields with greater accuracy, while SQUAD elements were used in geometrically complex regions. **Figure 8.19** shows a mesh

configuration that balances computational efficiency and modeling accuracy, especially in regions where stress concentrations and structural interactions are likely to occur.

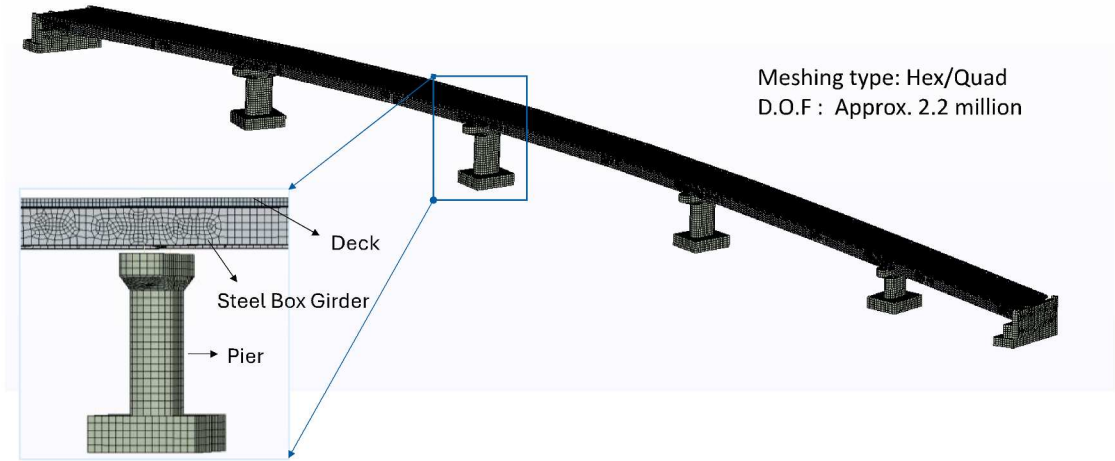


Figure 8. 19 Discretization

(f) Analysis type

In this study, nonlinear 3-D finite element analyses were performed to understand the complex behavior of material nonlinearities and boundary interactions, which are important in large-scale bridge structures, as shown in **Table 8.3**. Solid elements were employed for the model, which can accurately simulate volumetric stresses and strains under service and extreme loading conditions. A mesh size of 700 mm was selected to ensure a balance between computational cost and result accuracy, and a combination of hexahedral and quadrilateral elements was used to match the geometric complexity of the bridge. The final model achieved approximately 2.2 million degrees of freedom, reflecting the detailed discretization required for high-fidelity simulations.

Table 8. 3 Analysis type

Name	Type
Analysis	Non-Linear
Dimension	3- Dimension
Element	Solid
Mesh size	700 mm
Mesh Type	Hex/Quad
D.O.F	Aprox. 2.2 million

(g) Validation Results: Deformation-Based GNSS Observations vs. FEA under Fixed-Based Assumption

The numerical validation process compares Finite Element Analysis (FEA) results with GNSS-based displacement observations, assuming a Fixed-Based Assumption (soil-structure interaction is ignored) over two conditions: before and after bridge collision.

- Before Collision Scenario

In the scenario prior to the bridge collision, FEA results under fixed-base conditions revealed a temperature-induced displacement pattern that deviates significantly from GNSS-observed trends during non-summertime, as shown in **Figure 8.20**. This inconsistency suggests that thermal responses captured by the FEA model may not fully reflect the boundary conditions and actual structural behavior, particularly due to the idealized fixed support assumption. Temperature-induced effects in real bridges are influenced by boundary flexibility and substructure-soil interaction, which are simulated in this case, potentially leading to underestimation or misrepresentation of true displacement responses.

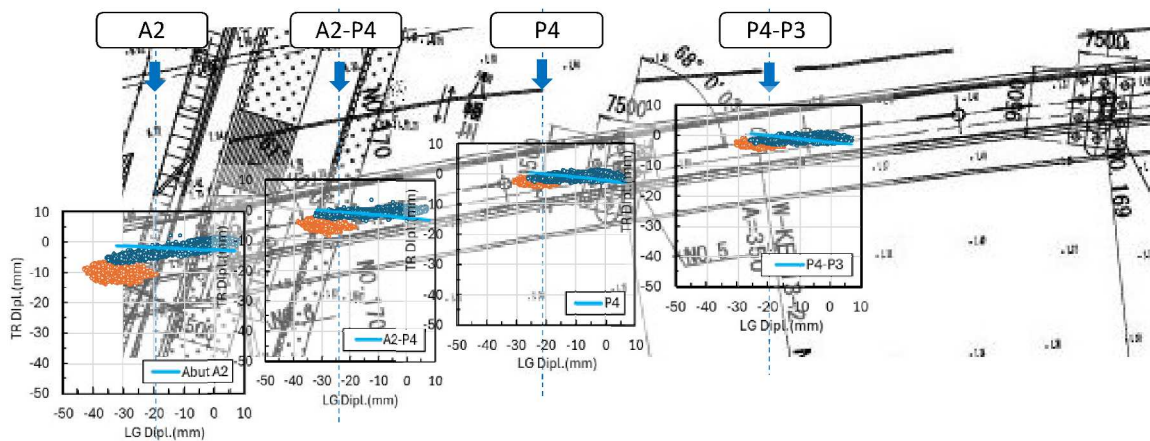


Figure 8. 20 Before collision

- After Collision Scenario

Post-collision simulation results also showed inconsistencies with GNSS data collected during the summer time, as shown in **Figure 8.21**. Deviations in the observed displacement patterns could be attributed to changes in boundary conditions and stiffness distributions due to the collision accident that are not fully captured by the fixed-base model. This highlights the limitations of ignoring soil-foundation interactions, especially when load paths and structural stiffnesses change due to structural damage or system nonlinearities. This mismatch emphasizes the importance of incorporating realistic boundary conditions to accurately simulate actual bridge behavior.

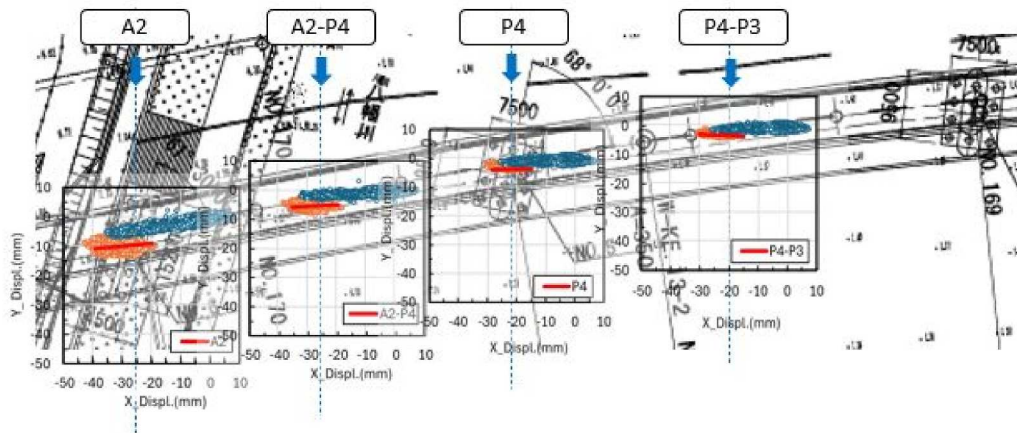


Figure 8.21 After Collision

(3) Case 2: Soil–Foundation Interaction Included

The second scenario incorporates soil-structure interaction (SSI) into the finite element model to more realistically represent boundary conditions. Instead of assuming rigid support, this model includes:

- **Pile Foundation Systems:** Bridge substructures are supported by pile foundations modeled with appropriate stiffness and nonlinear behavior to reflect axial, lateral, and rotational resistance.
- **Pile–Soil Interface Parameters:** Interface elements are implemented along the pile shafts to simulate slippage, separation, and load transfer characteristics. These are defined using appropriate normal and tangential stiffness coefficients based on geotechnical data.
- **Pile tip interaction:** The bearing behavior of the pile tip is included by specifying the end bearing stiffness, which is essential for understanding the vertical load transfer mechanism.
- **Surface interface parameters:** The contact surface between the pile tip and the soil boundary is modeled to reflect the potential for interaction due to differential pressure settlement and load redistribution.
- **Soil stratigraphy and layer properties:** The ground is modeled using multiple layers with distinct mechanical properties such as elastic modulus (E), Poisson's ratio (ν), cohesion (c), internal friction angle (ϕ), and unit volume weight (γ). These parameters are derived from detailed geotechnical investigations, including borehole profiles and laboratory tests.

These parameters are incorporated in order to simulate the realistic behavior of the bridge under thermal fluctuations.

(a) Full-Scale Finite Element Analysis (FEA) Model with Soil–Foundation Interaction

In order to realistically simulate the structural behavior of bridges, a full-scale finite element analysis (FEA) model incorporating soil-foundation interaction (SFI) was developed. This advanced modeling technique includes a detailed representation of pile foundations and reproduction of layered soil layers, capturing the geotechnical profile of the site as demonstrated in **Figure 8.22**.

Unlike the fixed support assumption, this model takes into account the relative flexibility and interaction between the foundation elements and the surrounding soil. Based on soil investigation data, key parameters such as the interface characteristics between the piles and the soil, the support conditions at the pile tips, and the soil stiffness of each layer were defined. This level of detail enables more accurate simulation of boundary conditions and load transfer mechanisms. By incorporating SFI, the model captures critical aspects of bridge behavior under service loads and environmental effects, such as temperature-induced deformations, more realistically

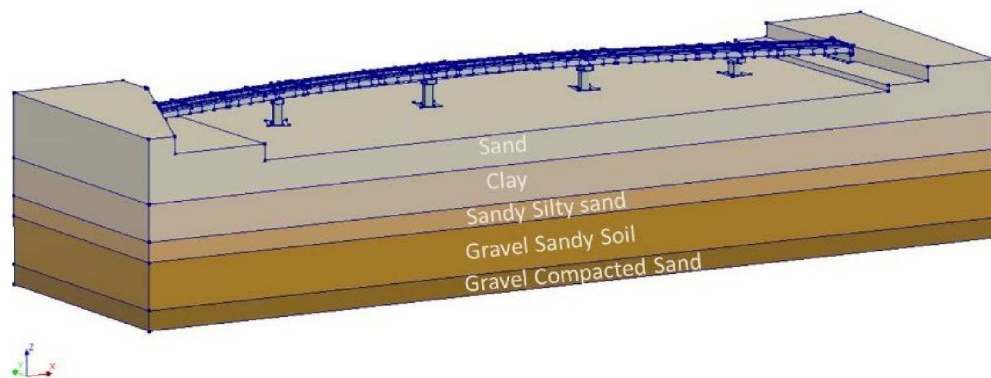


Figure 8. 22 Full-scale model

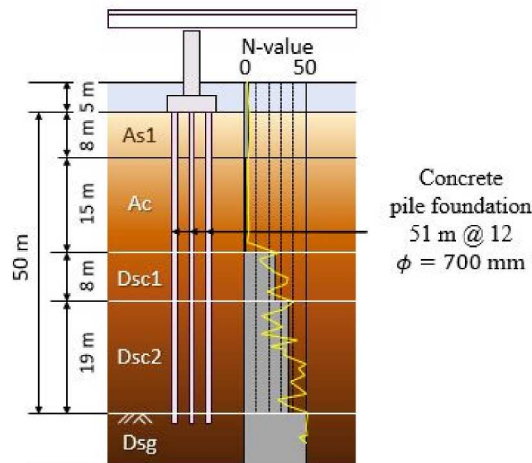
(b) Soil Properties and Subsurface Stratigraphy

A comprehensive geotechnical investigation was conducted to evaluate the foundation conditions supporting the bridge. The soil consists of five different soil layers, each with its unique mechanical properties as demonstrated in **Table 8.4**. Specifically, these are sand (AS1), clay (Ac), silty sand (Dsc1), gravelly sand (Dsc2), and dense gravelly compacted sand (Dsg). These layers were modeled using the Mohr-Coulomb failure criterion, which is suitable for simulating the elastic-plastic behavior of soil materials under varying load conditions.

Table 8. 4 Soil Properties

Soil Parameters	Symbols	unit	Layer 1 _Sand(AS1)	Layer 2 _Clay(Ac)	Layer 3_Sandy Silty Sand(Dsc1)	Layer 4_ Gravel sand Soil(Dsc2)	Layer 5_Gravelly compacted sand (Dsg)
Young's modulus	E	MPa	47.14	43.50	285.63	397.18	554.18
Poisson's ratio	ν		0.3	0.45	0.3	0.28	0.27
Saturated soil density	ρ	T/m3	1.6	1.5	1.8	2.0	2.2
Yield type			Mohr-Coulomb	Mohr-Coulomb	Mohr-Coulomb	Mohr-Coulomb	Mohr-Coulomb
Cohesion	c	MPa	0	0.01	0	0	0
Friction Angle	ϕ	°	30	15	30	38	42
Dilatancy angle	ψ	°	0	0	0	15	0
Lateral pressure ratio	K0		0.50	0.74	0.50	0.29	0.29

Furthermore, as shown in **Figure 8.23**, the bridge pier foundations consist of 12 concrete piles with a diameter of 700 mm and a length of 51 meters, extending through the soft upper layer to the deep dense sand layer (Dsg layer) to ensure sufficient tip bearing capacity and lateral friction. According to the N-value profile (standard penetration test), hardness and strength increase in depth, avoiding soft soil layers, supporting the rational use of deep foundations to utilize the resistance of the dense layer. The integration of this stratified soil profile into the full-scale FEA model enhances the accuracy of simulating soil–structure interaction effects on the bridge.

**Figure 8. 23** Subsurface Stratigraphy

(c) Pile Parameters

The pile parameters used in this study are summarized in **Table 8.5(a), (b), (c), and (d)**. These include the interface characteristics of the pile shaft, pile tip, and surrounding soil. These parameters are essential for accurately simulating the interaction between the pile and the soil and predicting the structural response of the bridge.

Table 8. 5(a) Pile Interface

Pile Interface			
Parameters	Symbols	Unit	Bending pile
Stiffness modulus normal to pile	Kn	kN/m ³	1.0e+10
Shear stiffness modulus along the pile	Kt	kN/m ³	1.0e+07
Shaft interface failure model			Ultimate shear force/ length
Maximum shear force per length of pile		kN/m	1.0e+08
Shaft interface normal stiffness			Linear

Table 8. 5(b) Pile Tip Parameters

Pile Tip Parameters			
Parameters	Symbols	Unit	Bending pile
Stiffness modulus normal to pile	Kn	kN/m ³	1.0e+10
Shear stiffness modulus along the pile	Kt	kN/m ³	1.0e+07
Shaft interface failure model			Ultimate shear force/ length
Maximum shear force per length of pile		kN/m	1.0e+08
Shaft interface normal stiffness			Linear

Table 8. 5(c) Surface Interface Parameters of pile tip

Surface Interface Parameters of pile tip				
Parameters			Pile Tip	
Normal stiffness modulus in pile direction	K_n	kN/m	1.0e+06	kN/m
Shear stiffness modulus normal to pile	K_s	kN/m	1.0e+05	kN/m
Pile tip failure model			Ultimate resistance force	
Ultimate pile tip resistance force		kN	500	kN

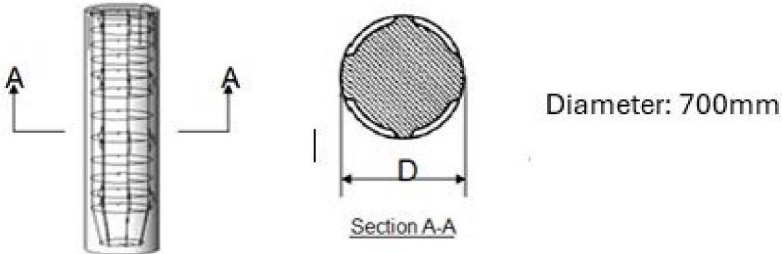
Geometrical properties of the pile	
	

Table 8. 5(d) Surface Interface Parameters of Soil

Surface Interface Parameters of Soil			
Parameters		Unit	3D surface inter- face
Normal stiffness modulus	K_z	kN/m ³	1.0e+05
Normal stiffness modulus	$K_x=K_y$	kN/m ³	1.0e+04
Model type			Coulomb friction
Cohesion	c	kN/m ²	0
Friction angle	ϕ	°	30
Dilatancy angle	φ	°	0
Interface opening model	Nonlinear soil bedding		
Maximum compressive stress		kN/m ²	200

(d) Soil–Foundation Interaction Meshing

The mesh configuration of the soil-foundation interaction model is shown in **Figure 8.24**. To ensure geometric fidelity and convergence efficiency in finite element analysis (FEA), a structured mesh with an average element size of 700 mm and a hexahedral/tetrahedral (Hex/Quad) mesh type was used for the bridge superstructure and foundation structure. This mesh size provides a balance between computational efficiency and the resolution required to capture stress gradients and displacement fields, especially in regions of load transfer such as pier-deck junctions and pile heads.

An 8-segment discretization method was adopted for the surrounding soil area, and hexahedral/quadrilateral elements were used. This meshing strategy enables accurate modeling of stress propagation and settlement behavior within soil blocks. Hexagonal elements are particularly well-suited for capturing the non-linear stress-strain response of soil in 3D analysis, as they offer superior numerical performance compared to tetrahedral elements. The resulting model has over 2.2 million degrees of freedom (DOF) and reflects the high resolution necessary to reliably simulate complex soil-structure interaction effects on the bridge body. The large DOF count enables accurate capture of local and global deformations to simulate realistic behavior conditions of the bridge.

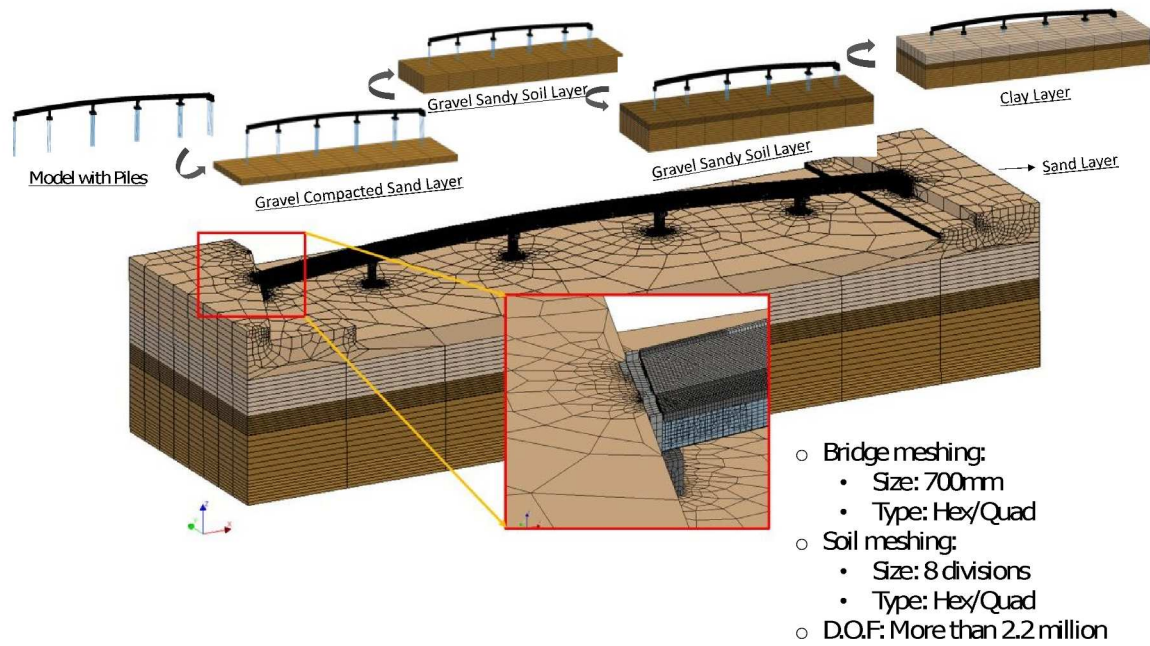


Figure 8. 24 Discretization/ Meshing

(e) Validation of Bridge Displacement: GNSS Observations vs. FEA with Soil–Foundation Interaction

To verify the developed finite element analysis (FEA) model, displacement data based on deformation obtained from global navigation satellite system (GNSS) monitoring and numerical simulation results considering soil-foundation interaction (SFI) were systematically compared as shown in **Figures 8.25** and **Figure 8.26**. Two behavioral cases were considered: (i) the *Before collision case*, where bridge components are

free to expand and contract, and (ii) the *After-collision case*, where thermal expansion leads to physical contact with structural boundaries (e.g., abutments), inducing constrained behavior.

In both cases, the bridge exhibited periodic deformation patterns with amplitudes and trends that correlate strongly with seasonal temperature fluctuations. The GNSS data revealed the temporal evolution of structural displacement with high accuracy, particularly in the longitudinal and transverse directions.

A particularly important engineering point is the observation that abnormal lateral deformation occurs in the superstructure. This phenomenon is believed to be caused by the longitudinal expansion of the bridge exceeding the initial design gap between adjacent structural elements (e.g., finger joints and abutment clearances). Once this threshold is exceeded, the interaction forces caused by the restraint effect induce lateral deformation, which becomes particularly pronounced during thermal expansion in summer.

By incorporating the interaction between the soil and the foundation into a finite element analysis (FEA) model, it has become possible to accurately simulate this coupled behavior. The interaction between the substructure and the surrounding soil plays an important role in constraining or redirecting movement, especially under loads caused by temperature changes. Horizontal deformation of the foundation system is transmitted to the superstructure, resulting in orthogonal displacement components that tend to be underestimated in simplified models.

Therefore, the adoption of Soil Foundation Interaction(SFI) significantly improves the predictive accuracy and physical reality of FEA models. This makes it possible to reproduce complex boundary conditions and constraints that are essential for understanding the actual behavior of bridge structures. This demonstrates that SFI modeling is an essential element in developing reliable digital twin systems for structural health monitoring and lifecycle bridge management.

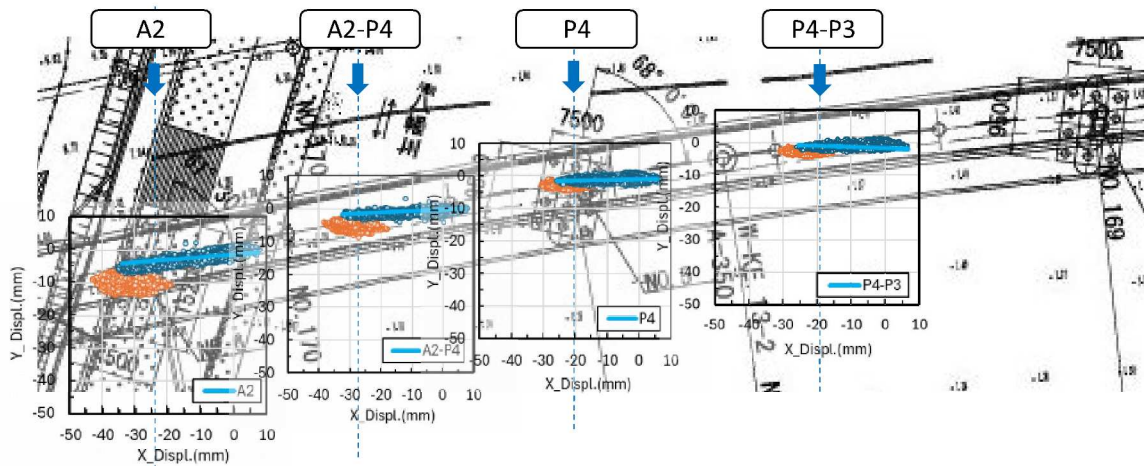


Figure 8.25 Case before Collision

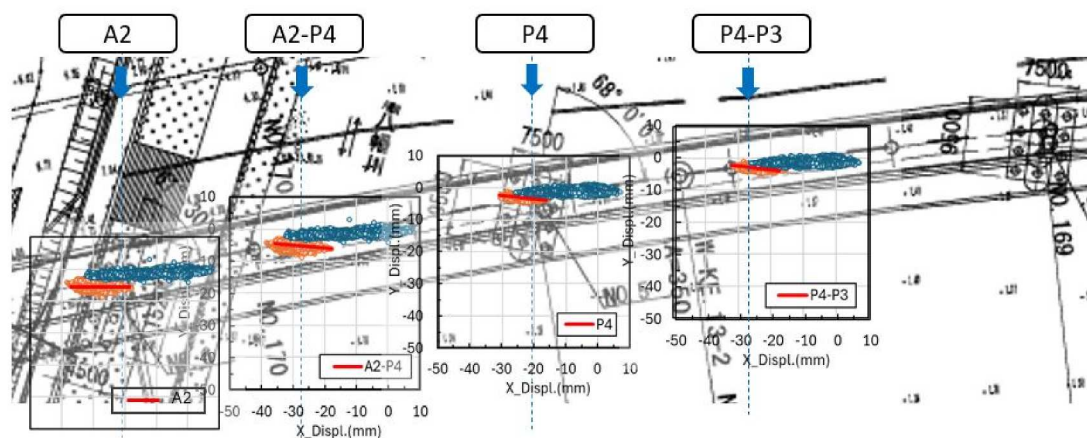


Figure 8. 26 Case after collision

8.6. Conclusions

This study successfully developed and validated a robust Operational Digital Twin (DT) framework for continuous displacement monitoring of continuous curved steel bridges by integrating high-precision GNSS observations and finite element analysis (FEA) within a Building Information Modeling (BIM) environment. Through the synergistic integration of monitoring, estimation, and physical verification, the proposed framework demonstrates its capability to function as a reliable engineering system rather than a static digital representation. The main conclusions of this study are summarized as follows:

1. Realization of an operational digital twin for complex bridge structures

A high-fidelity digital twin of a continuous curved steel bridge was successfully constructed using BIM, demonstrating its effectiveness in representing complex geometries and serving as a foundational platform for integrating real-time sensor data and numerical simulations. The parametric modeling strategy employing Generic Models and Adaptive Component Families, supported by Dynamo, proved essential for accurately capturing the geometric and structural characteristics of curved superstructures and substructures. This modeling approach establishes a scalable basis for operational deployment in real bridge environments.

2. High-precision monitoring of complex displacement behavior using GNSS

By implementing a multi-point GNSS monitoring system, the proposed framework effectively captured the three-dimensional displacement behavior of a curved bridge over a long-term observation period. Continuous monitoring over 436 days revealed clear diurnal and seasonal displacement patterns induced by temperature variations. In particular, curved bridge geometry amplified longitudinal displacements—reaching up to 43.6 mm at the abutment—and lateral movements of up to 10.9 mm, highlighting the necessity of three-dimensional, high-precision monitoring for such structures.

3. Robust BIM–FEA interoperability and physical verification

A seamless interoperability workflow between BIM (Revit) and FEA (DIANA FEA) was successfully implemented using IFC-based data exchange. This workflow enabled the generation of high-resolution numerical models capable of simulating bridge responses under realistic loading conditions. Focusing on temperature-induced behavior, systematic comparisons between GNSS-observed displacements and FEA-predicted deformations confirmed that the numerical model accurately reproduced actual structural responses. This physical verification process significantly enhances confidence in the predictive reliability of the digital twin.

4. Advancement of data-driven bridge management under operational conditions

The integrated DT framework provides a practical foundation for proactive bridge management by combining continuous monitoring with physics-based validation. The ability to distinguish temperature-induced displacements from load-related responses enables engineers to assess thermal fatigue, evaluate the performance of expansion joints, and support maintenance decision-making based on verified structural behavior. This data-driven approach contributes directly to improving the resilience, safety, and long-term durability of critical bridge infrastructure.

5. Addressing research gaps for curved bridge applications

The successful application of the proposed framework to a continuous curved steel bridge addresses a significant research gap in digital twin-based structural health monitoring. Curved bridges, characterized by complex geometries and boundary conditions, pose challenges to conventional SHM approaches. The results demonstrate that the proposed framework is well suited to such structures and provides clear advantages over traditional monitoring methodologies.

Overall, the incorporation of a physical verification layer substantially enhances the engineering reliability of the proposed approach. These results demonstrate that the proposed framework functions not merely as a digital representation, but as an Operational Digital Twin capable of integrating monitoring, estimation, and physical validation for engineering decision-making.

8.7. References

1. Tao, F.; Zhang, H.; Liu, A.; Nee, A.Y.C. Digital Twin in Industry: State-of-the-Art. *IEEE Trans. Ind. Inform.* **2019**, *15*, 2405–2415.
2. Turner, C.J.; Oyekan, J.; Stergioulas, L.; Griffin, D. Utilizing Industry 4.0 on the Construction Site: Challenges and Opportunities. *IEEE Trans. Ind. Inform.* **2021**, *17*, 746–756.
3. Broo, D.G.; Bravo-Haro, M.; Schooling, J. Design and implementation of a smart infrastructure digital twin. *Autom. Constr.* **2022**, *136*, 104171.
4. Tita, E. E., Watanabe, G., Shao, P., & Arii, K. (2023).: Development and Application of Digital Twin–BIM Technology for Bridge Management. *Applied Sciences*, *13*(13), 7435. <https://doi.org/10.3390/app13137435>

5. Tita, E. E., Watanabe, G., Ximenes, H. da C., & Viegas, H. M. S. (2024).: Initiatives in Dili of Timor-Leste for implementing traffic management using digital twin-BIM technology. *Intelligence, Informatics and Infrastructure*, 5(1), 42–56. https://doi.org/10.11532/jsceiiai.5.1_42
6. Gao, Y., Qian, S.; Li, Z., Wang, P., Wang, F., He, Q.: Digital Twin and Its Application in Transportation Infrastructure. In Proceedings of the 2021 IEEE 1st International Conference on Digital Twins and Parallel Intelligence (DTPI), Beijing, China, 15 July–15 August 2021; pp. 298–301.
7. Opoku, D.-G.J., Perera, S., Osei-Kyei, R., Rashidi, M.: Digital twin application in the construction industry: A literature review. *J. Build. Eng.* 2021, 40, 102726.
8. Zhou, Y., Wang, J., & Yang, H. (2019). Resilience of transportation systems: Concepts and comprehensive review. *IEEE Transactions on Intelligent Transportation Systems*, 20(12), 4262–4276. <https://doi.org/10.1109/TITS.2018.2883766>
9. Aktan, A. E., Farhey, D. N., Helmicki, A. J., Brown, D. L., Hunt, V. J., Lee, K.-L., & Levi, A. (1997). Structural identification for condition assessment: Experimental arts. *Journal of Structural Engineering*, 123(12), 1674–1684. [https://doi.org/10.1061/\(ASCE\)0733-9445\(1997\)123:12\(1674\)](https://doi.org/10.1061/(ASCE)0733-9445(1997)123:12(1674))
10. Catbas, F. N., Ciloglu, S. K., Hasancebi, O., Grimmelsman, K., & Aktan, A. E. (2007). Limitations in structural identification of large constructed structures. *Journal of Structural Engineering*, 133(8), 1051–1066. [https://doi.org/10.1061/\(ASCE\)0733-9445\(2007\)133:8\(1051\)](https://doi.org/10.1061/(ASCE)0733-9445(2007)133:8(1051))
11. Ye, X. W., Su, Y. H., & Han, J. P. (2014). Structural health monitoring of civil infrastructure using optical fiber sensing technology: A comprehensive review. *The Scientific World Journal*, 2014, Article ID 652329. <https://doi.org/10.1155/2014/652329>
12. Gómez, J., Casas, J. R., & Villalba, S. (2020). Structural health monitoring with distributed optical fiber sensors of tunnel lining affected by nearby construction activity. *Automation in Construction*, 117, 103261. <https://doi.org/10.1016/j.autcon.2020.103261>
13. Xie, Y., Zhang, S., Meng, X., Nguyen, D. T., Ye, G., & Li, H. (2024). An Innovative Sensor Integrated with GNSS and Accelerometer for Bridge Health Monitoring. *Remote Sensing*, 16(4), 607. <https://doi.org/10.3390/rs16040607>
14. Boje, C., Guerriero, A., Kubicki, S., & Rezgui, Y. (2020). Towards a semantic construction Digital Twin: Directions for future research. *Automation in Construction*, 114, 103179. <https://doi.org/10.1016/j.autcon.2020.103179>
15. Ministry of Land, Infrastructure, Transport and Tourism (MLIT). (2019). *Bridge Maintenance Strategy 2019*. Retrieved from <https://www.mlit.go.jp/>
16. Ministry of Land, Infrastructure, Transport and Tourism (MLIT). (2014). *Implementation of regular inspections for all bridges*. Retrieved from <https://www.mlit.go.jp/>
17. Niu, Y., Li, J., Zhou, S., et al. (2023). *Dynamic displacement estimation and modal analysis of long-span bridges integrating multi-GNSS and acceleration measurements*. *Journal of Infrastructure Preservation and Resilience*, 4(1), 9. <https://doi.org/10.1186/s43065-023-00077-6>
18. Xue, C., & Psimoulis, P. A. (2023). *Monitoring the dynamic response of a pedestrian bridge by using low-cost GNSS receivers*. *Engineering Structures*, 284, 115993. <https://doi.org/10.1016/j.eng-struct.2023.115993>

19. Li, X., Wang, L., Qu, X., Zhang, S., Shu, B., & Xu, H. (2023). *Bridge structure deformation prediction based on GNSS data using Kalman-ARIMA-GARCH model*. *Sensors*, 18(1), 298. <https://doi.org/10.3390/s18010298>
20. Wang, M., & Zhu, Z. (2024). *A data-driven approach for analyzing contributions of individual loading factors to GNSS-measured bridge displacements*. *Journal of Geodesy*. <https://doi.org/10.1007/s00190-024-01913-7>
21. Volk, R., Stengel, J., & Schultmann, F. (2014). *Building Information Modeling (BIM) for existing buildings — Literature review and future needs*. *Automation in Construction*, 38, 109–127. <https://doi.org/10.1016/j.autcon.2013.10.023>
22. Succar, B., Sher, W., & Williams, A. (2017). *An integrated approach to BIM competency assessment, acquisition and application*. *Automation in Construction*, 35, 174–189. <https://doi.org/10.1016/j.autcon.2013.05.016>
23. Marzouk, M. M., & Hisham, M. (2011). *Bridge Information Modeling in Sustainable Bridge Management*. In *ICSDC 2011: Integrating Sustainability Practices in the Construction Industry* (pp. 575–582). [https://doi.org/10.1061/41204\(426\)57](https://doi.org/10.1061/41204(426)57)
24. Sacks, R., Eastman, C. M., Lee, G., & Teicholz, P. (2018). *BIM Handbook: A Guide to Building Information Modeling* (3rd ed.). Wiley.

9. Discussions and Conclusions

9.1. Summary of Findings

This dissertation presented a practical and engineering-oriented framework for an operational digital twin of bridge infrastructure, designed to function under uncertain and noisy monitoring environments. Starting from the limitations of conventional digital twin implementations that primarily emphasize visualization and data integration, this research redefined the digital twin as a dynamic cyber–physical system capable of state estimation, physical verification, and decision support. Through a structured progression from conceptual definition (Chapter 1), critical review of related work (Chapter 2), and framework design (Chapter 3), the proposed approach was demonstrated at both asset and system levels using real-world bridge and traffic management applications (Chapters 4 and 5). Furthermore, the effectiveness of the operational digital twin under abnormal and emergency conditions was illustrated through a post-accident bridge case study (Chapter 6), followed by robust state estimation using data assimilation and machine learning techniques (Chapter 7) and physical verification through finite element analysis (Chapter 8). Collectively, these chapters establish a coherent digital twin framework that advances bridge infrastructure management from descriptive monitoring toward reliable, uncertainty-aware decision support.

9.2. Contributions to Knowledge

This dissertation makes several technical contributions to the development of an operational digital twin framework for bridge infrastructure under uncertain monitoring environments. The primary contribution lies in the systematic integration of monitoring, state estimation, and physical verification into a unified cyber–physical architecture, enabling the digital twin to function as an engineering decision-support system rather than a visualization-oriented information model:

1. This research established a robust displacement estimation framework for bridges based on GNSS observations by combining probabilistic data assimilation and machine learning techniques. By explicitly addressing the uncertainty, noise, and non-stationary characteristics inherent in long-term GNSS displacement data, the proposed approach enables stable and reliable estimation of structural states, even under abnormal and post-accident conditions. This contribution advances GNSS-based structural health monitoring from raw data interpretation toward uncertainty-aware state inference within a digital twin environment.
2. This dissertation introduced finite element analysis (FEA) as a physical verification layer within the digital twin framework. Unlike conventional digital twin implementations that rely solely on data-driven outputs, the proposed framework evaluates whether the estimated structural responses are consistent with fundamental principles of structural mechanics. This verification process prevents physically implausible interpretations and enhances the engineering reliability of the digital twin, particularly in safety-critical infrastructure applications.
3. The research demonstrated the effective integration of Building Information Modeling (BIM) as a semantic and geometric backbone for operational digital twins of bridge infrastructure. BIM was

not treated merely as a static geometric model, but as an interoperable platform that links monitoring data, analytical models, and simulation results across different lifecycle stages. This integration enabled seamless transitions between visualization, analysis, and decision support, reinforcing the operational nature of the proposed digital twin.

4. The proposed framework extended the scope of digital twins from asset-level structural monitoring to system-level applications, including traffic management and environmental impact assessment. By incorporating traffic simulation and policy evaluation within a digital twin environment, this dissertation demonstrated how infrastructure digital twins can support evidence-based decision-making beyond individual structures, contributing to broader transportation system management.

Collectively, these contributions redefine the role of digital twins in bridge infrastructure management by embedding uncertainty-aware estimation and physics-based verification into their core architecture. The proposed operational digital twin framework provides a foundation for more reliable, scalable, and decision-oriented digital twin applications, bridging the gap between monitoring technologies, analytical modeling, and practical infrastructure management.

9.3. Limitations of the Proposed Framework

Despite the demonstrated effectiveness of the proposed operational digital twin framework, several limitations remain and should be acknowledged. First, the reliability of state estimation strongly depends on the quality, spatial configuration, and continuity of monitoring data. Although the framework explicitly accounts for uncertainty and noise in GNSS observations, sparse sensor deployment or data outages may reduce estimation accuracy, particularly for complex structural behaviors.

Second, the current implementation assumes that finite element models reasonably represent the structural system and boundary conditions. In practice, uncertainties in material properties, boundary conditions, and structural deterioration may lead to discrepancies between simulated and actual responses. While the proposed physical verification layer enhances reliability, model updating and parameter calibration remain challenges, especially for long-term operation.

Third, the computational cost associated with data assimilation, machine learning, and finite element analysis limits the real-time applicability of the framework. Although suitable for offline or near-real-time assessment, full real-time operation may require further optimization, model reduction, or cloud-based computation strategies.

Finally, the generalizability of the proposed framework has been validated through selected bridge types and case studies. Application to a wider range of bridge forms, loading conditions, and environmental contexts will require additional verification and adaptation, particularly when transferring the framework to different geographic or operational settings.

These limitations highlight that the proposed framework represents a foundational step toward fully autonomous and scalable operational digital twins rather than a finalized solution.

9.4. Future Research Directions

Building upon the findings and limitations identified in this dissertation, several directions for future research are envisioned to further advance operational digital twin technologies for bridge infrastructure management. A primary direction involves the integration of multi-sensor data to enhance robustness and observability. Combining GNSS measurements with complementary sensing modalities such as accelerometers, inertial measurement units (IMUs), vision-based monitoring, and fiber-optic sensors would enable more comprehensive characterization of structural behavior and improve state estimation under diverse operational conditions.

Another important direction is the development of adaptive and automated model updating mechanisms. While this dissertation employed finite element analysis as a physical verification layer, future work should focus on coupling data assimilation results with automated parameter updating to continuously refine structural models. The incorporation of artificial intelligence and Bayesian inference techniques may enable self-updating digital twins that adapt to long-term structural changes, damage progression, and environmental effects.

Scalability and real-time operation also represent critical challenges for future research. Advancements in reduced-order modeling, surrogate modeling, and cloud-edge hybrid computing architectures could significantly reduce computational costs, allowing operational digital twins to function in near-real-time. Such developments are essential for practical deployment in emergency response, rapid post-event assessment, and continuous infrastructure management.

Furthermore, extending the proposed framework from individual bridges to network-level infrastructure systems present a promising research path. Integrating multiple asset-level digital twins into a unified platform would enable system-level optimization, risk prioritization, and coordinated maintenance planning across transportation networks. This extension would support evidence-based policy-making for infrastructure agencies and local governments.

Ultimately, future research should aim toward fully autonomous operational digital twins that seamlessly integrate sensing, estimation, verification, and decision-making processes. Such systems have the potential to transform bridge infrastructure management by enabling proactive maintenance, enhanced resilience, and data-driven governance in increasingly complex and uncertain environments.

Appendices

Appendix 1: Contextual Background, Motivation, and Research Framework

1.1 Background

Infrastructure is the backbone of modern society, supporting economic growth, social connectivity, and public safety. Among transportation networks, bridges are particularly critical; their structural integrity and operational efficiency directly affect mobility, commerce, and safety. However, bridges are increasingly challenged by aging, higher traffic loads, environmental exposure, and insufficient monitoring and maintenance strategies [1–4]. These factors accelerate deterioration, posing safety risks, operational inefficiencies, and significant economic burdens.

This challenge is particularly acute in developed countries. In Japan, much of the infrastructure constructed during the high-growth period of the 1960s and 1970s is approaching or exceeding its design service life. Over 40% of Japan’s approximately 730,000 bridges are more than 50 years old, with projections exceeding 60% by 2030 [5, 6]. In response, the Ministry of Land, Infrastructure, Transport and Tourism (MLIT) has shifted from reactive to preventive maintenance, implementing a nationwide inspection cycle every five years and promoting advanced technologies, including sensor-based monitoring, Digital Twins (DTs), and artificial intelligence, to support condition-based maintenance and service-life extension [7].

Aging infrastructure is similarly pressing worldwide. In Europe, a large portion of bridges and high-voltage transmission lines exceeds 40 years of age, and investment gaps constrain modernization efforts, threatening resilience and operational efficiency [8–11, 27]. In Germany, approximately 4,000 bridges require urgent modernization, with recent collapses underscoring the consequences of deferred maintenance [9]. In the United States, over 617,000 bridges exist, 42% of which are over 50 years old, and 7.5% are structurally deficient. Addressing a \$125 billion repair backlog requires increasing annual bridge spending from \$14.4 billion to \$22.7 billion to prevent further deterioration [12].

Conventional infrastructure management, dominated by periodic inspections and reactive maintenance, is increasingly inadequate. These methods provide only static snapshots, often overlooking hidden damage, ignoring dynamic environmental loads, and offering limited predictive insight into degradation pathways. Such limitations are manifested at two interconnected levels:

- Asset level: Individual bridges must maintain safety, serviceability, and durability. Traditional lifecycle management often fails to detect early signs of damage or deformation, leaving structures vulnerable to unexpected failures, as evidenced in our case study of the 2018 Prutt Truss Bridge collision in Yamaguchi Prefecture, Japan.
- System level: Infrastructure operates as an interconnected urban system. Rapid urbanization, as seen in cities like our case study in Dili of Timor-Leste, produces traffic congestion, air pollution, and cascading failures that traditional siloed management cannot efficiently address.

Effective infrastructure management requires understanding interactions between capacity, demand, and environmental impact.

Digital Twin (DT) technology provides a transformative solution to these challenges. A DT is a dynamic, virtual representation of physical assets continuously synchronized with real-world data. In civil infrastructure, DT enables real-time monitoring, predictive maintenance, and performance optimization, bridging the gap between observed structural conditions and actionable decision-making. It is essential to distinguish between two foundational concepts used throughout this dissertation: **Monitoring** and the **Digital Twin (DT)**. Monitoring refers to the collection and recording of physical sensor data—such as GNSS, LVDT, temperature, or accelerometer measurements—used to observe structural behavior in real time. By contrast, a **Digital Twin** is a dynamic, data-driven virtual counterpart of a physical bridge that continuously synchronizes real-world monitoring data with simulation models (BIM, FEA) and data-driven analytics (machine learning). A DT not only represents the current physical state but also enables prediction of future behavior and decision support for lifecycle management. When integrated with Building Information Modeling (BIM), the Internet of Things (IoT), and artificial intelligence (AI), the paradigm of Construction 4.0, DT allows simulation of structural responses, prediction of degradation pathways, optimized maintenance scheduling, and assessment of environmental impacts across entire infrastructure networks [13–17, 26].

Within the Architecture, Engineering, and Construction (AEC) sector, BIM is the most widely adopted form of DT, supporting planning, design, construction, operation, and maintenance of bridges, tunnels, and road networks. BIM enhances stakeholder collaboration, improves lifecycle performance, and facilitates data-driven decision-making [16, 18, 19]. For bridges, which experience complex, time-dependent loads from traffic, environmental fluctuations, and operational use, DT enables continuous monitoring of displacements and deformations, early anomaly detection, and informed maintenance planning, directly mitigating risks associated with aging infrastructure [20–25]. In addition to asset-level benefits, DT supports system-level management by enabling integrated analysis of urban infrastructure networks. Traffic simulations, performance evaluations, and environmental impact assessments can inform proactive interventions, optimize resource allocation, and enhance resilience. This holistic approach addresses both localized structural safety and the broader operational and environmental performance of transportation networks. To illustrate the connection between infrastructure challenges, conventional limitations, and the role of DT solutions, **Figure 1.1** presents the conceptual framework guiding this research. Infrastructure deterioration is driven by aging, higher traffic loads, and environmental exposure, creating vulnerabilities that conventional management approaches, such as periodic inspections and reactive maintenance, cannot adequately address. These limitations result in static and fragmented decision-making. By contrast, Digital Twin-based solutions, integrated with Building Information Modeling (BIM), Finite Element Analysis (FEA), Internet of Things (IoT), and Artificial Intelligence (AI), enable real-time monitoring, predictive maintenance, and holistic optimization. Together, these tools form a proactive and data-driven strategy for infrastructure lifecycle management.

In summary, aging infrastructure worldwide highlights the urgent need for a paradigm shift from reactive, fragmented practices to predictive and integrated strategies. Digital Twin technology offers this pathway, bridging asset-level monitoring and system-level optimization, and ultimately supporting the sustainable and resilient management of critical infrastructure.

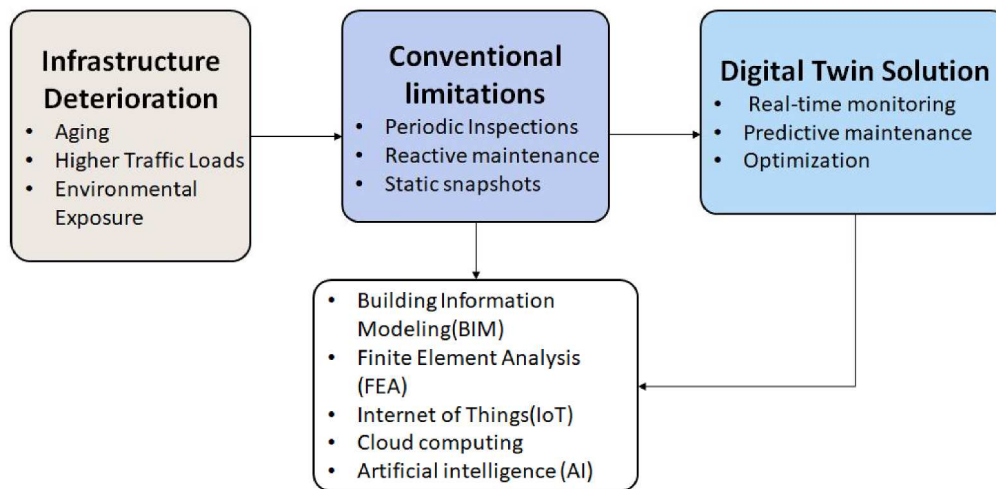


Figure 1. 4 Conceptual framework linking infrastructure deterioration, conventional management limitations, and Digital Twin solutions

1.2. Motivation

The motivation for this research arises from the urgent need to address the challenges posed by aging, increasingly complex infrastructure, and the limitations of conventional management practices. As established in the background, bridges and transportation networks worldwide are deteriorating under the combined pressures of age, increased traffic loads, and environmental exposure. Conventional approaches relying on periodic inspections and reactive maintenance provide only fragmented, static insights into infrastructure conditions. This situation necessitates a paradigm shift toward proactive, predictive, and integrated strategies.

Digital Twin (DT) technology offers transformative potential to enable this shift. By creating dynamic, continuously updated virtual representations of infrastructure assets, DT integrates real-time monitoring, predictive analytics, and lifecycle management into a unified framework. The convergence of high-precision Global Navigation Satellite System (GNSS) monitoring, Building Information Modeling (BIM), advanced Finite Element Analysis (FEA), and intelligent data analytics provides an unprecedented opportunity to overcome the fragmentation of current practice.

The core motivation of this research is therefore to develop, apply, and validate a unified and scalable Digital Twin framework that addresses challenges at both the asset level and the system level of infrastructure management. At the asset level, the research seeks to create robust DTs for structural health monitoring (SHM), enabling continuous assessment of safety, serviceability, and durability. At the system level, it aims to extend DTs to urban-scale applications, integrating transportation dynamics, environmental impacts, and infrastructure performance into a holistic decision-making platform.

The technological and methodological drivers of this research can be grouped as follows:

➤ **Asset-Level Drivers**

- **High-Fidelity Representation (BIM):** Digital Twins require robust geometric and semantic foundations. BIM provides this capability by creating detailed, data-rich models that serve as living digital replicas throughout the asset lifecycle.
- **Real-Time Sensing and Anomaly Detection (GNSS):** Continuous, high-precision GNSS monitoring captures true structural responses, including displacements, thermal deformations, and post-accident changes, enabling anomaly detection beyond the capacity of visual inspections.
- **Robust Data Processing (EnKF / RF):** Raw GNSS data is inherently noisy. Advanced filtering (e.g., Ensemble Kalman Filter) and machine learning algorithms (e.g., Random Forest) are essential for extracting reliable structural responses and identifying unexpected anomalies.
- **Physics-Based Validation (FEA with SSI):** Predictive capability requires validation against physical principles. FEA, including Soil–Structure Interaction (SSI), ensures DTs accurately reflect real-world structural behavior under complex loading conditions.

➤ **System-Level Drivers**

- **Holistic Simulation:** Infrastructure does not operate in isolation but as part of interconnected urban systems. Integrative simulation tools are required to analyze the interplay of traffic dynamics, infrastructure performance, and environmental impacts, supporting evidence-based planning and policy.

Thus, the motivation for this research lies in bridging the gap between emerging digital technologies and their practical application to infrastructure lifecycle management. By unifying BIM, GNSS, FEA, and advanced analytics in a validated DT framework, this work seeks to deliver transformative tools for both engineers and policymakers.

1.3. Problem Definition

Despite growing interest in the importance of data-driven proactive infrastructure management, a significant gap persists between the potential of digital technologies and their actual application in civil engineering practice. Current approaches remain fragmented, reactive, and lack in integration, limiting their effectiveness in addressing the growing challenges posed by aging infrastructure. This study identifies three interrelated core challenges:

- **Integration Challenges at the Asset Level**

At the individual structure level, management workflows remain fragmented. While BIM is widely adopted during design and construction, it is rarely leveraged as a dynamic, living model throughout the entire lifecycle. Similarly, even when collected, SHM data is often stored in isolated silos, disconnected from the asset's digital representation. Consequently, there is no unified, reliable source of information

regarding structural condition, making it difficult to verify performance, detect anomalies, or confidently predict deterioration.

- **System-Level Scale Problem**

Infrastructure extends beyond individual assets to entire urban systems. Yet, current tools are unable to analyze these broader interactions in an integrated manner. For example, traffic congestion both contributes to and results from infrastructure performance, with significant impacts on mobility and environmental quality. The absence of scalable frameworks capable of modeling and simulating these dynamics prevents policymakers from designing effective, evidence-based interventions.

- **Data-to-Decision Problem**

The adoption of high-precision sensors such as GNSS produces vast and complex datasets. However, this data is inherently noisy and cannot be directly translated into actionable insights. Current monitoring methods are often limited to tracking expected behavior and lack robust mechanisms for detecting unexpected anomalies that may signal emerging structural problems. The challenge lies in transforming raw data into reliable, actionable information for real-time decision-making. Taken together, these challenges reveal the absence of a unified, validated, and scalable DT framework that integrates BIM-based modeling, GNSS monitoring, and FEA simulation. Without such a framework, infrastructure management remains reactive, fragmented, and insufficiently predictive, limiting the ability to ensure safety, extend service life, and optimize system performance. These challenges demonstrate the absence of an integrated methodology capable of merging sensing technologies (GNSS), digital representation (BIM), numerical simulation (FEA), and advanced analytics (EnKF/RF) into a unified Digital Twin framework. This gap leads directly to the research question addressed in this dissertation.

1.4. Research Gap

Recent research highlights the growing application of Digital Twin (DT) concepts in civil infrastructure for bridge management, structural health monitoring (SHM), and transportation systems [13–19]. BIM-based DTs have been widely adopted for lifecycle documentation and visualization [16,18,19], while sensor-based monitoring methods, including GNSS, have demonstrated potential for long-term displacement measurement of large-scale structures [21–25]. Finite Element Analysis (FEA) also remains a fundamental tool for physics-based evaluation of structural performance [22,27].

Despite these advances, existing studies predominantly address these components **in isolation**. BIM models are typically static and weakly coupled with real-time monitoring data, SHM systems often operate independently of digital representations, and FEA is commonly applied offline rather than as an active component of a live DT framework [16,19]. Furthermore, although GNSS monitoring enables continuous displacement observation, its practical application is constrained by noise, environmental sensitivity, and limited use of robust data assimilation and machine learning techniques for anomaly detection and decision support [21–23,25].

In addition, most DT implementations remain focused on the **asset level**, with limited extension to system-level analysis integrating bridge performance, traffic dynamics, and environmental impacts, which are

essential for urban-scale infrastructure management and policy-making [20,26]. Consequently, a **validated, unified, and scalable Digital Twin framework** integrating BIM-based digital representation, GNSS-based displacement monitoring, data-driven estimation methods, and physics-based FEA—capable of supporting both asset-level SHM and system-level transportation analysis—remains absent from the current literature. Addressing this gap constitutes the central contribution of this research.

1.5. Core of Research Question

How can a digital twin framework integrating BIM, GNSS-based displacement monitoring, data-driven estimation methods, and finite element analysis (FEA) enhance the accuracy, efficiency, and decision-making capabilities of long-term bridge structural health monitoring and transport system analysis?

1.6. Research Hypothesis

A digital twin integrating BIM modelling, GNSS-based displacement monitoring, data assimilation techniques (extended Kalman filter), machine learning-based estimation (random forest), and physics-based finite element method simulation:

1. Improve displacement estimation accuracy by reducing noise and environmental bias.
2. Enable earlier identification of structural anomalies through synchronized comparison of measured and simulated behavior.
3. Facilitate improved decision-making for bridge management by integrating structural and system-level traffic analysis; and
4. Provide more comprehensive lifecycle insights than conventional monitoring approaches.

The results presented in subsequent chapters support this hypothesis by demonstrating the enhanced performance of the integrated DT workflow in both structural and transportation applications.

1.7. Research Aim and Objectives

The core aim of this study is to develop and validate a digital twin-based structural health monitoring (SHM) framework integrating Building Information Modelling (BIM), Global Navigation Satellite System (GNSS) displacement monitoring, data-driven estimation techniques, and finite element analysis (FEA), thereby enhancing the long-term performance evaluation of bridges and the assessment of transport systems.

This aim arises from identified research gaps: Existing monitoring systems are often operated in isolation, lacking the capability to establish a unified operational environment integrating real-time sensing, physics-based simulation, and predictive analytics. As emphasized in the preceding section, this constraint limits the ability of current structural health monitoring (SHM) methodologies to support preventive maintenance, anomaly detection, fault tolerance assessment, and system-level decision-making.

➤ Research Objectives

To address the research, aim and respond to the core questions, the dissertation established the following specific objectives:

Objective 1: Develop a BIM-based Digital Representation of Bridge Structures

- Create a high-fidelity BIM model that captures geometric, material, and structural attributes of the bridge.
- Establish data interoperability pathways between BIM, GNSS, and FEA environments.

Objective 2: Implement a GNSS-Based Real-Time Monitoring System

- Deploy GNSS sensors to measure long-term displacement of bridges under environmental and loading conditions.
- Characterize noise, drift, and environmental dependencies in GNSS displacement observations

Objective 3: Enhance Displacement Estimation Through Data-Driven Techniques

- Apply the Ensemble Kalman Filter (EnKF) and Random Forest (RF) algorithms to improve the precision and stability of GNSS displacement data.
- Extract interpretable engineering rules from the RF model related to thermal expansion and environmental influences.

Objective 4: Validate Bridge Behavior Using Finite Element Analysis

- Develop linear elastic FEA models to verify global deformation patterns derived from GNSS observations.
- Address the limitations of linear FEA and identify pathways toward nonlinear crack-progression modeling

Objective 5: Extend the Digital Twin to System-Level Transportation Analysis

- To apply DT for traffic simulation to assess traffic congestion and air pollution concentrations.

Objective 6: Demonstrate the Practical Benefits of the Digital Twin Framework

- To illustrate how synchronized sensing–simulation systems support bridge maintenance, accident assessment, and transportation planning.
- To provide an applicable methodology not only to long-span bridges but also scalable to medium- and short-span structures, with sensor-selection considerations

1.8. References

1. C. Chen, “Public infrastructure finance: Symposium introduction,” *J. Public Budgeting, Accounting & Financial Management*, vol. 30, no. 2, pp. 126–134, 2018. Doi: 10.1108/JPBAFM-06-2018-028
2. R. Zhao, Y. Yuan, X. Wei, R. Shen, K. Zheng, Y. Qian, Q. Pu, Q. Zhang, H. Liao, X. Li, C. Zhao, G. Xu, H. Gou, Z. Zhang, and C. Yu, “Review of annual progress of bridge engineering in 2019,” *Advances in Bridge Engineering*, vol. 1, no. 1, pp. 11, Oct. 2020. Doi: 10.1186/s43251-020-00011-w.
3. A. Gamil, M. S. Shrestha, M. Musarat, and A. Ahmed, “A comprehensive review of the key deterioration factors of concrete bridge decks,” *Buildings*, vol. 14, no. 11, p. 3425, 2024. Doi: 10.3390/buildings14113425
4. J. Jeong, Y. Park, H. Lee, and S. Kwon, “Heterogeneous deterioration process and risk of deficiencies of aging bridges for transportation asset management,” *Sustainability*, vol. 13, no. 13, p. 7094, 2021. Doi: 10.3390/su13137094
5. Y. Nemoto, “Considerations on infrastructure aging and renewal investment financing,” *Public Policy Review*, Policy Research Institute, Ministry of Finance, Japan, vol. 18, no. 2, Nov. 2022.
6. Ministry of Land, Infrastructure, Transport and Tourism (MLIT), *Bridge Maintenance Strategy 2019*. Tokyo, Japan: MLIT, 2019. [Online]. Available: <https://www.mlit.go.jp/>
7. Ministry of Land, Infrastructure, Transport and Tourism (MLIT), *Implementation of Regular Inspections for All Bridges*. Tokyo, Japan: MLIT, 2014. [Online]. Available: <https://www.mlit.go.jp/>
8. European Court of Auditors, “Review 01/2025: Making the EU electricity grid fit for net-zero,” European Court of Auditors, Apr. 1, 2025. [Online]. Available: https://www.eca.europa.eu/ECAPublications/RV-2025-01/RV-2025-01_EN.pdf
9. Federal Audit Office of Germany, “Slow refurbishment of dilapidated federal trunk road bridges,” Federal Audit Office of Germany, Apr. 29, 2025. [Online]. Available: https://www.bundesrechnungshof.de/SharedDocs/Downloads/EN/Berichte/brueckenmodernisierung-volltext.pdf?__blob=publicationFile&v=3
10. European Commission, “EU invests record €7 billion in sustainable, safe and smart transport infrastructure,” European Commission, Jul. 17, 2024. [Online]. Available: https://transport.ec.europa.eu/news-events/news/eu-invests-record-eu7-billion-sustainable-safe-and-smart-transport-infrastructure-2024-07-17_en
11. European Investment Bank, “EIB Municipalities Survey 2024-2025,” European Investment Bank, Apr. 8, 2025. [Online]. Available: https://www.eib.org/attachments/lucalli/20250028_080425_municipalities_survey_en.pdf

12. American Society of Civil Engineers, "2021 Infrastructure Report Card: Bridges," 2021. [Online]. Available: <https://2021.infrastructurereportcard.org/cat-item/bridges-infrastructure/>.
13. F. Tao, H. Zhang, A. Liu, and A. Y. C. Nee, "Digital twin in industry: State-of-the-art," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 4, pp. 2405–2415, Apr. 2019. Doi: 10.1109/TII.2018.2873186
14. C. J. Turner, J. Oyekan, L. Stergioulas, and D. Griffin, "Utilizing Industry 4.0 on the construction site: Challenges and opportunities," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 2, pp. 746–756, Feb. 2021. Doi: 10.1109/TII.2020.2977954
15. D. G. Broo, M. Bravo-Haro, and J. Schooling, "Design and implementation of a smart infrastructure digital twin," *Automation in Construction*, vol. 136, p. 104171, Feb. 2022. Doi: 10.1016/j.autcon.2022.104171
16. E. E. Tita, G. Watanabe, P. Shao, and K. Arii, "Development and application of digital twin BIM technology for bridge management," *Applied Sciences*, vol. 13, no. 13, p. 7435, Jul. 2023. Doi: 10.3390/app13137435
17. E. E. Tita, G. Watanabe, H. da C. Ximenes, and H. M. S. Viegas, "Initiatives in Dili of Timor-Leste for implementing traffic management using digital twin-BIM technology," *Intelligence, Informatics and Infrastructure*, vol. 5, no. 1, pp. 42–56, 2024. Doi: 10.11532/jsceiiai.5.1_42
18. Y. Gao, S. Qian, Z. Li, P. Wang, F. Wang, and Q. He, "Digital twin and its application in transportation infrastructure," in *Proc. 2021 IEEE 1st Int. Conf. Digital Twins and Parallel Intelligence (DTPI)*, Beijing, China, Jul. 15–Aug. 15, 2021, pp. 298–301. Doi: 10.1109/DTPI52967.2021.9540182
19. D.-G. J. Opoku, S. Perera, R. Osei-Kyei, and M. Rashidi, "Digital twin application in the construction industry: A literature review," *Journal of Building Engineering*, vol. 40, p. 102726, Nov. 2021. Doi: 10.1016/j.jobbe.2021.102726
20. Y. Zhou, J. Wang, and H. Yang, "Resilience of transportation systems: Concepts and comprehensive review," *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 12, pp. 4262–4276, Dec. 2019. Doi: 10.1109/TITS.2018.2883766
21. A. E. Aktan, D. N. Farhey, A. J. Helmicki, D. L. Brown, V. J. Hunt, K.-L. Lee, and A. Levi, "Structural identification for condition assessment: Experimental arts," *Journal of Structural Engineering*, vol. 123, no. 12, pp. 1674–1684, Dec. 1997. Doi: 10.1061/(ASCE)0733-9445(1997)123:12(1674)
22. F. N. Catbas, S. K. Ciloglu, O. Hasancebi, K. Grimmelsman, and A. E. Aktan, "Limitations in structural identification of large constructed structures," *Journal of Structural Engineering*, vol. 133, no. 8, pp. 1051–1066, Aug. 2007. Doi: 10.1061/(ASCE)0733-9445(2007)133:8(1051)
23. X. W. Ye, Y. H. Su, and J. P. Han, "Structural health monitoring of civil infrastructure using optical fiber sensing technology: A comprehensive review," *The Scientific World Journal*, vol. 2014, Art. ID 652329, 2014. Doi: 10.1155/2014/652329

24. J. Gómez, J. R. Casas, and S. Villalba, "Structural health monitoring with distributed optical fiber sensors of tunnel lining affected by nearby construction activity," *Automation in Construction*, vol. 117, p. 103261, Jul. 2020. Doi: 10.1016/j.autcon.2020.103261
25. Y. Xie, S. Zhang, X. Meng, D. T. Nguyen, G. Ye, and H. Li, "An innovative sensor integrated with GNSS and accelerometer for bridge health monitoring," *Remote Sensing*, vol. 16, no. 4, p. 607, Feb. 2024. Doi: 10.3390/rs16040607.
26. E. E. Tita, H. M. S. Viegas, and G. Watanabe, "Enhancing traffic management through digital twin-BIM: A case study in Dili city, Timor-Leste," in *Proc. 2023 Brawijaya Int. Conf. (BIC 2023)*, Atlantis Press, Oct. 2024, pp. 36–46. Doi: 10.2991/978-94-6463-525-6_5
27. A. Dinas, Th. N. Nikolaidis, and C. C. Baniotopoulos, "Sustainable restoration criteria for a historical steel railway bridge," *Procedia Environmental Sciences*, vol. 38, pp. 578–585, 2017, doi: 10.1016/j.proenv.2017.03.133.

Appendix 2: Review of Digital Technology and Digital Transformation (DX)

2.1 Introduction

This chapter comprehensively outlines digital twin technology and its transformative role in civil infrastructure, focusing on structural health monitoring (SHM), data filtering, advanced structural analysis using finite element analysis (FEA), and traffic management. Beginning within the context of Industry 4.0, it highlights innovative technologies such as cyber-physical systems, the Internet of Things (IoT), artificial intelligence (AI), and cloud/edge computing as key drivers of digital transformation (DX). These technologies have reshaped infrastructure management by enabling a shift from reactive maintenance to a predictive and intelligent decision-making framework. The concept of digital twins is introduced as a core technology for smart civil infrastructure, integrating real-time monitoring, simulation, and predictive analytics into a dynamic, data-driven digital replica of physical assets. This chapter outlines cutting-edge structural health monitoring (SHM) technologies, including GNSS, accelerometers, fiber optic sensing, UAV-based inspections, and wireless sensor networks, analyzing their application specifically to displacement, strain, vibration, and monitoring of bridges. Advanced data analytics are applied to anomaly detection, sensor fusion, and machine learning-based degradation modeling, while finite element analysis (FEA) is presented as a tool for simulation, verification, and validation. Finally, digital twins in traffic management are examined in relation to mobility, congestion, and environmental impacts. This chapter concludes by identifying research gaps in interoperability, scalability, and the integration of AI and simulation, establishing the foundation for a digital twin-based structural health monitoring (SHM) framework.

2.2. Industry 4.0 & Revolutionary Technology

The Fourth Industrial Revolution, widely known as Industry 4.0 (I4.0), represents a fundamental paradigm shift in how industries design, produce, operate, and manage assets. Unlike earlier revolutions driven by steam power, electricity, and automation, I4.0 is defined by the convergence of cyber-physical systems (CPS), the Internet of Things (IoT), cloud and edge computing, artificial intelligence (AI), big data analytics, and advanced robotics into highly integrated value chains [1], [2]. As illustrated in Figure 2.1, the evolution from mechanization to cyber-physical integration demonstrates how each industrial revolution has progressively transformed both production systems and daily life. From a global perspective, this revolution promotes digitally networked ecosystem in which machines, sensors, humans, and processes continuously exchange information to enable autonomous, real-time decision-making [3], [4].

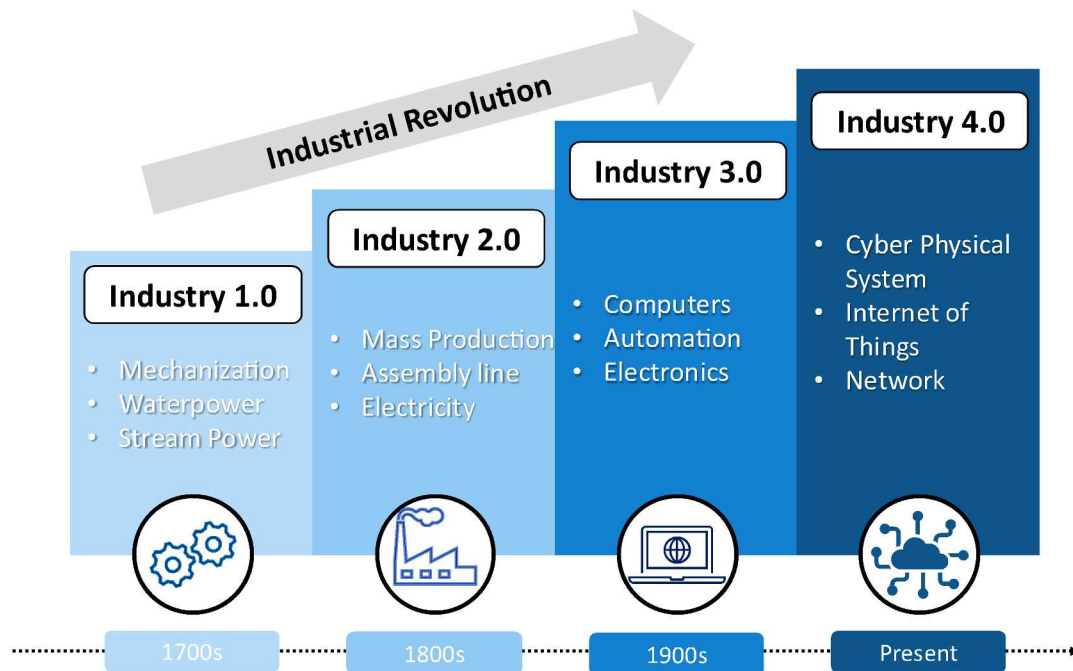


Figure 2. 2 The four industrial revolutions: from mechanization (Industry 1.0) to cyber-physical integration (Industry 4.0).

At the macroeconomic level, Industry 4.0 is widely regarded as a driver of productivity, resilience, and sustainability across diverse sectors such as manufacturing, energy, logistics, and healthcare [5]. New business models such as “everything-as-a-service” and predictive maintenance are transforming the global economy, while governments worldwide have launched national initiatives to accelerate digital adoption (e.g., Germany’s *Industrie 4.0*, China’s *Made in China 2025*, and the U.S. *Industrial Internet Consortium*) [6], [7]. Despite this momentum, adoption remains uneven due to challenges in interoperability standards, cybersecurity risks, and human–machine collaboration frameworks [8]–[10].

While manufacturing has been the early proving ground of Industry 4.0, the civil and infrastructure sector is beginning to adapt these technologies to its unique demands. Unlike manufacturing, which emphasizes short production cycles, civil infrastructure is long-lived, capital-intensive, and critically safety-dependent. As such, the emphasis of digital transformation in civil engineering is not only on efficiency, but also on lifecycle management, resilience, and sustainability [11], [12]. This transition is particularly relevant as global infrastructure faces increasing pressures from urbanization, climate change, and aging assets. To illustrate this transition, **Figure 2.2** highlights how Industry 4.0 concepts and technologies are being mapped into civil and infrastructure engineering, demonstrating the progressive adaptation of digital tools, such as BIM and IoT-enabled monitoring, to support lifecycle-based asset management.

One of the most transformative technologies bridging Industry 4.0 and the civil sector is the Digital Twin (DT). Originally developed in product lifecycle management, DTs are now recognized as a core

enabler of Industry 4.0 in the built environment [13]. Within civil infrastructure, Building Information Modeling (BIM) provides the geometric and informational foundation, while sensor networks (e.g., GNSS, accelerometers, strain gauges, vision systems) supply continuous real-time data. This integration enables DTs to support Structural Health Monitoring (SHM), traffic flow modeling, and environmental assessment, thereby allowing engineers to move from reactive maintenance toward predictive and prescriptive asset management [14]–[17]. In this way, **Figure 2.2** also demonstrates how DT–BIM integration operationalizes the closed-loop intelligence principle of Industry 4.0 across the entire lifecycle of civil infrastructure assets.

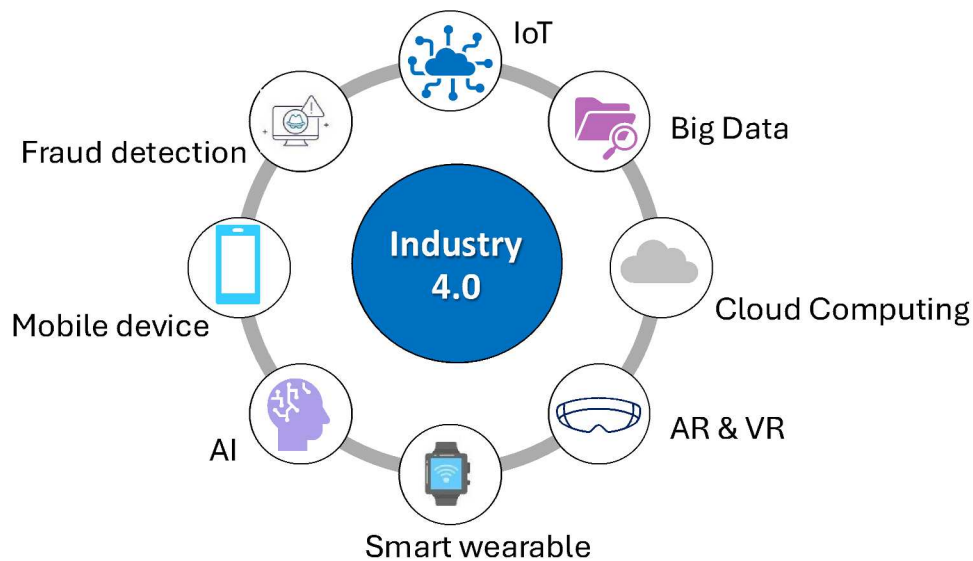


Figure 2. 3 Application of Industry 4.0 concepts in civil and infrastructure engineering.

Moreover, the revolutionary technologies of I4.0 are reshaping how infrastructure systems are designed, validated, and managed. Through CPS, simulation models and physical measurements can be continuously coupled, allowing finite element analysis (FEA) models to be updated in real time with sensor data for anomaly detection and structural performance validation [14], [18]. Similarly, the fusion of IoT-driven traffic data with AI and cloud analytics enables the development of system-level digital twins for urban mobility. These twins enhance congestion forecasting, environmental impact assessment, and policy testing, thereby extending the industry 4.0 paradigm from factories to cities [19]–[21].

This evolution parallels the shift from “smart factories” in manufacturing to “smart infrastructure” in civil engineering, bridges, tunnels, and transportation systems that can sense, think, and adapt in real time. Such a transformation underscores the role of Industry 4.0 as not merely a technological revolution, but a redefinition of infrastructure management where safety, sustainability, and resilience are governed by continuous, data-driven intelligence [12], [14], [16],[17].

2.3. Digital Twin Paradigm for Civil Infrastructure

The digital twin (DT) paradigm has emerged as a transformative framework in infrastructure engineering, enabling the creation of a dynamic, continuously updated virtual representation throughout the entire lifecycle of physical assets. Unlike traditional monitoring systems, whose primary functions are the collection, recording, and visualization of sensor-based measurements, digital twins establish a bidirectional and adaptive connection between the physical system and its virtual counterpart [13]. This mutual interaction enables not only observation but also interpretation, simulation, prediction, and intelligent decision support.

The concept of digital twins, initially developed for product lifecycle management and the aerospace sector, has progressively expanded into civil and infrastructure engineering, providing advanced capabilities for asset lifecycle management, real-time structural assessment, predictive analytics, and decision-making [14], [22], [23]. Conventional monitoring methods typically employ sensors such as GNSS, LVDTs, accelerometers, and IoT devices to measure displacement, temperature, vibration, and load effects. Whilst these systems provide important insights into structural behavior, they often operate independently of simulation tools and predictive models. Consequently, conventional monitoring primarily answers the question: **‘What is the current state of the structure?’**

In contrast, digital twins integrate diverse sources of information—such as monitoring data, finite element analysis (FEA), machine learning models, and building information modelling (BIM)—into a unified, continuously updated computational environment. By synchronizing physics-based and data-driven models with real-time data, the DT evolves alongside the physical asset, capturing its current structural state while simultaneously simulating potential future behavior under various operational and environmental scenarios. Consequently, the digital twin moves beyond the descriptive nature of traditional monitoring, enabling it to address higher-level questions such as: **‘Why is the structure exhibiting this behavior?’**

‘What will happen next under changing conditions?’

As illustrated in **Figure 2.3**, the Digital Twin paradigm for civil infrastructure is structured as a multi-layer ecosystem, extending the traditional three foundational pillars—physical assets, digital models, and data flows—into an operational framework suitable for long-term monitoring and decision support. At its foundation, the physical asset layer is instrumented through a variety of sensors, whose measurements are transmitted through the data acquisition and communication layer. These data feed the Digital Twin Core, composed of BIM, FEA, GIS, and AI/ML models that replicate and predict asset behavior. The integration and intelligent layer enable real-time synchronization, anomaly detection, SHM, and system-level analysis, while the decision-making layer delivers actionable insights for maintenance, safety, and transportation planning. This architecture ensures continuous interaction between real and virtual systems, forming the essential feedback loop of the Digital Twin.

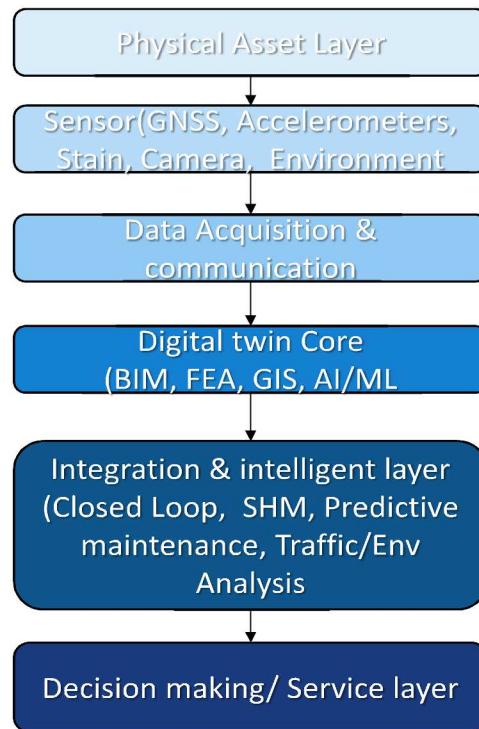


Figure 2. 4 Conceptual Framework of Digital Twin for Civil Infrastructure

In the civil infrastructure sector, digital twins (DT) are increasingly recognized as essential for addressing challenges such as aging assets, urbanization, and sustainability. Unlike static models such as Building Information Modeling (BIM), which primarily provide geometric and semantic information, DT integrates sensor data (IoT, GNSS, strain gauges, accelerometers), advanced simulations (finite element analysis), and AI-driven analytics to form a continuously updated virtual environment [12], [16],[24]. This dynamic collaboration enables engineers to assess structural integrity in real time, predict deterioration, and optimize maintenance schedules.

A number of studies have highlighted DT as a key driver for lifecycle-based asset management. Liu et al. [16] provides a thorough review of digital twin technologies in civil infrastructure, showing how frameworks integrating BIM, sensor networks (IoT), and simulation are contributing to improved maintenance planning and structural health prediction. Similarly, Sakr et al. [25] presents a methodology for visualizing structural health monitoring (SHM) data through DTs, demonstrating that real-time visual analytics enhances decision support for asset managers. From a practical demonstration perspective, Armijo & Zamora-Sánchez [26] report a case study in which DT, IoT sensing, and machine learning are integrated to monitor a railway bridge over time; their findings reveal the effectiveness of DT-based anomaly detection and suggest scalability for broader infrastructure management contexts.

Figure 2.4 provides a schematic representation of DT applications at different scales, from individual bridge components to city-wide systems. This illustrates how DTs integrate data across levels to provide both micro- and macro-scale insights for decision-makers.

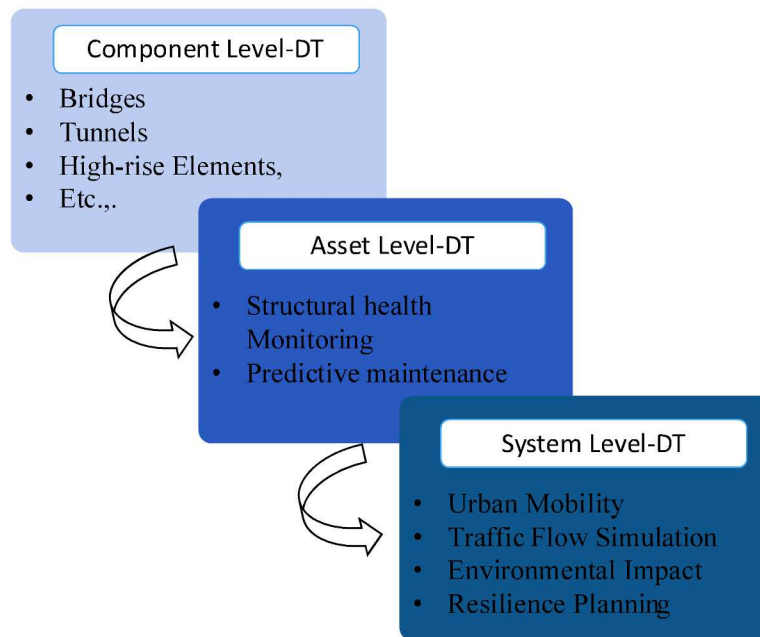


Figure 2. 5 Multi-Scale Application of Digital Twins

A significant aspect of the digital twin (DT) paradigm in civil infrastructure is its ability to integrate multiscale data and models. At the asset level, DTs are increasingly applied to monitoring bridges, tunnels, and high-rise buildings, where sensors such as GNSS, accelerometers, and vision-based systems are employed for displacement tracking and anomaly detection [27], [28]. At the system level, DTs support urban mobility analysis, traffic flow simulation, and environmental assessment, thereby aligning infrastructure management with broader sustainability and resilience goals [27], [29]. These multiscale applications demonstrate the paradigm's flexibility, spanning from component-level fatigue detection to city-wide resilience planning.

Despite these advances, several challenges remain. First, interoperability and standardization issues still hinder seamless integration of BIM, IoT, and simulation tools, as highlighted in recent reviews [17], [30]. Second, data quality and reliability are persistent concerns, since noisy or incomplete sensor datasets can compromise the accuracy of DT models and limit their value for decision-making [17], [27]. Third, the computational complexity of real-time DT updates, particularly when coupling high-fidelity finite element analyses with continuous sensor data streams, demands scalable digital architectures based on cloud and edge computing [29]. Finally, cybersecurity, governance, and ethical considerations remain underdeveloped, raising critical questions around data ownership, accountability, and algorithmic transparency in safety-critical infrastructure systems [17], [30].

Overall, the DT paradigm in civil infrastructure extends beyond traditional BIM or SHM by enabling continuous, real-time synchronization of physical and virtual assets. Through the integration of IoT, GNSS, advanced simulations, and AI, DTs have the potential to revolutionize infrastructure lifecycle management.

2.4. Structural Health Monitoring (SHM) technology for bridges

Structural Health Monitoring (SHM) has become an essential strategy in modern civil engineering to ensure the safety, durability, and resilience of bridge infrastructure. Bridges are critical assets in transportation networks, yet they are constantly exposed to operational loads, environmental impacts, and abnormal events such as earthquakes, high winds, and vehicle collisions. Traditional inspection-based approaches relying on manual visual inspections are labor-intensive, subjective, and prone to missing hidden or early-stage damage. To address these limitations, SHM introduces a systematic, data-driven approach utilizing sensors, automated data collection, and computational models to continuously or periodically assess bridge integrity [31].

The purpose of SHM extends beyond damage detection to include early anomaly detection, performance evaluation, optimization of lifecycle maintenance, and cost reduction [32]. With rapid advances in sensing technology, wireless communication, artificial intelligence, and digital twin integration, SHM has evolved into an interdisciplinary field bridging structural engineering, computer science, and data analysis, collaborating to achieve the goal of a smart bridge monitoring system. The following are the current state of bridge SHM, categorized by sensor technology, data acquisition and processing methods, integration with digital modeling, and challenges.

2.4.1. Sensor Technologies and Data Acquisition

The foundation of the SHM system lies in its ability to capture reliable structural responses under diverse loading and environmental conditions. Sensors commonly used in bridges include strain gauges, accelerometers, displacement transducers, temperature sensors, fiber Bragg grating (FBG) sensors, and global navigation satellite system (GNSS) receivers [33].

- **GNSS-Based Monitoring**

GNSS technologies have proven especially valuable for long-span bridges as demonstrated in **Figure 2.5**. GNSS based positioning system [34], where traditional contact-based sensors face deployment and maintenance challenges. Xi et al. [35] demonstrated the application of multi-GNSS observations for bridge monitoring, achieving millimeter-level precision in three-dimensional displacements. An et al. [36] further enhanced this by integrating GNSS with attitude determination methods and filtering algorithms, improving accuracy in both displacement and rotation monitoring of long-span bridges. These approaches illustrate the role of GNSS as a robust tool for real-time displacement tracking under dynamic environmental conditions.

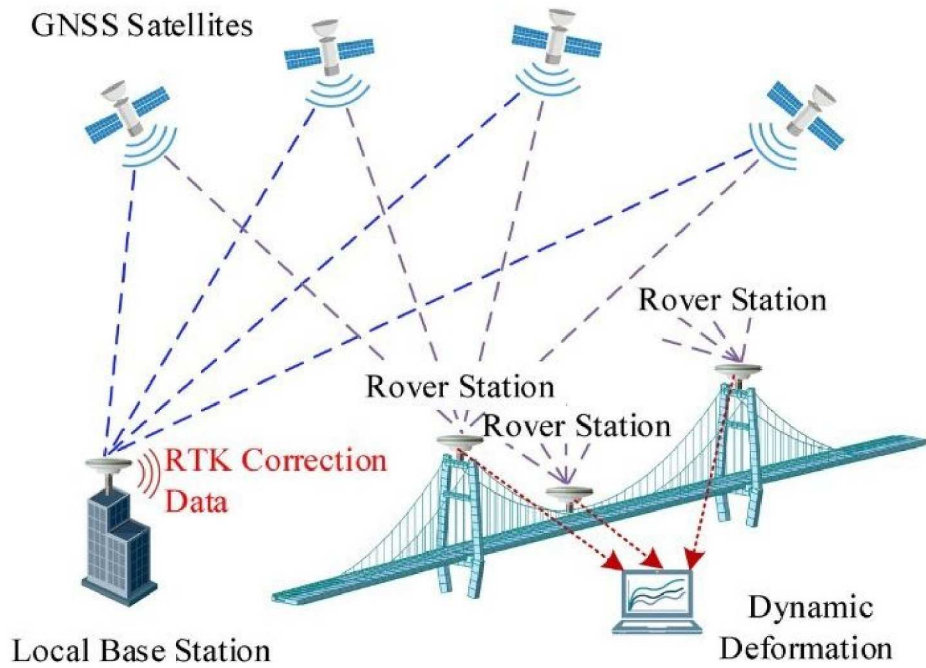


Figure 2. 6 GNSS-based positioning technology for bridge Monitoring [34]

- **Vibration and Accelerometer-Based Monitoring**

Accelerometers remain the primary instrument for bridge structural health monitoring (SHM) due to their effectiveness in capturing vibration characteristics under traffic and environmental excitation, as shown in **Figure 2.6**. Vibration and Accelerometer-Based Monitoring [37]. Analysis of mode parameters such as natural frequency, mode shape, and damping ratio provides insights into stiffness degradation and potential structural damage [38]. The introduction of wireless accelerometer networks has significantly enhanced scalability, reduced wiring costs, and enabled distributed dynamic monitoring across entire bridge spans.

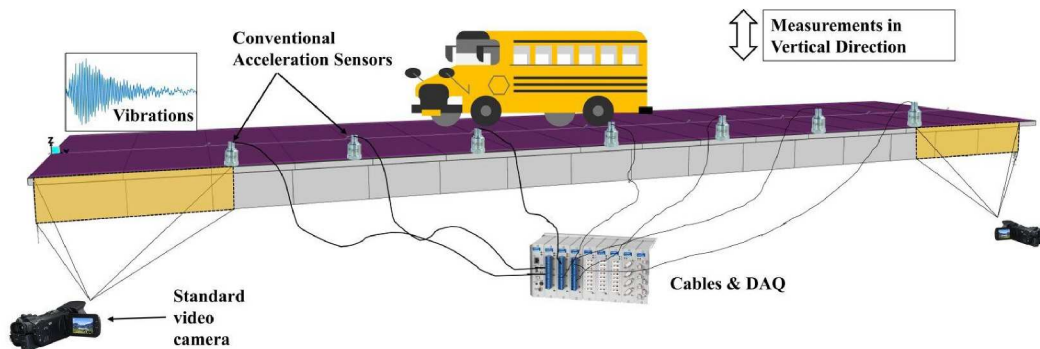


Figure 2. 7 Vibration and Accelerometer-Based Monitoring [37]

- **Fiber Optic and Strain-Based Monitoring**

FBG sensors are increasingly being integrated into bridge components to measure strain and temperature. Their immunity to electromagnetic interference, durability, and embeddability within structural materials make them highly suitable for long-term structural health monitoring (SHM). Marques et al. [39] emphasized the role of FBGs in detecting localized strain, crack initiation, and fatigue progression, particularly in steel and composite bridges.

- **Vision-Based and Non-Contact Sensing**

Recent advances in computer vision and photogrammetry have enabled the introduction of non-contact structural health monitoring (SHM) techniques, as demonstrated in **Figure 2.7**. Displacement Monitoring using UAV [40]. High-speed cameras, drones, and laser scanners are being utilized for displacement tracking, surface crack detection, and corrosion assessment [40], [41]. Vision-based systems offer full-area monitoring capabilities but are susceptible to lighting conditions and occlusions, requiring extensive calibration. These methods are increasingly integrated with AI algorithms for automated defect recognition.

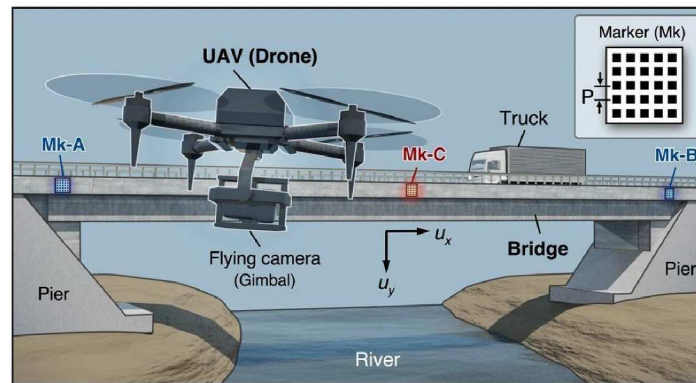


Figure 2. 8 Displacement Monitoring using UAV (Drone)[40]

2.4.2. Wireless Sensor Networks and Energy Harvesting

The widespread adoption of wireless sensor networks (WSNs) has enabled the dense deployment of sensors without extensive wiring. Chen [42] reviewed optimal placement strategies for wireless sensors in bridges, emphasizing the trade-offs between spatial coverage, redundancy, and energy efficiency. However, challenges such as synchronization, packet loss, and long-term durability remain.

In a parallel trend, development is advancing for self-powered structural health monitoring (SHM) systems utilizing energy harvesting technology. Harvesters utilizing solar, wind, and vibration energy are being investigated as power sources for wireless sensor network (WSN) nodes, reducing the need for battery replacement and enhancing sustainability [43], [44]. Such systems are particularly promising for long-term SHM in remote or inaccessible bridges.

2.4.3. Data Processing and Anomaly Detection

Large-scale SHM deployments generate vast amounts of heterogeneous data. Therefore, efficient data processing and robust anomaly detection are essential.

- **Anomaly and Outlier Detection**

Sensor data is often contained by noise, bias, or environmental interference. Deng et al. [45] reviewed anomaly detection techniques in SHM, highlighting methods such as statistical filtering, wavelet analysis, and robust reconstruction. Ye et al. [46] introduced a deep learning-based approach for automatic anomaly detection in bridge SHM, demonstrating superior performance over conventional threshold-based methods in identifying sensor failures and false signals.

- **Damage Detection and Diagnosis**

Damage detection methods in SHM are commonly classified into four levels: (1) existence of damage, (2) localization, (3) quantification of severity, and (4) prediction of remaining service life [47]. Modal analysis-based approaches are effective in global condition assessment, while strain-based techniques provide localized damage detection. Recent developments in machine learning and deep learning such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), allow for advanced pattern recognition in SHM data [48], [49].

- **Multi-Sensor Data Fusion**

Integrating heterogeneous sensor data improves robustness and accuracy in SHM. GNSS sensors capture low-frequency displacements, while accelerometers capture high-frequency vibrations. Combining them provides comprehensive structural response information [50], [51].

2.4.4. Integration with Structural Models and Digital Twins

A transformative trend involves integrating SHM data with finite element analysis (FEA) models, and digital twin (DT) platforms can be seen in **Figure 2.8** about a physical bridge model with its Digital twin model. Naderi [52] noted that DTs continuously updated with SHM data provide predictive capabilities that support lifecycle management and resilience assessment. Jiménez Ríos et al. [53] validated DT-based anomaly detection for bridges, demonstrating a method that dynamically synchronizes sensor data streams with a virtual model to achieve real-time anomaly detection.

This integration bridges the gap between monitoring and decision-making, enabling predictive maintenance strategies, real-time risk assessment, and preventive asset management.

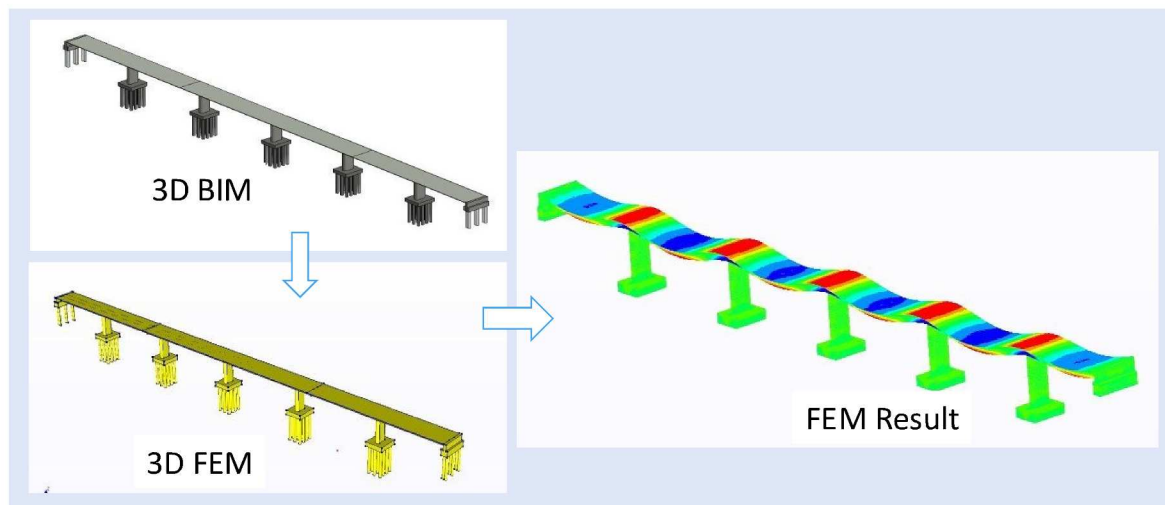


Figure 2. 9 Physical bridge model with its Digital twin model

2.4.5. Challenges in Bridge SHM

Despite progress, several significant challenges remain:

- **Data quality and reliability:** Sensor drift, noise, and missing data compromise reliability. Long-term sensor durability and calibration remain ongoing challenges.
- **Scalability and cost:** High-density SHM deployment across entire bridge assets is economically challenging. A prioritization framework is needed to optimize monitoring resources.
- **Interoperability and Standardization:** The lack of standard protocols for SHM data limits interoperability between different systems and vendors.
- **Real-Time Processing:** Scalable cloud and edge computing architectures are required to process continuous data streams in real time.
- **Cybersecurity and Governance:** Increasing reliance on wireless transmission and digital transformation (DT) integration raises concerns regarding cybersecurity, data ownership, and governance.

2.5. Advanced Data Analytics for SHM

As civil infrastructure grows increasingly complex and deteriorates, there is a demand for analytical tools that process vast streams of heterogeneous data while delivering accurate real-time insights. In this context, advanced data analytics has emerged as a transformative element for structural health monitoring (SHM). Broadly speaking, data analytics refers to the process of generating actionable insights through the collection, processing, modeling, and interpretation of sensor data. This process extends beyond traditional statistical analysis, integrating techniques such as signal processing, machine learning (ML), artificial intelligence (AI), and data assimilation.

Across the entire infrastructure sector, advanced data analytics has played a crucial role in managing smart cities, transportation systems, energy grids, and water networks [54]. These systems share three common characteristics:

- Data is large-scale and multimodal, sourced from IoT devices, satellites, drones, wireless sensor networks, etc.
- It is often streamed in real-time, requiring online algorithms for processing.
- Safety and performance are paramount, as analytical errors can lead to severe consequences.

In civil engineering, these challenges are further exacerbated in Structural Health Monitoring (SHM) for bridges. This is because data is required to support predictive maintenance, safety assurance, and lifecycle management for assets subjected to diverse loading conditions.

This section reviews the role of advanced data analysis in SHM. We begin with a broad overview of analytical paradigms, gradually narrowing our focus to discuss state estimation using data assimilation techniques and predictive modeling using machine learning, specifically Random Forest (RF).

2.5.1. Advanced Data Analytics in Civil Infrastructure

Civil infrastructure is characterized by heterogeneous data sources and scales. For example, data ranges from material-level strain measurements to structural-level displacement responses and system-level traffic patterns. Traditional methods such as threshold-based alarms and regression analysis are increasingly inadequate for handling such multi-source, high-frequency data.

The literature highlights several new directions in infrastructure data analysis:

- Data Assimilation: Combining sensor data with numerical models to perform accurate state estimation [55].
- Big Data Architecture: Management and analysis of streaming sensor data utilizing cloud/edge computing frameworks [56].
- AI/Machine Learning Applications: Anomaly detection, damage classification, and degradation trend prediction [57].
- Digital Twin Integration: Real-time synchronization between physical infrastructure and its digital replica [58].

A common challenge across these approaches is the need to address uncertainty in measurements and models. Factors such as noise, missing data, environmental variability, and computational complexity all require methods that balance robustness, accuracy, and scalability.

2.5.2. Data Analytics for SHM of Bridges

When assessing the structural health monitoring (SHM) of bridges, advanced data analysis primarily serves two functions: (a) state estimation: inferring the true state of the structure from noisy, incomplete data, and (b) predictive modeling: forecasting future states or detecting anomalies.

Recent studies have emphasized that multi-sensor fusion and model-based updating play a central role in advancing self-health monitoring (SHM) for bridges [59]. For example:

- GNSS provides low-frequency displacement data, while accelerometers capture high-frequency vibration signatures.
- Vision systems detect cracks or spalling, while fiber Bragg grating sensors provide localized strain data.
- Finite Element Analysis (FEA) models simulate structural responses but require updating with real-time data.

To manage these diverse data streams, analytical methods such as Kalman filters (KF) and Ensemble Kalman filters (EnKF), along with machine learning algorithms like Random Forests (RF), are employed. Together, these tools form the foundation of an advanced SHM framework, facilitating the transition from reactive inspections to predictive and intelligent maintenance.

2.5.3. Data Assimilation Techniques for State Estimation

(a) Kalman Filter (KF)

• Overview

The Kalman Filter (KF) is one of the most influential algorithms in estimation theory, introduced by Rudolf E. Kalman in 1960. Originally developed for aerospace navigation (e.g., the Apollo program), the KF has become central to control engineering, robotics, economics, and structural health monitoring (SHM). Its appeal lies in its recursive and optimal estimation capabilities. It fuses noisy sensor data with a mathematical model to estimate the most probable system state in real time.

In SHM, the Kalman Filter (KF) is useful because bridge sensor data (particularly displacement measurements from GNSS and accelerometers) inherently contain noise. The KF corrects errors by incorporating prior knowledge from structural models (such as finite element models or state-space representations) into a recursive framework, thereby generating physically consistent state estimates, improving monitoring reliability [60], [61].

• Mathematical Formulation

The KF operates on a linear state-space model, which consists of a system (state) model and an observation (measurement) model:

$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1}, \quad w_{k-1} \sim N(0, Q) \quad (2.1)$$

$$z_k = Hx_k + v_k, \quad v_k \sim N(0, R) \quad (2.2)$$

Where:

- x_k = state vector (e.g., displacement, velocity, modal parameters),
- u_k = Input vector (e.g., traffic load, wind, earthquake excitation),
- z_k = observation vector (e.g., sensor readings),
- A = state transition matrix, B = input matrix, H = measurement matrix,
- Q = process noise covariance, R = measurement noise covariance.

The filter proceeds recursively in two steps:

1. Prediction (Time Update):

$$\hat{x}_{k|k-1} = A\hat{x}_{k|k-1} + Bu_{k-1} \quad (2.3)$$

$$P_{k|k-1} = AP_{k|k-1}A^T + Q \quad (2.4)$$

2. Correction (Measurement update)

$$K_k = P_{k|k-1}H^T(HP_{k|k-1}H^T + R)^{-1} \quad (2.5)$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k(z_k - H\hat{x}_{k|k-1}) \quad (2.6)$$

$$P_{k|k} = (I - K_kH)P_{k|k-1} \quad (2.7)$$

Here, K_k is the **Kalman Gain**, which balances trust between model predictions and sensor measurements. If R is small (accurate sensors), the KF relies more on measurements; if Q is small (accurate model), the KF relies more on predictions.

The Kalman Filter (KF) can be intuitively understood as a dynamic weighted averaging process that combines model-based predictions and sensor-based observations according to their respective uncertainties. This balance is critically important in bridge monitoring. This is because sensor data often exhibits fluctuating accuracy and reliability. For example, GNSS displacement measurements are susceptible to atmospheric and multipath errors, while accelerometers capture high-frequency vibrations but suffer from long-term drift. The KF adjusts for these discrepancies, generating a smoothed, physically consistent estimate of the structural state [62], [63].

In structural health monitoring (SHM) for bridges, the Kalman filter (KF) has been applied in multiple domains. First, it significantly improves the accuracy of GNSS-based displacement monitoring, enabling reliable estimation of deflection in long-span bridges under dynamic loading [62]. Second, KF-based frameworks support mode identification and vibration analysis, where mode parameters like frequency and damping ratio serve as indicators of stiffness loss and structural degradation [64]. Third, KF provides a mathematically rigorous multi-sensor fusion method. By combining the complementary strengths of GNSS and accelerometers, it generates drift-free, accurate displacement time-series data [65]. Finally, KF integration with finite element method (FEM) models is advancing, establishing a digital twin application foundation where measured data continuously updates simulation outputs, maintaining real-time synchronization between physical and virtual structures [66].

Despite its versatility, classical KF has inherent limitations. It assumes linearity of system dynamics and Gaussian noise distributions, both of which are rarely satisfied in real-world SHM contexts, especially under seismic loading or extreme wind conditions. Additionally, KF suffers from scalability challenges in high-dimensional state spaces, as the covariance update step is computationally demanding. These limitations have motivated extensions such as the Extended Kalman Filter (EKF), which linearizes nonlinear dynamics, and the Ensemble Kalman Filter (EnKF), which provides a scalable framework for large, high-dimensional SHM problems.

In summary, KF serves as the foundational technology for SHM analysis, providing robust state estimation and sensor fusion capabilities. Its integration with FEM and digital twin frameworks positions it as a critical enabling technology for intelligent real-time monitoring. Meanwhile, its extended variants (EKF, EnKF) ensure adaptability to nonlinear, data-intensive structural systems.

(b) Extended Kalman Filter (EKF)

The EKF generalizes the classical KF by linearizing the nonlinear state-space model around the current estimate using a Taylor expansion. This makes the EKF the standard approach for slightly nonlinear systems, such as the dynamic behavior of bridges under moderate excitation [67].

- **Formulation**

For a nonlinear dynamical system:

1. State equation

$$x_k = f(x_{k-1}, u_{k-1}) + w_{k-1}, \quad w_{k-1} \sim N(0, Q) \quad (2.8)$$

2. Measurement equation

$$z_k = h(x_k) + v_k, \quad v_k \sim N(0, R) \quad (2.9)$$

Where $f(\cdot)$ and $h(\cdot)$ are nonlinear functions.

- **Linearization**

The Extended Kalman Filter (EKF) linearizes around the current estimate using Jacobians:

$$F_k = \left. \frac{\partial f}{\partial x} \right|_{\hat{x}_{k-1}}, \quad H_k = \left. \frac{\partial h}{\partial x} \right|_{\hat{x}_{k-1}} \quad (2.10)$$

- **Recursive Steps**

1. Prediction

$$\hat{x}_{k|k-1} = f(\hat{x}_{k-1|k-1}, u_{k-1}) \quad (2.11)$$

$$P_{k|k-1} = F_k P_{k-1|k-1} F_k^T + Q \quad (2.12)$$

2. Correction

$$K_k = P_{k|k-1} H_k^T (H_k P_{k|k-1} H_k^T + R)^{-1} \quad (2.13)$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k (z_k - h(\hat{x}_{k|k-1})) \quad (2.13)$$

$$P_{k|k} = (I - K_k H_k) P_{k|k-1} \quad (2.14)$$

- **Applications and Limitations of the Extended Kalman Filter in SHM**

The EKF has been widely applied in structural health monitoring (SHM) due to its ability to capture nonlinear structural dynamics.

- Bridge vibration monitoring: EKF has been employed for nonlinear modal identification, particularly under seismic excitations, where bridge structures exhibit strong nonlinear responses. Lee and Yun [67] demonstrated that EKF can track nonlinear dynamic parameters in reinforced concrete bridge piers during earthquake loading, making it highly effective for monitoring stiffness degradation and damage initiation.
- Damage detection: EKF-based model updating approaches have been applied to detect nonlinear changes in structural properties, such as stiffness reductions or damping variations caused by cracks, material deterioration, or joint loosening [67]. By assimilating measurement feedback, EKF enables damage detection and localization in bridge systems.
- Sensor fusion: EKF has also been used in combining GNSS and accelerometer data. Since GNSS captures global, low-frequency displacement trends while accelerometers capture high-frequency vibrations, EKF effectively manages the nonlinear transformation between displacement and velocity. Kim et al. [68] applied a two-stage Kalman filter to integrate RTK-GNSS and accelerometer signals, achieving accurate displacement estimation for long-span bridges.
- Model updating in GNSS/attitude determination: Recent studies have highlighted EKF's role in GNSS-based SHM. However, limitations have been observed when systems are highly nonlinear. An et al. [69] compared EKF with the Unscented Kalman Filter (UKF) for integrated displacement and attitude determination in bridge monitoring, concluding that while EKF is useful, UKF provides superior accuracy under strongly nonlinear conditions.

Despite its versatility, the EKF has several limitations. Its reliance on first-order linearization makes it prone to divergence under strong nonlinearities, such as those arising during extreme seismic events or nonlinear soil–structure interaction. Furthermore, the EKF is computationally more demanding than the classical KF, due to the requirement of Jacobian evaluations at each iteration. Nonetheless, it remains computationally feasible for medium-scale SHM applications, particularly for bridges with manageable degrees of freedom [67], [68].

(c) Ensemble Kalman Filter (EnKF)

EnKF was developed to address scalability issues in KF and EKF for high-dimensional systems such as weather forecasting and has recently gained attention in the SHM field for civil engineering structures [70]. Unlike EKF, which requires the Jacobian, EnKF employs a Monte Carlo method that propagates an ensemble of state realizations.

- **Formulation**

Given an ensemble of N states at time k :

$$\{x_k^i\}_{i=1}^N \quad (2.15)$$

The forecast mean and covariance are approximate as:

$$\hat{x}_{k|k-1} = \frac{1}{N} \sum_{i=1}^N x_{k|k-1}^i \quad (2.16)$$

$$P_{k|k-1} = \frac{1}{N-1} \sum_{i=1}^N (x_{k|k-1}^i - \hat{x}_{k|k-1})(x_{k|k-1}^i - \hat{x}_{k|k-1})^T \quad (2.17)$$

Each ensemble member is updated as:

$$x_{k|k}^i = x_{k|k-1}^i + K_k(z_k^i - Hx_{k|k-1}^i) \quad (2.18)$$

where z_k^i is perturbed with noise to maintain ensemble diversity.

- **Applications and Limitations of the Ensemble Kalman Filter in SHM**

The Ensemble Kalman Filter (EnKF) has emerged as a powerful alternative to the classical Kalman Filter (KF) and Extended Kalman Filter (EKF), proving particularly useful for large-scale, nonlinear, and high-dimensional problems characteristic of civil infrastructure systems. Its primary advantage lies in avoiding the explicit computation of large covariance matrices. This is computationally infeasible for systems with thousands of degrees of freedom (DOF), such as long-span bridges or high-accuracy finite element models. Instead, the EnKF uses a set of realizations to approximate state statistics, making it computationally manageable and scalable. Furthermore, unlike the EKF, the EnKF does not require linearization of nonlinear functions via the Jacobian, allowing it to naturally handle nonlinear system dynamics without approximation errors. These characteristics make the EnKF particularly well-suited for structural health monitoring (SHM) applications, where both model and data stream complexity continue to increase.

Multiple applications in Structural Health Monitoring (SHM) demonstrate the versatility of the Extended Kalman Filter (EnKF). In GNSS-based monitoring of long-span bridges, EnKF assimilates noisy displacement measurements with finite element method (FEM) predictions, enabling reliable real-time estimation of structural condition [71], [72]. In earthquake response tracking, EnKF is utilized to update nonlinear bridge models during seismic events, enabling near-real-time safety assessments and rapid post-event evaluations [73], [74]. Furthermore, EnKF is increasingly integrated into digital twin frameworks, enabling continuous synchronization between physical measurements and large-scale digital models of infrastructure assets. This real-time consistency enhances predictive maintenance and supports data-driven decision-making at both the asset and system levels [75].

Despite these advantages, the EnKF is not without limitations. The filter's accuracy strongly depends on the ensemble size. Too few components cause filter divergence, reducing the reliability of state estimation. Conversely, very large ensembles significantly increase computational cost, posing problems for real-time structural health monitoring (SHM) applications requiring rapid updates. Furthermore, the filter's performance is extremely sensitive to the specification of the covariance matrix for processing noise and measurement noise, necessitating careful tuning to balance measurement reliability and model accuracy.

In summary, EnKF represents a significant advancement in data assimilation techniques for SHM. Its scalability, ability to handle nonlinearities, and compatibility with digital twin frameworks make it a promising tool for monitoring and managing complex civil infrastructure systems. However, its dependence on ensemble size and noise tuning highlights the importance of refining the methodology to ensure robust real-time performance for safety-critical applications such as bridges.

(d) Machine Learning Applications for Predictive Modeling

Data assimilation is a model-based approach, whereas machine learning (ML) provides a data-driven approach for discovering patterns within SHM datasets. Among the many ML techniques, Random Forest (RF) is widely applied for predictive modeling in structural engineering.

- **Random Forest (RF)**

Random Forest (RF) is particularly well-suited for SHM due to its robustness to noise and its ability to rank feature importance. RF constructs multiple decision trees on random subsets of the data and features.

For regression:

$$\hat{f}(x) = \frac{1}{B} \sum_{b=1}^B h_b(x) \quad (2.19)$$

For classification:

$$\hat{c}(x) = \arg \max \sum_{b=1}^B I(h_b(x) = c) \quad (2.20)$$

where $h_b(x)$ is the b -th decision tree, and I is the indicator function.

RF is nonparametric, robust against overfitting, and interpretable through feature importance metrics. In the context of bridge structural health monitoring (SHM) applications, Random Forest (RF) is used for the following purposes: (a) Classifying damaged and sound states from vibration characteristics [76], (b) Predicting displacement/strain progression under variable traffic loads [77], (c) Integrating multimodal data (GNSS, strain, temperature) for anomaly detection [78], [79].

Combining RF with data assimilation enables hybrid analysis: KF/EnKF estimates latent structural states, which are then fed into RF for damage classification and remaining life prediction. This integration presents a promising path toward real-time, intelligent structural health monitoring (SHM).

2.6. Advanced Simulation for Structural Validation based on FEA

2.6.1. Overview of FEA

Finite Element Analysis (FEA) is a numerical method for solving complex engineering problems by discretizing a continuous physical domain into smaller subdomains, known as finite elements. Each element is described by interpolation functions (shape) that approximate the displacements, which are then assembled into a global system of equations.

The origins of FEA date back to Turner, Clough, Martin, and Topp (1956), who introduced the method for aerospace applications [80]. Clough (1960) later introduced the term finite element method (FEM)[81], and Zienkiewicz and Taylor (from 1971) formalized its application to structural mechanics[82]. Over time, FEA has evolved into a versatile tool capable of solving problems in statics, dynamics, heat transfer, fluid mechanics, and Multiphysics [83], [82].

The standard finite element formulation for linear elasticity is derived from the principle of virtual work and expressed as:

$$Ku = F \quad (2.21)$$

Where K is the global stiffness matrix, u is the nodal displacement vector, and F is the external load vector. The element stiffness matrix is given by:

$$Ke = \int_V B^T DB dV \quad (2.22)$$

with B as the strain–displacement matrix, D the constitutive elasticity matrix, and V the element volume. Stress–strain relationships follow Hooke’s law:

$$\sigma = DBu \quad (2.23)$$

This equation provides the theoretical basis for static structural analysis. Extensions for dynamic, non-linear, and thermal analyses have expanded the capabilities of FEA, making it indispensable for civil engineering problems such as long-span bridges. In the context of structural health monitoring (SHM) and digital twin (DT) frameworks, FEA enables the validation of monitoring data, the identification of anomalies, and the prediction of degradation. By integrating field measurements (GNSS, accelerometers, fiber optic sensors) with FEA simulations, digital models can be continuously calibrated to reflect the actual condition of the infrastructure [84].

2.6.2. Structural validation through FEA

- **Static Structural Validation**

Structural validation usually begins with comparing simulated displacements and stresses with monitoring data. For linear static conditions, equilibrium is described by:

$$Ku = F \quad (2.24)$$

where deviations between calculated and measured displacements indicate potential anomalies due to errors or damage to sensors [85].

- **Dynamic Simulation for Bridge Validation**

Bridges are subjected to dynamic excitation from traffic, wind, and seismic forces. The governing dynamic finite element method (FEM) equations are as follows:

$$M\ddot{u}(t) + C\dot{u}(t) + Ku(t) = F(t) \quad (2.25)$$

Where M is the global mass matrix, C is the damping matrix, and $F(t)$ is the time-varying load. Modal analysis, frequency response, and time history simulations allow for the validation of measured natural frequencies, damping ratios, and vibration amplitudes [86].

- **Thermal Analysis in Bridge Validation**

Temperature effects are extremely important in steel box girder bridges, and temperature gradients induce displacements comparable to those caused by traffic loads. Thermal effects are considered as follows:

$$Ku = F + F_{th} \quad (2.26)$$

With thermal strain:

$$\varepsilon_{th} = \alpha \Delta T I \quad (2.27)$$

And corresponding stress:

$$\sigma_{th} = D \varepsilon_{th} = D \alpha \Delta T I \quad (2.28)$$

The equivalent nodal thermal force vector is:

$$F_{th} = \int_V B^T D \varepsilon_{th} dV \quad (2.29)$$

Combining thermal FEA simulation with temperature sensors enables the distinction between displacement caused by environmental factors and displacement caused by degradation [87].

- **Nonlinear and Damage Simulations**

To achieve realistic verification requires nonlinear modeling to capture cracking, yielding, and large deformations of the structure. The equation for the Nonlinear simulation is as follows:

$$K_T(u) \Delta u = \Delta F \quad (2.30)$$

where K_T is the tangential stiffness matrix. This is critical in seismic validation, fatigue analysis, and chain collapse analysis [88].

2.7. Digital Twins for Traffic Management

Traffic congestion, infrastructure deterioration, and environmental sustainability issues are being made more serious by the rapid increase in vehicle ownership and accelerating urbanization. As modern transportation systems grow increasingly complex, traditional traffic management approaches based primarily on static models and reactive strategies are proving inadequate. In this context, digital twin (DT) technology has emerged as a transformative paradigm, offering the capability to create real-time, data-driven, and continuously updated digital replicas of physical transportation networks[89], [90].

The concept of the digital twin extends traditional traffic modeling by facilitating a bi-directional exchange of information between the physical and virtual domains. In contrast to static models, DTs dynamically integrate a variety of data sources, including roadway sensors, GNSS-based vehicle tracking, and traffic cameras, as well as connected and autonomous vehicles (CAVs), to continuously reflect real-time traffic conditions [91], [92].

2.7.1. Functional Framework of DT-Based Traffic Management

The DT-enabled traffic management system is considered to be composed of the following three basic layers:

- (a) Data Collection Layer: Aggregates data from Internet of Things (IoT) devices, edge computing nodes, Vehicle Ad Hoc Networks (VANETs), and satellite navigation systems to capture vehicle dynamics, road occupancy, weather conditions, and emissions [93].
- (b) Modeling and Simulation Layer: Integrate traffic simulation environments (such as microscopic agent-based models and macroscopic flow models) with infrastructure models generated by BIM. Currently, machine learning (ML) and artificial intelligence (AI) techniques are increasingly being utilized to improve prediction accuracy [94], [95].
- (c) Decision and Control Layer: ensures the effectiveness and robustness of the transportation network by offering operational solutions, including dynamic rerouting, adaptive signal control, congestion reduction, and emergency response planning [96].

This layered approach ensures interoperability, scalability, and real-time adaptability, promoting continuous alignment between physical transportation systems and their digital counterparts.

2.7.2. Application in Modern Transportation Systems

In the field of transportation systems, particularly traffic management, the adoption of Digital Twin technology covers a wide range of applications:

- Real-Time Congestion Monitoring and Control: DTs enable the visualization of traffic conditions in a three-dimensional digital environment, allowing traffic operators to dynamically detect and manage congestion hotspots [97].
- Predictive Traffic Forecasting: By integrating historical datasets with real-time sensor feeds, the DT platform predicts traffic congestion patterns, optimizes signal timing, and provides commuters with predictive route guidance[98].
- Construction and Work-Zone Traffic Management: In infrastructure development and construction projects, DT-BIM integration supports diversion route simulations, minimizes congestion, and enhances road user safety [99].
- Incident and Emergency Response: DT provides situational awareness by directly mapping accidents, hazardous events, and natural disasters onto BIM-based road models, thereby improving response times and coordination [100].
- Sustainability and Emission Monitoring: Traffic data sets (DTs) are increasingly being utilized to evaluate energy consumption and greenhouse gas emissions associated with traffic flows, enabling environmentally conscious traffic management strategies [101].

2.7. 3. Integration with Emerging Technologies

The potential of DT-based traffic management is amplified through integration with emerging technologies:

- Artificial Intelligence (AI) and Machine Learning (ML): Support advanced traffic prediction, anomaly detection, and adaptive control strategies [98].
- 5G and Vehicle-to-Everything (V2X) Communication: Enable ultra-low latency data exchange between vehicles and infrastructure, fostering cooperative traffic management in mixed human-autonomous traffic systems [100].

- Edge and Cloud Computing: Facilitate scalable data storage and processing, ensuring real-time responsiveness and system-wide scalability [101].
- Big Data Analytics: Support pattern recognition, risk analysis, and policy development at urban and regional scales.

The DT in traffic management has made remarkable progress, yet multiple technical and operational challenges persist. Data interoperability remains a significant issue due to the heterogeneity of data formats, sensor accuracy, and communication protocols [53]. The computational load of real-time DT simulations in large-scale networks poses scalability challenges, while cybersecurity vulnerabilities associated with IoT and V2X infrastructure raise concerns regarding privacy and system resilience. Furthermore, ensuring model fidelity through continuous calibration and validation against real-world measurements is essential to avoid discrepancies between the physical and digital worlds.

2.8. References

1. M. A. M. S. Lemstra and M. A. de Mesquita, "Industry 4.0: a tertiary literature review," *Technological Forecasting and Social Change*, vol. 186, pt. B, p. 122204, 2023. doi: [10.1016/j.techfore.2022.122204](https://doi.org/10.1016/j.techfore.2022.122204).
2. acatech – National Academy of Science and Engineering and Forschungsunion, *Recommendations for implementing the strategic initiative INDUSTRIE 4.0: Final report of the Industrie 4.0 Working Group*. Germany: acatech, Apr. 2013. [Online]. Available: <https://en.acatech.de/publication/recommendations-for-implementing-the-strategic-initiative-industrie-4-0-final-report-of-the-industrie-4-0-working-group/>
3. Y. Liao, F. Deschamps, E. de F. R. Loures, and L. F. P. Ramos, "Past, present and future of Industry 4.0 – a systematic literature review and research agenda proposal," *International Journal of Production Research*, vol. 55, no. 12, pp. 3609–3629, 2017. doi: [10.1080/00207543.2017.1308576](https://doi.org/10.1080/00207543.2017.1308576).
4. M. Mariani and M. Borghi, "Industry 4.0: A bibliometric review of its managerial intellectual structure and potential evolution in the service industries," *Technological Forecasting and Social Change*, vol. 149, p. 119752, 2019. doi: [10.1016/j.techfore.2019.119752](https://doi.org/10.1016/j.techfore.2019.119752).
5. The application of industry 4.0 technologies in pandemic management: Literature review and case study, *Healthcare Analytics*, vol. 1, p. 100008, 2021. doi: [10.1016/j.health.2021.100008](https://doi.org/10.1016/j.health.2021.100008).
6. W. P. Neumann, S. Winkelhaus, E. H. Grosse, and C. H. Glock, "Industry 4.0 and the human factor – A systems framework and analysis methodology for successful development," *International Journal of Production Economics*, vol. 233, p. 107992, 2021. doi: [10.1016/j.ijpe.2020.107992](https://doi.org/10.1016/j.ijpe.2020.107992).
7. B. Rana and S. S. Rathore, "Industry 4.0 – Applications, challenges and opportunities in industries and academia: A review," *Materials Today: Proceedings*, vol. 79, pt. 2, pp. 389–394, 2023. doi: [10.1016/j.matpr.2022.12.162](https://doi.org/10.1016/j.matpr.2022.12.162).
8. S. Weyer, M. Schmitt, M. Ohmer, and D. Gorecky, "Towards Industry 4.0 – Standardization as the crucial challenge for highly modular, multi-vendor production systems," *IFAC-PapersOnLine*, vol. 48, no. 3, pp. 579–584, 2015. doi: [10.1016/j.ifacol.2015.06.143](https://doi.org/10.1016/j.ifacol.2015.06.143).
9. H. Nayernia, H. Bahemia, and S. Papagiannidis, "A systematic review of the implementation of Industry 4.0 from the organisational perspective," *International Journal of Production Research*, vol. 60, no. 14, pp. 4365–4396, 2021. doi: [10.1080/00207543.2021.2002964](https://doi.org/10.1080/00207543.2021.2002964)

10. B. Bajic, A. Rikalovic, N. Suzic, and V. Piuri, "Industry 4.0 Implementation Challenges and Opportunities: A Managerial Perspective," *IEEE Systems Journal*, vol. 15, no. 1, pp. 546–559, Mar. 2021. doi: [10.1109/JSYST.2020.3023041](https://doi.org/10.1109/JSYST.2020.3023041).
11. F. Zahedi, H. Alavi, J. M. Sardroud, and H. Dang, "Digital Twins in the Sustainable Construction Industry," *Buildings*, vol. 14, no. 11, p. 3613, 2024. doi: [10.3390/buildings14113613](https://doi.org/10.3390/buildings14113613).
12. X. Li, F.-L. Zhang, W. Xiang, W.-X. Liu, and S.-J. Fu, "Structural health monitoring system based on digital twins and real-time data-driven methods," *Structures*, vol. 70, p. 107739, 2024. doi: [10.1016/j.istruc.2024.107739](https://doi.org/10.1016/j.istruc.2024.107739).
13. S. Boschert and R. Rosen, "Digital Twin—The Simulation Aspect," in *Mechatronic Futures*, P. Hehenberger and D. Bradley, Eds. Cham, Switzerland: Springer, 2016. doi: [10.1007/978-3-319-32156-1_5](https://doi.org/10.1007/978-3-319-32156-1_5).
14. X. Hu, G. Olgun, and R. H. Assaad, "An intelligent BIM-enabled digital twin framework for real-time structural health monitoring using wireless IoT sensing, digital signal processing, and structural analysis," *Expert Systems with Applications*, vol. 252, pt. A, p. 124204, 2024. doi: [10.1016/j.eswa.2024.124204](https://doi.org/10.1016/j.eswa.2024.124204).
15. E. E. Tita, G. Watanabe, P. Shao, and K. Aarii, "Development and Application of Digital Twin—BIM Technology for Bridge Management," *Applied Sciences*, vol. 13, no. 13, p. 7435, 2023. doi: [10.3390/app13137435](https://doi.org/10.3390/app13137435).
16. C. Liu, P. Zhang, and X. Xu, "Literature review of digital twin technologies for civil infrastructure," *Journal of Infrastructure Intelligence and Resilience*, vol. 2, no. 3, p. 100050, 2023. doi: [10.1016/j.iintel.2023.100050](https://doi.org/10.1016/j.iintel.2023.100050).
17. H. Omrany, K. M. Al-Obaidi, A. Husain, and A. Ghaffarianhoseini, "Digital Twins in the Construction Industry: A Comprehensive Review of Current Implementations, Enabling Technologies, and Future Directions," *Sustainability*, vol. 15, no. 14, p. 10908, 2023. doi: [10.3390/su151410908](https://doi.org/10.3390/su151410908).
18. E. P. Hinchy, C. Carcagno, N. P. O'Dowd, and C. T. McCarthy, "Using finite element analysis to develop a digital twin of a manufacturing bending operation," *Procedia CIRP*, vol. 93, pp. 568–574, 2020. doi: [10.1016/j.procir.2020.03.031](https://doi.org/10.1016/j.procir.2020.03.031).
19. E. E. Tita, G. Watanabe, H. da C. Ximenes, and H. M. S. Viegas, "Initiatives in Dili of Timor-Leste for implementing traffic management using digital twin-BIM technology," *Intelligence, Informatics and Infrastructure*, vol. 5, no. 1, pp. 42–56, May 2024. doi: [10.11532/jsceiiai.5.1_42](https://doi.org/10.11532/jsceiiai.5.1_42).
20. A. Afshari, J. Lee, and D. Besenski, "A Digital Twin Platform for Real-Time Intersection Traffic Monitoring, Performance Evaluation, and Calibration," *Infrastructures*, vol. 10, no. 8, p. 204, 2025. doi: [10.3390/infrastructures10080204](https://doi.org/10.3390/infrastructures10080204).
21. K. Kušić, R. Schumann, and E. Ivanjko, "A digital twin in transportation: Real-time synergy of traffic data streams and simulation for virtualizing motorway dynamics," *Advanced Engineering Informatics*, vol. 55, p. 101858, 2023. doi: [10.1016/j.aei.2022.101858](https://doi.org/10.1016/j.aei.2022.101858).
22. M. Grieves and J. Vickers, "Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems," in *Transdisciplinary Perspectives on Complex Systems*, J. Kahlen, S. Flumerfelt, and A. Alves, Eds. Cham, Switzerland: Springer, 2017. doi: [10.1007/978-3-319-38756-7_4](https://doi.org/10.1007/978-3-319-38756-7_4).
23. Y. Gao, G. Xiong, Z. Hu, C. Chai, and H. Li, "Bridge Digital Twin for Practical Bridge Operation and Maintenance by Integrating GIS and BIM," *Buildings*, vol. 14, no. 12, p. 3731, 2024. doi: [10.3390/buildings14123731](https://doi.org/10.3390/buildings14123731).

24. Z. Sun, S. Jayasinghe, A. Sidiq, F. Shahrivar, M. Mahmoodian, and S. Setunge, "Approach Towards the Development of Digital Twin for Structural Health Monitoring of Civil Infrastructure: A Comprehensive Review," *Sensors*, vol. 25, no. 1, p. 59, 2025. doi: [10.3390/s25010059](https://doi.org/10.3390/s25010059).
25. M. Sakr and A. Sadhu, "Visualization of structural health monitoring information using Internet-of-Things integrated with building information modeling," *Journal of Infrastructure Intelligence and Resilience*, vol. 2, no. 3, p. 100053, 2023. doi: [10.1016/j.iintel.2023.100053](https://doi.org/10.1016/j.iintel.2023.100053).
26. A. Armijo and D. Zamora-Sánchez, "Integration of Railway Bridge Structural Health Monitoring into the Internet of Things with a Digital Twin: A Case Study," *Sensors*, vol. 24, no. 7, p. 2115, 2024. doi: [10.3390/s24072115](https://doi.org/10.3390/s24072115).
27. H. Naderi and A. Shojaei, "Digital twinning of civil infrastructures: Current state of model architectures, interoperability solutions, and future prospects," *Automation in Construction*, vol. 149, p. 104785, 2023. doi: [10.1016/j.autcon.2023.104785](https://doi.org/10.1016/j.autcon.2023.104785).
28. A. Jiménez Rios, V. Plevris, and M. Nogal, "Bridge management through digital twin-based anomaly detection systems: A systematic review," *Frontiers in Built Environment*, vol. 9, 2023. doi: [10.3389/fbuil.2023.1176621](https://doi.org/10.3389/fbuil.2023.1176621).
29. T. D. Moshood, J. O. B. Rotimi, W. Shahzad, and J. A. Bamgbade, "Infrastructure digital twin technology: A new paradigm for future construction industry," *Technology in Society*, vol. 77, p. 102519, 2024. doi: [10.1016/j.techsoc.2024.102519](https://doi.org/10.1016/j.techsoc.2024.102519).
30. T. D. Nguyen and S. Adhikari, "The Role of BIM in Integrating Digital Twin in Building Construction: A Literature Review," *Sustainability*, vol. 15, no. 13, p. 10462, 2023. doi: [10.3390/su151310462](https://doi.org/10.3390/su151310462).
31. Z. Deng, M. Huang, N. Wan, and J. Zhang, "The Current Development of Structural Health Monitoring for Bridges: A Review," *Buildings*, vol. 13, no. 6, p. 1360, 2023. doi: [10.3390/buildings13061360](https://doi.org/10.3390/buildings13061360).
32. B. Glisic and D. Inaudi, *Fibre Optic Methods for Structural Health Monitoring*. Chichester, U.K.: Wiley, 2007. [Online]. Available: <https://doi.org/10.1002/9780470517819>
33. C. R. Farrar and K. Worden, "An Introduction to Structural Health Monitoring," in *New Trends in Vibration Based Structural Health Monitoring*, A. Deraemaeker and K. Worden, Eds. Vienna, Austria: Springer, 2010, CISM Courses and Lectures, vol. 520. doi: [10.1007/978-3-7091-0399-9_1](https://doi.org/10.1007/978-3-7091-0399-9_1).
34. J. Yu, X. Meng, B. Yan, B. Xu, Q. Fan, and Y. Xie, "Global Navigation Satellite System-based positioning technology for structural health monitoring: a review," *Structural Control and Health Monitoring*, vol. 27, no. 1, p. e2467, Oct. 2019. doi: [10.1002/stc.2467](https://doi.org/10.1002/stc.2467).
35. R. Xi, Q. He, and X. Meng, "Bridge monitoring using multi-GNSS observations with high cutoff elevations: A case study," *Measurement*, vol. 168, p. 108303, 2021. doi: [10.1016/j.measurement.2020.108303](https://doi.org/10.1016/j.measurement.2020.108303).
36. X. An, X. Meng, L. Hu, *et al.*, "GNSS integrated displacement and attitude determination for structural health monitoring of long-span bridges," *Satellite Navigation*, vol. 6, p. 19, 2025. doi: [10.1186/s43020-025-00174-9](https://doi.org/10.1186/s43020-025-00174-9).
37. S. Gonen and E. Erduran, "A Hybrid Method for Vibration-Based Bridge Damage Detection," *Remote Sensing*, vol. 14, no. 23, p. 6054, 2022. doi: [10.3390/rs14236054](https://doi.org/10.3390/rs14236054).
38. O. Avci, O. Abdeljaber, S. Kiranyaz, M. Hussein, M. Gabbouj, and D. J. Inman, "A review of vibration-based damage detection in civil structures: From traditional methods to Machine Learning and Deep Learning applications," *Mechanical Systems and Signal Processing*, vol. 147, p. 107077, 2021. doi: [10.1016/j.ymssp.2020.107077](https://doi.org/10.1016/j.ymssp.2020.107077).

39. N. V. Golovastikov, N. L. Kazanskiy, and S. N. Khonina, "Optical Fiber-Based Structural Health Monitoring: Advancements, Applications, and Integration with Artificial Intelligence for Civil and Urban Infrastructure," *Photonics*, vol. 12, no. 6, p. 615, 2025. doi: [10.3390/photonics12060615](https://doi.org/10.3390/photonics12060615).
40. S. Ri, J. Ye, N. Toyama, *et al.*, "Drone-based displacement measurement of infrastructures utilizing phase information," *Nature Communications*, vol. 15, p. 395, 2024. doi: [10.1038/s41467-023-44649-2](https://doi.org/10.1038/s41467-023-44649-2).
41. Z. Peng, J. Li, H. Hao, and Y. Zhong, "Smart structural health monitoring using computer vision and edge computing," *Engineering Structures*, vol. 319, p. 118809, 2024. doi: [10.1016/j.eng-struct.2024.118809](https://doi.org/10.1016/j.eng-struct.2024.118809).
42. G. Chen, W. Shi, L. Yu, J. Huang, J. Wei, and J. Wang, "Wireless Sensor Placement Optimization for Bridge Health Monitoring: A Critical Review," *Buildings*, vol. 14, no. 3, p. 856, 2024. doi: [10.3390/buildings14030856](https://doi.org/10.3390/buildings14030856).
43. B. Y. L. Ávila, C. A. G. Vázquez, O. P. Baluja, D. T. Cotfas, and P. A. Cotfas, "Energy harvesting techniques for wireless sensor networks: A systematic literature review," *Energy Strategy Reviews*, vol. 57, p. 101617, 2025. doi: [10.1016/j.esr.2024.101617](https://doi.org/10.1016/j.esr.2024.101617).
44. A. J. Williams, M. F. Torquato, I. M. Cameron, A. A. Fahmy, and J. Sienz, "Survey of Energy Harvesting Technologies for Wireless Sensor Networks," *IEEE Access*, vol. 9, pp. 77493–77510, 2021. doi: [10.1109/ACCESS.2021.3083697](https://doi.org/10.1109/ACCESS.2021.3083697).
45. Y. Deng, Y. Zhao, H. Ju, T.-H. Yi, and A. Li, "Abnormal data detection for structural health monitoring: State-of-the-art review," *Developments in the Built Environment*, vol. 17, p. 100337, 2024. doi: [10.1016/j.dibe.2024.100337](https://doi.org/10.1016/j.dibe.2024.100337).
46. X. Ye, P. Wu, A. Liu, X. Zhan, Z. Wang, and Y. Zhao, "A Deep Learning-Based Method for Automatic Abnormal Data Detection: Case Study for Bridge Structural Health Monitoring," *International Journal of Structural Stability and Dynamics*, vol. 23, no. 11, 2023. doi: [10.1142/S0219455423501312](https://doi.org/10.1142/S0219455423501312).
47. C. R. Farrar and K. Worden, "An Introduction to Structural Health Monitoring," *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, vol. 365, no. 1851, pp. 303–315, 2007. doi: [10.1098/rsta.2006.1928](https://doi.org/10.1098/rsta.2006.1928).
48. Y.-J. Cha, R. Ali, J. Lewis, and O. Büyüköztürk, "Deep learning-based structural health monitoring," *Automation in Construction*, vol. 161, p. 105328, 2024. doi: [10.1016/j.autcon.2024.105328](https://doi.org/10.1016/j.autcon.2024.105328).
49. J. Jia and Y. Li, "Deep Learning for Structural Health Monitoring: Data, Algorithms, Applications, Challenges, and Trends," *Sensors*, vol. 23, no. 21, p. 8824, 2023. doi: [10.3390/s23218824](https://doi.org/10.3390/s23218824).
50. S. Hassani, U. Dackermann, M. Mousavi, and J. Li, "A systematic review of data fusion techniques for optimized structural health monitoring," *Information Fusion*, vol. 103, p. 102136, 2024. doi: [10.1016/j.inffus.2023.102136](https://doi.org/10.1016/j.inffus.2023.102136).
51. O. Hakimi, H. Liu, and O. Abudayyeh, "Deep learning-driven multi-level data fusion framework for predictive maintenance and structural health monitoring of concrete bridge decks," *Automation in Construction*, vol. 175, p. 106180, 2025. doi: [10.1016/j.autcon.2025.106180](https://doi.org/10.1016/j.autcon.2025.106180).
52. H. Naderi and A. Shojaei, "Digital twinning of civil infrastructures: Current state of model architectures, interoperability solutions, and future prospects," *Automation in Construction*, vol. 149, p. 104785, 2023. doi: [10.1016/j.autcon.2023.104785](https://doi.org/10.1016/j.autcon.2023.104785).
53. A. Jiménez Rios, V. Plevris, and M. Nogal, "Bridge management through digital twin-based anomaly detection systems: A systematic review," *Frontiers in Built Environment*, vol. 9, Art. no. 1176621, 2023. doi: [10.3389/fbuil.2023.1176621](https://doi.org/10.3389/fbuil.2023.1176621).

54. A. Entezami, H. Sarmadi, B. Behkamal, and S. Mariani, "Big Data Analytics and Structural Health Monitoring: A Statistical Pattern Recognition-Based Approach," *Sensors*, vol. 20, no. 8, p. 2328, 2020. doi: [10.3390/s20082328](https://doi.org/10.3390/s20082328).
55. C. R. Farrar and K. Worden, "An Introduction to Structural Health Monitoring," in *New Trends in Vibration Based Structural Health Monitoring*, A. Deraemaeker and K. Worden, Eds. Vienna, Austria: Springer, 2010, CISM Courses and Lectures, vol. 520. doi: [10.1007/978-3-7091-0399-9_1](https://doi.org/10.1007/978-3-7091-0399-9_1).
56. H. Naderi and A. Shojaei, "Digital twinning of civil infrastructures: Current state of model architectures, interoperability solutions, and future prospects," *Automation in Construction*, vol. 149, p. 104785, 2023. doi: [10.1016/j.autcon.2023.104785](https://doi.org/10.1016/j.autcon.2023.104785).
57. V. M. Di Mucci, A. Cardellicchio, S. Ruggieri, A. Nettis, V. Renò, and G. Uva, "Artificial intelligence in structural health management of existing bridges," *Automation in Construction*, vol. 167, p. 105719, 2024. doi: [10.1016/j.autcon.2024.105719](https://doi.org/10.1016/j.autcon.2024.105719).
58. A. Jiménez Rios, V. Plevris, and M. Nogal, "Bridge management through digital twin-based anomaly detection systems: A systematic review," *Frontiers in Built Environment*, vol. 9, Art. no. 1176621, 2023. doi: [10.3389/fbuil.2023.1176621](https://doi.org/10.3389/fbuil.2023.1176621).
59. Z. Deng, M. Huang, N. Wan, and J. Zhang, "The Current Development of Structural Health Monitoring for Bridges: A Review," *Buildings*, vol. 13, no. 6, p. 1360, 2023. doi: [10.3390/buildings13061360](https://doi.org/10.3390/buildings13061360).
60. X. Qu, X. Ding, Y. L. Xu, *et al.*, "Real-time outlier detection in integrated GNSS and accelerometer structural health monitoring systems based on a robust multi-rate Kalman filter," *Journal of Geodesy*, vol. 97, no. 38, 2023. doi: [10.1007/s00190-023-01724-2](https://doi.org/10.1007/s00190-023-01724-2).
61. P. Kähler and Y. Petryna, "Vibration monitoring of structures with indirect load identification and Kalman update," *Procedia Structural Integrity*, vol. 64, pp. 1248–1255, 2024. doi: [10.1016/j.prostr.2024.09.193](https://doi.org/10.1016/j.prostr.2024.09.193).
62. X. Qu, X. Ding, Y. L. Xu, *et al.*, "Real-time outlier detection in integrated GNSS and accelerometer structural health monitoring systems based on a robust multi-rate Kalman filter," *Journal of Geodesy*, vol. 97, no. 38, 2023. doi: [10.1007/s00190-023-01724-2](https://doi.org/10.1007/s00190-023-01724-2).
63. P. Kähler and Y. Petryna, "Vibration monitoring of structures with indirect load identification and Kalman update," *Procedia Structural Integrity*, vol. 64, pp. 1248–1255, 2024, doi: [10.1016/j.prostr.2024.09.193](https://doi.org/10.1016/j.prostr.2024.09.193).
64. M. Díaz, P.-É. Charbonnel, and L. Chamoin, "A new Kalman filter approach for structural parameter tracking: Application to the monitoring of damaging structures tested on shaking-tables," *Mechanical Systems and Signal Processing*, vol. 182, p. 109529, 2023, doi: [10.1016/j.ymssp.2022.109529](https://doi.org/10.1016/j.ymssp.2022.109529).
65. V. M. Rădulescu, G. M. T. Rădulescu, S. M. Naş, A. T. Rădulescu, and C. M. Rădulescu, "Structural health monitoring of bridges under the influence of natural environmental factors and geomatic technologies: A literature review and bibliometric analysis," *Buildings*, vol. 14, p. 2811, 2024, doi: [10.3390/buildings14092811](https://doi.org/10.3390/buildings14092811).
66. X. Li, F.-L. Zhang, W. Xiang, W.-X. Liu, and S.-J. Fu, "Structural health monitoring system based on digital twins and real-time data-driven methods," *Structures*, vol. 70, p. 107739, 2024, doi: [10.1016/j.istruc.2024.107739](https://doi.org/10.1016/j.istruc.2024.107739).
67. K. J. Lee and C. B. Yun, "Extended Kalman Filter for Identification of Nonlinear Earthquake Responses of Bridges," *IFAC Proc. Volumes*, vol. 41, no. 2, pp. 15768–15773, 2008, doi: [10.3182/20080706-5-KR-1001.02666](https://doi.org/10.3182/20080706-5-KR-1001.02666).

68. K. Kim and H. Sohn, "Dynamic Displacement Estimation for Long-Span Bridges Using Acceleration and Heuristically Enhanced Displacement Measurements of Real-Time Kinematic Global Navigation System," *Sensors*, vol. 20, no. 18, p. 5092, 2020, doi: [10.3390/s20185092](https://doi.org/10.3390/s20185092).
69. X. An, X. Meng, L. Hu, *et al.*, "GNSS integrated displacement and attitude determination for structural health monitoring of long-span bridges," *Satellite Navigation*, vol. 6, no. 19, 2025, doi: [10.1186/s43020-025-00174-9](https://doi.org/10.1186/s43020-025-00174-9).
70. G. Evensen, "The Ensemble Kalman Filter: theoretical formulation and practical implementation," *Ocean Dynamics*, vol. 53, pp. 343–367, 2003, doi: [10.1007/s10236-003-0036-9](https://doi.org/10.1007/s10236-003-0036-9).
71. M. Diaz, P.-É. Charbonnel, and L. Chamoin, "A new Kalman filter approach for structural parameter tracking: Application to the monitoring of damaging structures tested on shaking-tables," *Mechanical Systems and Signal Processing*, vol. 182, p. 109529, 2023, doi: [10.1016/j.ymssp.2022.109529](https://doi.org/10.1016/j.ymssp.2022.109529).
72. H. Qiu, L. Rosafalco, A. Ghisi, and S. Mariani, "Structural Health-Monitoring Strategy Based on Adaptive Kalman Filtering," *Eng. Proc.*, vol. 82, p. 76, 2024, doi: [10.3390/ecsa-11-20493](https://doi.org/10.3390/ecsa-11-20493).
73. M. Diaz, P.-É. Charbonnel, and L. Chamoin, "A new Kalman filter approach for structural parameter tracking: Application to the monitoring of damaging structures tested on shaking-tables," *Mech. Syst. Signal Process.*, vol. 182, p. 109529, 2023, doi: [10.1016/j.ymssp.2022.109529](https://doi.org/10.1016/j.ymssp.2022.109529).
74. M. Kano, Y. Tanaka, D. Sato, *et al.*, "Data assimilation for fault slip monitoring and short-term prediction of spatial-temporal evolution of slow slip events: application to the 2010 long-term slow slip event in the Bungo Channel, Japan," *Earth Planets Space*, vol. 76, no. 57, 2024, doi: [10.1186/s40623-024-02004-9](https://doi.org/10.1186/s40623-024-02004-9).
75. H. Naderi and A. Shojaei, "Digital twinning of civil infrastructures: Current state of model architectures, interoperability solutions, and future prospects," *Automation in Construction*, vol. 149, p. 104785, 2023, doi: [10.1016/j.autcon.2023.104785](https://doi.org/10.1016/j.autcon.2023.104785).
76. I. Santos-Vila, R. Soto, E. Vega, B. Crawford, and A. Peña, "Damage Detection on Real Bridges Using Machine Learning Techniques: A Systematic Review," *Applied Sciences*, vol. 15, no. 16, p. 8884, 2025, doi: [10.3390/app15168884](https://doi.org/10.3390/app15168884).
77. Y.-J. Cha, R. Ali, J. Lewis, and O. Büyüköztürk, "Deep learning-based structural health monitoring," *Automation in Construction*, vol. 161, p. 105328, 2024, doi: [10.1016/j.autcon.2024.105328](https://doi.org/10.1016/j.autcon.2024.105328).
78. F. Ponsi, C. Castagnetti, E. Bassoli, F. Mancini, and L. Vincenzi, "Multi-sensor and Multi-frequency Data Fusion for Structural Health Monitoring," in *Proc. 10th Int. Operational Modal Analysis Conf. (IOMAC 2024)*, C. Rainieri, C. Gentile, and M. Aenlle López, Eds., Lecture Notes in Civil Engineering, vol. 515. Cham, Switzerland: Springer, 2024, pp. [online]. doi: [10.1007/978-3-031-61425-5_28](https://doi.org/10.1007/978-3-031-61425-5_28).
79. O. Hakimi, H. Liu, and O. Abudayyeh, "Deep learning-driven multi-level data fusion framework for predictive maintenance and structural health monitoring of concrete bridge decks," *Automation in Construction*, vol. 175, p. 106180, 2025, doi: [10.1016/j.autcon.2025.106180](https://doi.org/10.1016/j.autcon.2025.106180).
80. M. J. Turner, R. W. Clough, H. C. Martin, and L. J. Topp, "Stiffness and deflection analysis of complex structures," *Journal of Aeronautical Sciences*, vol. 23, no. 9, pp. 805–823, 1956, doi: [10.2514/8.3664](https://doi.org/10.2514/8.3664).
81. R. W. Clough, "The finite element method in plane stress analysis," *Proc. 2nd ASCE Conf. Electron. Comput.*, Pittsburgh, PA, USA, 1960, pp. 345–378.
82. K.-J. Bathe, *Finite Element Procedures*. Englewood Cliffs, NJ, USA: Prentice Hall, 1995.
83. O. C. Zienkiewicz, R. L. Taylor, and J. Z. Zhu, *The Finite Element Method*. Oxford, U.K.: Elsevier, 2013.

84. C. R. Farrar and K. Worden, "An introduction to structural health monitoring," *Philos. Trans. R. Soc. A: Math., Phys. Eng. Sci.*, vol. 365, no. 1851, pp. 303–315, Jan. 2007, doi: 10.1098/rsta.2006.1928.
85. B. Glišić and D. Inaudi, *Fibre Optic Methods for Structural Health Monitoring*. Chichester, U.K.: Wiley, 2007, doi: 10.1002/9780470517819.
86. O. Avci, O. Abdeljaber, S. Kiranyaz, M. Hussein, M. Gabbouj, and D. J. Inman, "A review of vibration-based damage detection in civil structures: From traditional methods to Machine Learning and Deep Learning applications," *Mech. Syst. Signal Process.*, vol. 147, p. 107077, Jan. 2021, doi: 10.1016/j.ymssp.2020.107077.
87. X. Li, F.-L. Zhang, W. Xiang, W.-X. Liu, and S.-J. Fu, "Structural health monitoring system based on digital twins and real-time data-driven methods," *Structures*, vol. 70, p. 107739, 2024, doi: 10.1016/j.istruc.2024.107739.
88. Z. Deng, M. Huang, N. Wan, and J. Zhang, "The current development of structural health monitoring for bridges: A review," *Buildings*, vol. 13, no. 6, p. 1360, 2023, doi: 10.3390/buildings13061360.
89. H. Naderi and A. Shojaei, "Digital twinning of civil infrastructures: Current state of model architectures, interoperability solutions, and future prospects," *Automation in Construction*, vol. 149, p. 104785, 2023. doi: 10.1016/j.autcon.2023.104785.
90. A. Jiménez Rios, V. Plevris, and M. Nogal, "Bridge management through digital twin-based anomaly detection systems: A systematic review," *Frontiers in Built Environment*, vol. 9, p. 1176621, 2023. doi: 10.3389/fbuil.2023.1176621.
91. X. Li, F.-L. Zhang, W. Xiang, W.-X. Liu, and S.-J. Fu, "Structural health monitoring system based on digital twins and real-time data-driven methods," *Structures*, vol. 70, p. 107739, 2024. doi: 10.1016/j.istruc.2024.107739.
92. V. M. Di Mucci, A. Cardellicchio, S. Ruggieri, A. Nettis, V. Renò, and G. Uva, "Artificial intelligence in structural health management of existing bridges," *Automation in Construction*, vol. 167, p. 105719, 2024. doi: 10.1016/j.autcon.2024.105719.
93. Z. Peng, J. Li, H. Hao, and Y. Zhong, "Smart structural health monitoring using computer vision and edge computing," *Engineering Structures*, vol. 319, p. 118809, 2024. doi: 10.1016/j.eng-struct.2024.118809.
94. O. Hakimi, H. Liu, and O. Abudayyeh, "Deep learning-driven multi-level data fusion framework for predictive maintenance and structural health monitoring of concrete bridge decks," *Automation in Construction*, vol. 175, p. 106180, 2025. doi: 10.1016/j.autcon.2025.106180.
95. S. Gonen and E. Erduran, "A hybrid method for vibration-based bridge damage detection," *Remote Sensing*, vol. 14, no. 23, p. 6054, 2022. doi: 10.3390/rs14236054.
96. S. Ri, J. Ye, N. Toyama, *et al.*, "Drone-based displacement measurement of infrastructures utilizing phase information," *Nature Communications*, vol. 15, p. 395, 2024. doi: 10.1038/s41467-023-44649-2.
97. S. Hassani, U. Dackermann, M. Mousavi, and J. Li, "A systematic review of data fusion techniques for optimized structural health monitoring," *Information Fusion*, vol. 103, p. 102136, 2024. doi: 10.1016/j.inffus.2023.102136.
98. O. Avci, O. Abdeljaber, S. Kiranyaz, M. Hussein, M. Gabbouj, and D. J. Inman, "A review of vibration-based damage detection in civil structures: From traditional methods to machine learning and deep learning applications," *Mechanical Systems and Signal Processing*, vol. 147, p. 107077, 2021. doi: 10.1016/j.ymssp.2020.107077.

99. J. Yu, X. Meng, B. Yan, B. Xu, Q. Fan, and Y. Xie, "Global Navigation Satellite System-based positioning technology for structural health monitoring: A review," *Structural Control and Health Monitoring*, vol. 27, no. 1, p. e2467, 2019. doi: 10.1002/stc.2467.
100. P. Kähler and Y. Petryna, "Vibration monitoring of structures with indirect load identification and Kalman update," *Procedia Structural Integrity*, vol. 64, pp. 1248–1255, 2024. doi: 10.1016/j.prostr.2024.09.193.
101. A. Entezami, H. Sarmadi, B. Behkamal, and S. Mariani, "Big data analytics and structural health monitoring: A statistical pattern recognition-based approach," *Sensors*, vol. 20, no. 8, p. 2328, Apr. 2020. doi: 10.3390/s20082328.

Appendix 3: Summary Table of Representative Related Works

The following table summarizes approximately 8–12 representative studies from the literature review (Chapter 2) that establish the technical foundations for this research. These works cover key areas such as Digital Twin applications, GNSS-based structural health monitoring, and data-driven analysis.

Author (Year)	Focus / Method	Key Limitation Addressed / Noted
Niu et al. (2023)	Multi-GNSS and acceleration integration for dynamic bridge displacement.	High complexity in accurately capturing the full 3D behavior of asymmetric or curved structures.
Xue & Psimoulis (2023)	Feasibility of low-cost GNSS receivers for monitoring pedestrian bridges.	Lower signal-to-noise ratios compared to geodetic-grade sensors, limiting precision in small-scale movements.
Li et al. (2024)	Integrated DT framework for real-time SHM using wireless IoT sensing and structural analysis.	Primarily data-driven; often lacks direct physics-based validation through high-fidelity finite element models.
Wang & Zhu (2024)	Analysis of loading factors influencing GNSS-derived structural displacements.	Difficulty in isolating structural anomalies from diurnal and seasonal thermal fluctuations.
Yu et al. (2019)	Comprehensive review of GNSS-based positioning for infrastructure SHM.	Identification of significant gaps in the real-time interoperability between sensing data and digital models (BIM).
Avci et al. (2021)	Machine learning applications for vibration-based structural damage detection.	Requires extremely large training datasets, which are often unavailable for aging or unique bridge assets.
Kähler & Petryna (2024)	Kalman filter update for indirect load identification in structural monitoring.	Focuses heavily on high-frequency vibrations rather than long-term static or semi-static deformations.
Wada et al. (2025)	Interpretation of 3D deformation behavior in bridges during construction phases using GNSS.	Specific to construction states; less focus on the long-term operational maintenance phase of the infrastructure.
Sato & Imai (2024)	Streamlining infrastructure inspections by integrating GNSS, IoT, and satellite SAR.	Focuses on improving manual inspection efficiency rather than providing an automated, self-updating Digital Twin.
Hotta et al. (2024)	Feasibility study on understanding structural deformation during bridge construction using GNSS.	Analysis is restricted to short-term temporary construction states rather than full lifecycle monitoring.
Hassani et al. (2024)	Systematic review of multi-sensor data fusion techniques for optimized SHM.	Challenges remain in managing the inherent noise and "drift" in high-precision sensor datasets like GNSS.
Jiménez Rios et al. (2023)	Systematic review of bridge management through DT-based anomaly detection systems.	Highlights current limitations in the scalability and standardized architectural frameworks for multi-layer Digital Twins.