

Full length article

Revamping structural health monitoring of advanced rail transit systems: A paradigmatic shift from digital shadows to digital twins

Mujib Olamide Adeagbo, Su-Mei Wang^{*}, Yi-Qing Ni^{*}*Department of Civil and Environmental Engineering, The Hong Kong Polytechnic University, Hong Kong, China**National Rail Transit Electrification and Automation Engineering Technology Research Center (Hong Kong Branch), Hong Kong, China*

ARTICLE INFO

Keywords:

Digitalization
Digital shadow
Digital twin
Structural health monitoring
Advanced rail transit

ABSTRACT

Advanced rail transit systems (ARTS), including high-speed rail and maglev trains, provide enhanced transportation options to meet the growing demand for efficient transportation systems. However, they present unique challenges in maintaining the safety and performance of their infrastructures. Structural health monitoring (SHM) has emerged as an essential practice to forestall the potential consequences of structural defects in ARTS. Recently, digital twins and digital shadows have been successfully employed in various industries to monitor the state of physical systems. However, their application for structural health monitoring in ARTS remains largely unexplored. Hence, this article explores the potential of digital twins and digital shadows, in improving structural health monitoring in ARTS. Due to the digital twins' ability to bi-directional communication between a real system and its virtual replica, this article presents a comprehensive literature survey on their enablers and capabilities. Meanwhile, a framework for digital twins-based monitoring in ARTS is also proposed. The key distinctions and benefits of digital twins over other Industry 4.0 digital representation concepts, such as real-time monitoring, optimization, prediction, simulation, and decision-making, are identified. The paper highlights the significant opportunities that digital twins, especially, can offer to improve health monitoring. Similarly, limitations and bottlenecks that must be tackled in future research for implementations are also acknowledged. Finally, harnessing the power of digital twins can catalyze a transformative shift in ARTS, leading to more effective monitoring, enhanced safety, and improved performance.

1. Introduction

Transportation networks, including roads and railways, play a crucial role in societal development and the economy [1]. With the increasing demand for efficient transportation, rail transit has emerged as a reliable, efficient, and sustainable option. However, the pursuit of higher speeds, increased loads, and growing passenger volumes pose challenges to rail infrastructure, particularly in advanced rail transit systems (ARTS). These systems, such as high-speed rail, maglev, automated metros, and hyperloop, have been developed to address these challenges and improve the overall performance of the railway industry [2–4]. The rail transit system in China has grown exponentially in the last few decades, boasting the most extensive public transport network in the world [5]. Other regions, such as Eastern Asia and Europe, have also witnessed significant progress in implementing ARTS, led by countries like Germany, Japan, and South Korea [6]. Despite these advancements, rail infrastructure faces challenges from loadings,

environmental factors, and human-induced effects, impacting its condition [7]. Regular monitoring is essential to assess operational characteristics, detect anomalies, and prevent discomfort, risks, and failures [8]. Structural health monitoring (SHM) is crucial for extending the life of rail assets through proactive maintenance [8].

SHM systems rely on sensor networks to continuously measure structural and environmental data in order to detect anomalous conditions [9]. Various sensing technologies, including strain sensors, accelerometers, and displacement transducers, enable integrated and distributed measurements inside and outside the structure [10]. Despite extensive research, the industry still relies on visual inspections, which could be inefficient [11]. Autonomous real-time systems are crucial for providing engineers with timely information about structural conditions [12]. Early detection of structural malfunctions in critical components like train bogies [13], railway signal systems [14], maglev suspension systems [15], track systems, etc. [16] increases service life and reduces maintenance costs.

^{*} Corresponding authors.

E-mail addresses: may.sm.wang@polyu.edu.hk (S.-M. Wang), ceyqni@polyu.edu.hk (Y.-Q. Ni).

<https://doi.org/10.1016/j.aei.2024.102450>

Received 5 June 2023; Received in revised form 4 January 2024; Accepted 27 February 2024

Available online 6 March 2024

1474-0346/© 2024 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY-NC license (<http://creativecommons.org/licenses/by-nc/4.0/>).

While conventional SHM techniques that rely on direct sensor data analysis or model updating are gaining recognition, their reliability in detecting structural issues accurately and promptly depends on their correct deployment [17]. However, traditional SHM techniques face several challenges, resulting in a low acceptance rate in related industries. These challenges include data sufficiency and management, disruption of service or normal use of structures, interference risks, lack of real-time measurement and inference automation, uncertainties, deployment costs, sensor configuration issues, and a lack of uniform methodology in implementation [18]. Digitalized SHM involving digital shadows (DS), or digital twins (DT) can address some of these limitations.

The advent of Industry 4.0 [19] and the emerging Industry 5.0 [20] hold tremendous potential for advancing sustainability and resilience in various sectors, particularly in transportation systems. The combination of technologies introduced allows for intelligent decision-making, predictive maintenance, and sustainable practices, leading us toward a future that balances economic growth, environmental responsibility, and enhanced resiliency [21].

Industry 4.0 concepts such as building information modeling (BIM), cyber-physical systems (CPS), DT, DS, big data, artificial intelligence (AI), machine learning (ML), cloud computing, internet of things (IoT), and sensor networks have gained popularity in the architecture, engineering, and construction (AEC) industry. These advancements reflect the increasing digitization and convergence of the AEC industry with other sectors. However, the AEC industry has been slow to adapt to the digital trend, posing challenges for infrastructural digitalization, smart infrastructures (SI), and SHM [8]. While the AEC industry has been relatively less digitized, full-scale digitalization is anticipated to result in substantial cost savings during different construction phases. Fig. 1 (a) shows the increasing worldwide relative search volume for the search term “digital twin” over a five-year period, between June 2018 and May 2023. The search volume is presented on a scale of 0 to 100, with 100 representing the highest search volume observed. On the other hand, Fig. 1 (b) shows the relative distribution of 8815 research documents related to “digital twin”, “digital twins”, “digital shadow” or “digital shadows” available on the Web of Science database between 2014 and 2023. The exponentially growing bar chart also highlights the growing scientific interest in the concept of digital twins.

The concept of DT can be ambiguous due to varying interpretations [22]. The U.S. National Aeronautics and Space Administration (NASA) defines DT as a simulation that incorporates multiple scales, physics, and stochastic elements, using the best available models and updated

information to mirror the life cycle of its physical twin [23]. On the other hand, a DS enables one-way information exchange between the physical structure/object and the digital representation, with limited manual communication between the digital entity and the physical entity [24].

DTs have gained traction in manufacturing, automotive production, aerospace, and healthcare sectors [25,26]. Despite these advancements, the full implementation of DTs in complex systems like railways for enhancing reliability, competitiveness, and efficiency, delivering high-quality services remains unexplored [27]. While extensive research has been conducted on DT in the AEC industry and related fields (Table 1), there is often discrepancies in its usage and definition across these studies. Finding clear guidelines and technical reports on developing DT platforms for complex systems like rail transit is challenging. Additionally, there is a limited number of DT-related papers in the AEC industry, particularly in the context of railways. However, there is significant potential for DTs in areas like SHM. Furthermore, there is a lack of studies combining ARTS, DTs, and SHM. Meanwhile, integration of these aspects through DTs and establishing formalized frameworks are crucial.

The main contribution of this paper is to provide a comprehensive review of the existing literature on DTs and related concepts, clarify digitalization concepts, bridge the gap between SHM and DT, and propose a framework for SHM-DT in ARTS. The paper aims to establish a generally applicable technical framework for developing SHM-DTs in the advanced rail transit industry.

The paper is organized as follows: Section 2 critically reviews the concept of SHM, including the need for SHM, types of maintenance, and enablers. Section 3 discusses the concept of digitalization, highlighting the various levels of virtualization and their applications. Section 4 discusses the enablers of DT and its requirements. Section 5 focuses on applying DT technology in SHM for the railway industry and other sectors. Section 6 proposes a conceptual framework for designing SHM-DTs for ARTS. Section 7 explores other aspects of the rail transit industry where DT adoption would be beneficial. Section 8 discusses barriers to fully realizing DT’s potential and proposes future works to address them. Finally, in Section 9, concluding remarks are provided.

2. Overview and evolution of structural health monitoring (SHM)

This section provides an overview of SHM from a general perspective. It discusses the necessity for SHM, the classification of SHM

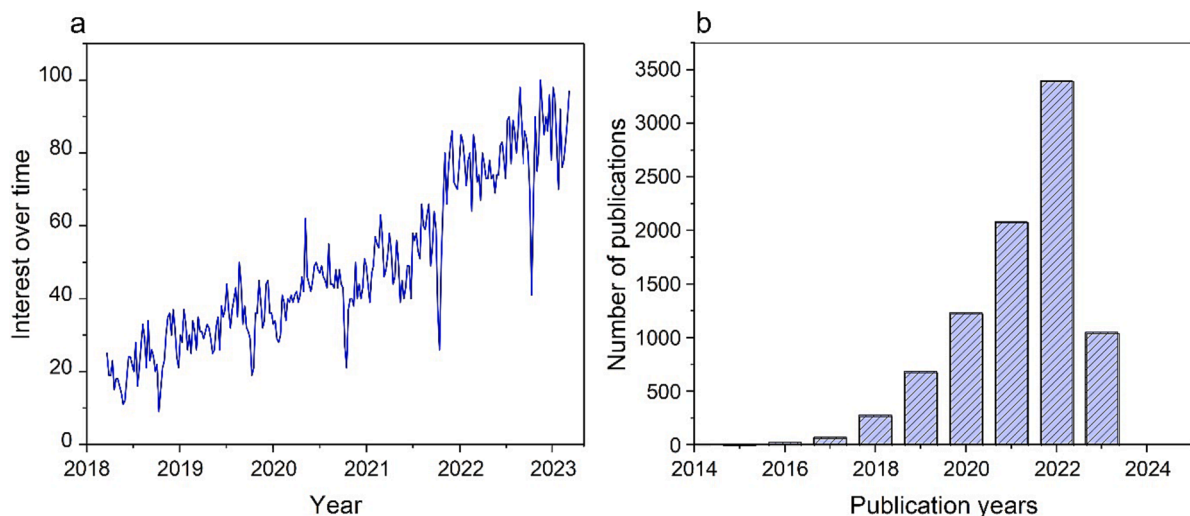


Fig. 1. (a) The increasing interest in worldwide search for “digital twins” on Google search engine (2018 – 2023); (b) The exponential growth of the total publications regarding “digital twins” on the Web of Science (2014 – 2023).

Table 1
Some literature review papers on DT in relation to general practice and the AEC industry.

S/ N	Reference	Focus	Theme
1	Ahleroff et al [28]	Developed a holistic reference architecture model for DTs	Generic
	Barricelli et al [29]	Surveyed the definitions, characteristics, applications, and design of DTs	
	Lim et al. [30]	Focused on the concept, techniques, innovation, challenges, and applications of DT	
	Zheng et al. [31]	Offered an overview of cognitive DTs' difficulties and prospects	
	Jones et al. [32]	Presented a comprehensive characterization analysis on DTs	
	Wu et al. [33]	Analyzed DT application fields, functions, and development trends	
	Botín-Sanabria et al. [34]	Presented a comprehensive evaluation of DT technology, implementation, problems, and limitations	
2	Fang et al. [35]	Analyzed modelling in DT, including the techniques and methods	Enablers and Barriers
	Perno et al. [36]	Discussed the facilitators and hurdles to DT implementation in the process industry	
3	Aidan et al. [37]	Analyzed the enabling technologies, challenges, and application of DT in various industries	AEC
	Broo and Schooling [38]	Studied infrastructure DTs' current practices, challenges, and strategies	
	Boje et al. [39]	Reviewed the BIM-centered construction DT	
	Delgado and Oyedele [40]	Proposed a framework for adopting DT in the built environment industry	
	Al-Sehrawy and Kumar [41]	Reviewed the DT concept as regards its origin, features applications and implementation hurdles	
	Jiang et al. [42]	Provided a state-of-the-art analysis of DT implementation in the civil engineering sector	
	Bado et al. [8]	Reviewed civil engineering DTs based on distribution sensing	
4	Juarez et al. [22]	Discussed communication strategies involved in DT implementation	Sensors and sensing networks Communications and networks
	Mashaly [43]	Discussed networking requirements for the DT	
6	Shahat et al. [44]	Discussed the potential of DTs in smart city implementation	Smart and sustainable city
	Ferré-Bigorra et al. [45]	Presented a review on the adoption of DTs in urban cities	
	Corrado et al. [46]	Examined the sustainability-benefiting implementations of DTs	
7	Errandonea et al. [47]	Reviewed the usage and potentials of DT in maintenance	Maintenance and Disaster Prevention
	Yu and He [48]	Reviewed DT application in infrastructure disaster prevention and mitigation	
8	Dirnfeld et al. [49]*	Discussed the role of AI in DTs for railway sector	Railway Transport
9	Liu et al. [50]	Examined the use of AR in DT applications	Immersive technologies and visualization
10	Rathore et al. [51]	Discussed the cognitive roles of AI, and ML in the creation of digital twins	Cognition and analytics

*A number of the literature included in this review are of integration level lower than DTs and would at most be classified as digital shadows.

practices, and the enabling technologies that drive advancements in SHM.

2.1. The necessity for SHM

SHM is primarily concerned with monitoring and detecting degradations and defects that impact a structure's ability to perform its intended purpose, as well as the material and geometric properties [52]. Based on the information obtained from the structure, SHM can be categorized into four phases [53], i.e. damage localization, life prediction, identification, and damage assessment, as shown in Table 2.

In general, for all types of rail transit systems, whether conventional or advanced, monitoring is particularly crucial for track/guideway components such as curvatures, slopes, irregularities, and turnouts [54]. Abnormal loads can impact the bogie (in high-speed rails) or the levitation bogies (in maglev trains) and can also lead to fatigue issues [55]. In maglev trains, the dynamic contact between the electromagnet and the guideway [56] and irregularities in the guideway [15] can cause resonance and vehicle instability [57]. Resorting to traditional maintenance practices in railway would lead to under- or over-maintenance [58]. Therefore, there is a need for improved, digitized, continuous, and real-time-based maintenance.

2.2. Classification of SHM

2.2.1. Based on variation of measured system properties

SHM methods often require measuring the responses of a structure to infer the structure's condition [59]. There are two main groups in this regard: static SHM involving slowly varying system responses; and dynamic SHM involving dynamically varying properties [53].

2.2.2. Based on measured system properties

SHM can be classified into vibration-based and non-vibration-based methods based on the measured system properties. They are vibration-based SHM which could involve free, forced, or ambient responses [60]; and non-vibration-based SHM [61].

2.2.3. Based on modeling

SHM practices can also be classified based on the analytics methodology, specifically, the approach used for system condition identification [53]. The main categories are physics model-based SHM which involves updating system models based on measured system responses; and data-driven SHM involving statistical methods and/or ML algorithms.

2.3. Advanced SHM enablers

The advent of some modern devices and the gradual convergence of civil engineering with various other fields [62] have recently led to advancement in SHM. In the realm of sensing and measurements, modern devices have overcome many limitations of conventional sensors, offering improved precision and coverage. These enable the

Table 2
Phases of structural health diagnosis.

S/ N	Phases	Focus
1	Identification	Determine the presence of defects on a global scale
2	Localization	Pinpoint the location and area of damage within a system
3	Assessment	Evaluate the type, level, and intensity of damage in system components
4	Life Prediction	Estimate the remaining life of the structure or system.

measurement of new structural characteristics, including electrical impedance and guided wave responses, offering integrated, quasi-distributed, and distributed measurements [10]. Examples of these new sensor technologies include optical fiber sensors (OFS), global positioning systems (GPS), micro-mechanical systems (MEMS), radar-based systems (e.g., LiDAR), vision-based systems, smart wireless sensors, etc. [17].

Other aspects, such as automation and data management speed, have also been enhanced through wireless sensors, high-speed computers, new ML techniques, cloud computing, and high-speed connectivity [63]. Issues with traditional SHM such as data inundation, cable length constraints, and interference caused by long cables [64] can also be prevented with new technologies.

In addition, the rapid advancement of information and communication technology has resulted in the incorporation of computer-aided technologies into SHM practices. Concepts such as computer-aided engineering, BIM (building information modeling), etc., have become ubiquitous in the SHM field. Indeed, newer concepts such as ML, the internet of things (IoT), big data, cloud computing, DT, and sensor networks are also gaining traction.

3. Digitalization for SHM: Between digital model (DM), digital shadow (DS), and digital twin (DT)

This section explores digitalization and aims to clarify the various concepts associated with it. The distinction between these concepts is crucial to avoid the confusion often encountered in literature. Additionally, the application and impact of digitalization in the AEC industry and other sectors will be discussed.

3.1. The concept of digitalization and modeling

The integration of computer-aided technologies and information technologies into the AEC industry is grounded in the virtualization of physical systems or objects, collectively known as “digitalization”. In essence, digitalization involves creating a digital representation or model of a physical system [65]. DT represents the pinnacle of the digitalization process [8] in engineering and management, as it provides a framework to automate and optimize the “cradle-to-grave” processes associated with operating a civil engineering asset. Therefore, the question arises: where, when, and how does a model evolve into a DT?

3.2. The simplification of digital modeling levels and their key attributes

Within the realm of digitalization, several concepts closely related to DTs, such as simulation, emulation, DS, CPS, digital thread, and BIM exist [47]. In the AEC industry especially, finding clear guidelines, and semantics that differentiate various aspects of digitalization is quite challenging. In their literature review, Liu et al. [66] observed that over half of the studies described digital models or DSs, despite claiming to focus on DTs. The definitions of concepts also vary so much that they are sometimes incorrect [67–69], resulting in their misuse [70]. Hence, it is essential to differentiate these concepts.

3.2.1. Simplification of the terms: DM, DS, DT, and digital thread

A DM is the foundational level of virtualization and refers to the virtual representation of a simulated or real object that does not involve any information interchange between the real and virtual counterparts [71]. On the other hand, a DS represents a virtual object that allows for automatic unidirectional information exchange between the real and virtual objects. Changes in the state of the real object are reflected in the virtual object, but there is no automatic reverse information exchange [47]. A DT surpasses the capabilities of a DS by enabling mutual bidirectional information exchange between a real object and its virtual counterpart throughout the entity’s lifecycle. Finally, a digital thread is the continuous connection of all digital representations throughout the

different phases of a product’s lifecycle, enabling traceability from requirements to retirement [72,73].

3.2.2. Clarifying misconceptions among similar concepts

This sub-section seeks to clarify distinctions between DTs, BIM, CPS, and smart infrastructures (SI).

a) Between DT and BIM

While BIM can manage digital information and be considered a digital model of a physical asset [74], it does not fulfill the requirements to be fully considered a DT. Although, high level BIMs with sensors exist [75,76], a DT goes beyond by enabling bidirectional information interchange with the real object throughout its life cycle, including real-time visualization, data analysis, and feedback [77,78].

b) Between DT and CPS

While CPS emphasizes the computing and communication capabilities of the cyber world to the physical [79–82], a DT provides a detailed representation of the physical process and can thus incorporate CPS technologies as part of its communication module [83].

c) Between DT and SI

SI combines sensory networks with physical infrastructure for monitoring and better-informed decision-making [84]. While SI focuses on the physical asset itself using real-time data, DTs focus on virtual replication of the physical asset and its behaviours based on real and historical data.

Based on the characteristics of the digitalization concepts discussed above and the cited references, Table 3 provides a summary of the attributes for clearer understanding. Meanwhile, the increasing complexities of digitalization concepts, and their interactions are presented in Fig. 2.

3.3. Aspects and definition of DT

A comprehensive collection of DT’s definitions can be found in [85]. According to the Industrial Internet Consortium (IIC) [86], DT is defined as “a formal digital representation of some asset, process, or system that captures attributes and behaviors of that entity suitable for communication, storage, interpretation, or processing within a certain context.”.

According to Grieves [87], a digital twin consists of three main components: (i) physical objects in the real world, (ii) digital objects in the virtual world, and (iii) connections linking the digital and physical world. Based on these, the key characteristics of DTs are:

1. Virtual representation: DTs are virtual replicas of real-world physical assets (the physical or real twin).
2. Communication: DTs incorporate information from real-world data measurements, enriching their geometric and graphical data.
3. Self-evolution: DTs can automatically update themselves with new real-time data, evolving alongside the physical twin.

3.3.1. Applications case studies of DT in the AEC and railway industry

DTs have found applications in various areas of the AEC industry. For railways, frameworks such as In2Smart [88], have been developed to facilitate the digitalization of railway intelligent asset management and monitoring practices. Other implementations of DTs in smart construction have also been reported [89]. For power and energy management, DTs have been developed to control electric railway power systems [90], track a power transformer’s voltage distribution [91], and provide on-line analysis for energy management [92,93]. DTs have also found application in smart city development in Singapore [94], Herrenberg

Table 3
Comparison of attributes of the digitalization concepts.

Attributes	DM	DS	DT	Digital Thread	BIM	Higher-level BIM	CPS	SI
Physical part	x	✓	✓	✓	x	✓	✓	✓
Virtual model	✓	✓	✓	✓	✓	✓	x	x
Connection between the physical and virtual world	x	✓	✓	✓	x	✓	✓	✓
Automatic feedback to the physical world	x	x	✓	✓	x	x	x	✓
Visualization	✓	✓	✓	✓	✓	✓	x	x
Analytics and semantics	x	✓	✓	✓	x	✓	✓	✓
Real data and behavior history	x	x	✓	✓	x	x	x	✓
Design phase to end-of-life	x	x	x	✓	x	x	x	x
Maintenance focused	x	✓	✓	x	x	x	x	✓

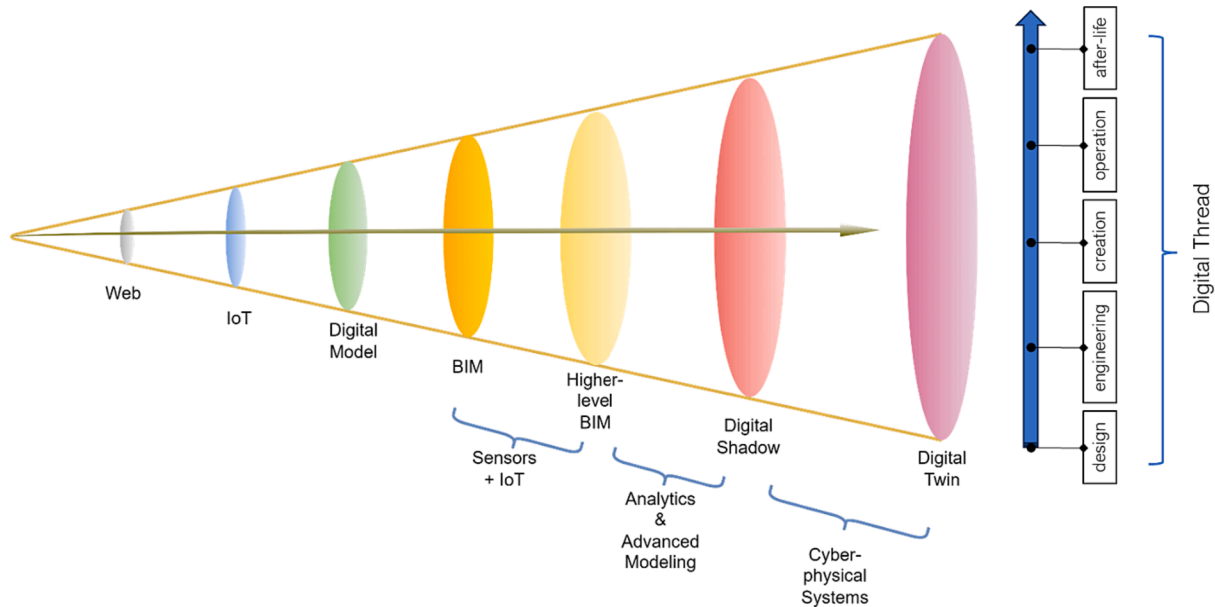


Fig. 2. The increasing complexities of digitalization concepts, as well as their interaction.

[95], Zurich [96], etc.

3.3.2. Application case studies in other industries

DTs have made significant impacts in various industries for enhancing, planning and productivity. Beyond its usage by NASA, other studies (e.g., [97]) have reported usage in the space and aeronautics field. In the production industry, DTs have been applied to product identification and position tracking [82], predictive maintenance [98], sustainable manufacturing [99], and many other areas of smart manufacturing [100–103]. Sustainability-related DT applications have also emerged such as decarbonization in ship routing [104], sustainable offshore exploration [105], etc. In the health area, DTs have been applied to personal health monitoring [106], and in many other applications [107–110].

4. Perspectives on the composition of a DT: Enablers and requirements

Based on the preceding discussions, it is evident that DT represents a convergence of multiple technologies, including data analytics and AI, haptics and IoT, cybersecurity, and communication networks [106]. In this section, we discuss the enablers and requirements necessary for the design of DTs.

4.1. Enablers

Advancements in AI, broadband connectivity, sensor technology, big data techniques, and computing technologies, have facilitated the

emergence of DTs in the past decade [29]. In this section, the major enablers for DTs emergence and implementations are discussed.

4.1.1. Sensors and sensing system

New wired and wireless networking protocols incorporate data encryption functionality [43], to remove the barrier of installation costs [111] and data security concerns. The rise of advanced sensing technology e.g., optical fibers [112–114] has enabled sensing networks capable of measuring various responses from target structures, in multiple directions and high frequencies. Others like laser scan sensors can carry out reverse engineering for faster modeling [76].

4.1.2. Enhanced modeling and computation

Simulation methods such as discrete-event simulation, finite element method (FEM), computational fluid dynamics (CFD) etc., are common nowadays [22]. Rasheed et al. [115] highlighted developments in computational hardware as major factors contributing to the advancement of DT, as they enabled extensive data processing, improved accuracy [49], cost benefits and portability [116].

4.1.3. AI/ML

AI techniques, particularly ML methods [117], have found extensive use in extracting valuable information from available data, guiding decision-making, reducing human efforts, and achieving a high level of automation in processes [118]. More recently, deep learning (DL) methods have been developed, offering even greater efficiency in data analytics [119,120].

4.1.4. Big data

Big data involves collecting and analyzing massive amounts of data from various sources, incorporating advanced data cleaning, mining, and analysis techniques to DTs [121].

4.1.5. Cloud computing and storage

The emergence of cloud services makes the computation, storage, and retrieval of massive amounts of data easy. Since DTs are constantly being updated with a continuous, this technology has enhanced their implementation e.g., [110,122].

4.1.6. Internet-of-things

IoT, and its industrial counterpart (IIoT), which enable seamless communication among devices and sensors, can help in collecting massive amounts of data required by DTs [49]. Incorporating IoT and/or IIoT into DT architecture enhances data collection, sorting, visualization, control relays, self-diagnostics and even self-repairing [123,124].

4.1.7. Networks and communications

Communication technologies for enhanced interoperability and proper data exchange [49] such as 5G, 6G, and WiFi are major DT enablers, allowing communication between the physical and the virtual twins, as well as within the cyber world.

4.1.8. Immersive technologies

Technologies overlaying the physical and cyber world together, like augmented reality (AR), virtual reality (VR), and mixed reality (MR) have enhanced the creation of DTs, especially in the domain of visualization, training [49] and better understanding [125].

4.2. Requirements for a DT

In the literature, specific requirements exist for a DT to be fully functional. Based on these requirements, researchers have classified DTs into various layers/kinds; including five layers [126], three layers [121], and seven layers [127]. Ghitta and Siham [121] opined that the architectures of DT vary depending on the digital twins' field of applications, intended services and benefits, and related technologies and concepts.

In this section, the requirements for DTs are discussed. Fig. 3 presents a schematic highlighting the full intricacies and details of the DT for a complex system like ARTS.

4.2.1. Modeling

In DT architecture, the most important component is the modeling/virtualizing aspect. Several kinds of modeling could be involved, including geometric virtual modeling using CAD software; mechanics-based modeling for analysis, simulation and predictions [128]; multi-physics modeling; multiscale modeling for incorporating various spatial and temporal scales [129]; data-driven modeling [130]; statistical modeling [131]; hybrid modeling combining physics-based and data-driven approaches [132–134]; surrogate modeling [135]; and reduced modeling to capture only the essential physics [136,137].

4.2.2. Sensors and data collection

One of the three major characteristics of the DT is the information exchange between the physical and virtual twins via sensors and sensing systems. Sensor data comprises a range of information, including operational data, behavior descriptions, engineering data, inspection reports, and maintenance history [8]. For data collection, certain considerations including the kind of data to measure as well as optimization of locations are paramount [138,139].

4.2.3. Simulation

Simulation in DTs serves several purposes, including evaluation of unobservable responses [140], response prediction to future events [29], predictive maintenance [141], decision-making and control strategies, visualization of the physical twin's state, as well as training of surrogate models for analysis purposes [142], leading to improved decision-making, and proactive maintenance strategies [143].

4.2.4. Visualization/ user interface

The visualization and user interface component of the DT is essential, as it facilitates human-machine interaction, and allows control actions and decisions to be relayed. The user interface must be user-friendly, semi- or fully automated for deriving insights, decision support, predictions and implementation processes [25]. Platforms include immersive technologies [83,125], web applications [7], live graphs [144] etc.

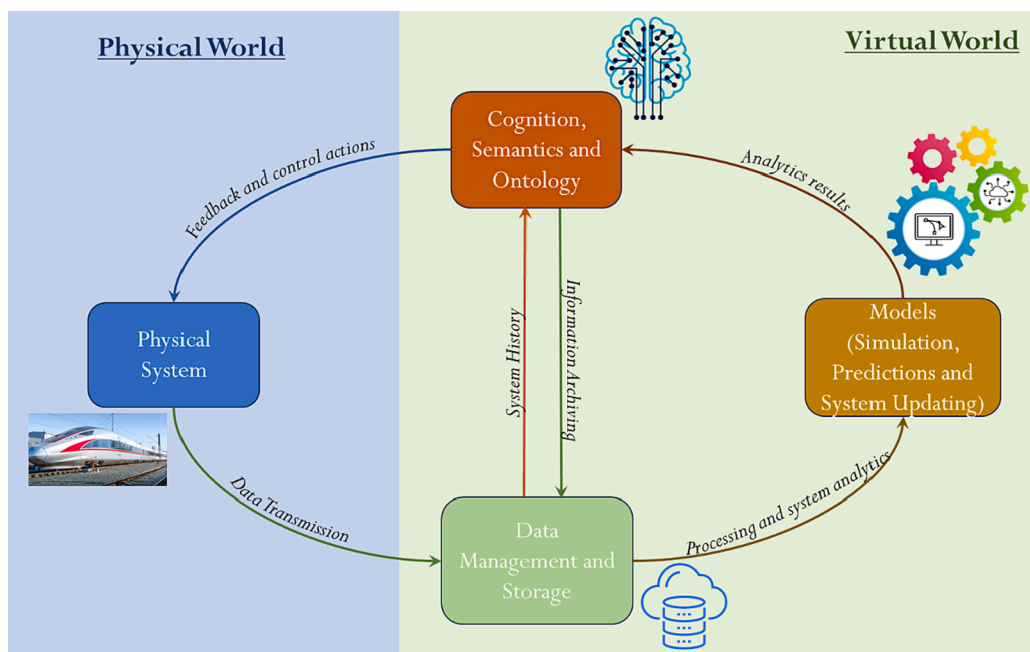


Fig. 3. Schematic illustrating the full intricacies about the digital twin of an ARTS.

4.2.5. Decision and control

For DTs' decision support system of DTs, decision-making and selecting intervention actions could be formalized into stable architectures like decision trees [8]. Semantics and ontologies have also been proposed in the literature [145], especially in cases where aggregation of several components of sub-systems DTs is necessary. Data-driven assisted cognition functions are also possible by incorporating ML/DL algorithms.

4.2.6. Full autonomy

An essential requirement of DTs is autonomy, reflected in self-adaptation and self-parametrization capabilities, allowing the virtual twin to automatically mimic the real twin throughout its whole lifecycle. One of the ways to implement full autonomy is by the development of highly modularized and parameterized DTs, allowing system decentralization [146].

4.2.7. Data handling and management

Since a DT is expected to mirror the behavior of the real twin throughout its entire lifecycle, humongous amounts of data would be collected from the physical world. Data handling protocols include ontology [145], extensible markup language [147], and the standard for the exchange of product model data [148]. On the other hand, data management concepts ensure the quality [149], fusion/integration of data [150] as well as data security [151].

4.2.8. Twin and data storage

While storing data and the entire DT in a cloud-based system may appear straightforward, it is not optimal [7]. According to Schnicke and Kuhn [152], data that requires frequent refreshing should be stored on the edge, while infrequently updated data can be stored on the cloud.

4.2.9. Self-updating ability and adaptability

The DT of a physical entity is expected to exist as several representations of the physical system over time (almost like a video), with a refresh/changing rate equal to the updating frequency of the virtual model behavior [8]. It is important for the DT to update itself based on available data streams and also reconfigure in adaptation to the evolution of the physical system itself [153,154]. In traditional model updating, calibration of models involves a computationally exhaustive process, hence making it impracticable for DT [128].

4.2.10. Communication and interactions

In DTs, especially for distributed systems involving networked twins [256], communication between components of each DT and several DTs is paramount. Four levels of communication are considered: (a) real twin to virtual twin, relying on sensor data transmission and maintenance report feeding [155]; (b) DT to other DTs, for modulated complex systems [22]; (c) virtual space intercommunication [156]; and (d) virtual twin to real twin, for relaying decisions, control actions, and feedbacks [157].

4.2.11. Uncertainty considerations

Uncertainties can arise in prediction results and inferences from various sources, including modeling, response measurement, data storage, measurement noise, errors, timing, and analog-to-digital conversion [90]. Model updating approaches, such as Bayesian methods [158], can also be utilized to calibrate the structural model's parameters, ensuring that the predicted response aligns with the measured response [159–162].

5. Digitally enhanced SHM

With the rapid development of digitalization, researchers are revolutionizing SHM systems with digitalization to benefit the industry [1,47]. Hence, in this section, the benefits, and roles of digitalization in

emerging practices of SHM and maintenance, both in the AEC industry and other industries are explored.

5.1. The benefits of digitalized SHM

Digitalized SHMs can address some of these limitations suffered by traditional SHMs in the following aspects:

- a) Reduction in uncertainties: The comprehensive data integration by DTs reduces uncertainties in simulations and predictions, improving accuracy and precision [8]
- b) Better coordination of assets and increased efficiency: DTs facilitate the convergence of infrastructure networks, which improves efficiency, cost reductions, and better maintenance practices [65].
- c) Continuous replication of physical system characteristics: DTs' continuous collection and generation of operational data enable close to real-time simulation and decision-making for improved efficiency [143].
- d) Enhanced damage detection efficiency: Continuous and automatic monitoring with DTs overcomes the limitation of traditional SHM, enabling timely intervention.
- e) Better prediction of "what if" scenarios: DTs allow testing and assessment of long- and short-term decisions and actions before implementation [8,27].
- f) Enhancement of lifetime support for systems: DTs are able to automate and optimize the "cradle-to-grave" processes associated with operating civil engineering assets [8].
- g) Decision-making support: A key aspect of DTs is feedback, empowering infrastructure managers and decision-makers with tools to effectively control, monitor, and optimize physical assets [27,163].
- h) Maintenance approach selection: DTs facilitate establishing condition-based, preventive approaches [164], as well as proactive maintenance [8].
- i) Potential for infrastructure automation: DTs enable seamless bidirectional information exchange between the real and virtual twins, enabling automation.
- j) Sustainability and environmental impact: Optimizing interventions and scheduling with DTs extends the service life of infrastructures while reducing their environmental impacts.

5.2. Applications of digitally enhanced SHM

The railway industry has seen various studies and applications of digital-based SHM, primarily utilizing conventional model updating. These studies have focused on monitoring ballasted tracks [160,165], rails [166], slab tracks [167,168], wheels [169], high-speed rail [169,170], railway bridges [171], maglev train [172], wave-based approach [173], vision-based approach [174], and advanced sensing techniques [166,175]. Meanwhile, new technologies, particularly DS and DT, have recently emerged to enhance conventional SHM practices, both within and outside the AEC industry. In the manufacturing sector, DTs have been used for predictive maintenance of robots [176], machine reconditioning [156] and fault diagnosis [177]. DTs have also found usage in SHM related to smart infrastructures, especially in bridges [178–181], vertical transportation [136], smart and sustainable transportation [137,182]. This section explores the applications of digitalization in various forms to SHM in the railway and other industries.

5.2.1. Case studies of DTs in railway systems

An extensive amount of research on the application of DTs to SHM in railway systems focuses on civil infrastructure aspects, particularly railway bridges [141,183], with less emphasis on other railway aspects. For railway vehicles, Efaanov [184] proposed a conceptual model for the DT of infrastructure facilities and rolling stock of trains; Wu et al. [58] developed a DT-based fault diagnosis framework for high-speed train bogies; while Ferdousi et al. [185] designed the RailTwin

framework to monitor heavy freight rail cars. For tracks, Yang et al. [122] presented a DT-based methodology for predictive maintenance of railway switch machines, while Bernal et al. [142] proposed a DT-based methodology for preventing train derailments. For rail power systems, Ahmadi et al. [90] proposed a DT implementation in controlling and monitoring electric railway power systems, Ikeda [2] developed DTs to maintain electric railway power supply systems, while Rodriguez et al. [186] discussed DT implementation for state estimation of electric power train components. Other implementations of DTs in urban rail transit have also been explored [146,187].

5.2.2. Case studies of DSs in railway systems

Many studies in the railway industry that claim to be based on DTs are DSs or at a lower level in the hierarchy of DMs discussed earlier. Some studies utilizing DS have focused on integrating data-driven models into decision-making frameworks for railway maintenance and examining various assets. Morant et al. [188] and Yang et al. [189] considered the maintenance of rail line signaling systems. Núñez et al. [190], Jamshidi et al. [191], and Consilvio et al. [192] focused on rail track maintenance. Liu et al. [116] proposed a cyber-twins framework for high-speed railway prognosis. Similarly, other studies involving smart high-speed railway platform monitoring [193], urban railway evaluations [194], and IoT-based railway maintenance [195] have been reported.

5.2.3. Case studies of lower-level virtual representations in railway systems

This section encompasses all virtual representations of railway systems lower than DS. Most studies in the AEC industry fall into this category, with many erroneously labeled as DTs. In some studies, BIM was used to create models for railway buildings [196], track turnout systems [197], and railway tracks [198]. Also, Hamarat et al. [199] devised a technique for evaluating fatigue damage in intricate railway turnout crossings. Avizzano et al. [200] introduced a hybrid algorithm for reconstructing rolling stocks from a sequence of images.

Most studies focusing on online monitoring of railway data only analyze monitoring data without conducting comprehensive real-time equipment status analysis, resulting in one-sided communications [122]. Numerous online monitoring applications for high-speed rail can be found in the literature, including wheel defect identification [170,201], turnout system [202], bogie condition [203], train vehicle condition [204], and maglev suspension system [16,172].

6. A conceptual framework for the SHM-focused advanced rail transit systems DT

Primarily, ARTS comprises five sectors: track (or guideway); civil structures (such as buildings, and bridges); electrical/power systems; telecommunications; and signaling/authorization systems [205]. Owing to its complexity, it is difficult to create a single DT for the entire system, even for a single purpose like SHM. A practicable idea is the creation of networked DTs replicating different systems and processes [25]. Each ARTS sector is interconnected at a global level. Hence, for SHM, all these sectors must be fully incorporated and catered to.

In this section, a framework that caters to the implementation need is formulated for the interoperability of DTs towards obtaining a “fully twinned” ARTS.

6.1. Sensor and response collection

In this aspect, the following tasks are required:

- (a) Identification of possible systems conditions and responses sensitive to changes in these conditions.
- (b) Selection of proper sensors and sensing technologies for system responses.

- (c) Selection of sensors for environmental conditions to reduce epistemic uncertainties.
- (d) Identifying the required measurement accuracy level.
- (e) Optimization of sensor quantity, locations, and configurations.
- (f) Optimization of sampling rate for each considered quantity or sensor class.

6.2. Data pre-processing, storage and management

For the handling of data, we propose using a fusion of edge, fog and cloud technology [7,206]. The following steps are necessary:

- a. Data sources classification into static, semi-static and dynamic data.
- b. Determination of proper data storage using cloud, edge, and fog.
- c. Preprocessing and model training.
- d. Deployment of processed data and trained models.

6.3. Modulation and distributed system

In ARTS, modulation of DTs is essential. The networked DTs can collaborate to diagnose faults and solve system problems [146]. To achieve modulation, several actions are required:

- a) Definition of system's sub-systems and their respective components.
- b) Definition of sub-system's levels and components.
- c) Definition of each unit, component, level, and sub-level with necessary interaction nodes.
- d) Hierarchical evaluation of granulation.
- e) Sensors and sensor locations' virtualization.

6.4. Modeling

The modeling of each component of ARTS must be able to describe the components in five essential aspects: geometry, physics, capability, behavior, and rule to give the DT an actual “mirroring” outlook. The following actions are proposed for modeling:

- a) Multiphysics modeling of the system from bottom to top.
- b) Establishment of data-driven model for each system level.
- c) Creation of hybridized models for each sub-system DTs.
- d) Surrogate meta-modeling based on the created hybrid high-fidelity models.
- e) Interaction of models at different system levels.

The interactions and functions of the various modeling levels and techniques for a DT are presented in Fig. 4.

6.5. Model updating and uncertainty considerations

Thelen et al. [207] have defined “real-time” as the minimum computational speed required to achieve seamless and uninterrupted optimization, prediction, and control of the system of interest. The necessary tasks for real-time optimum system refreshing are presented below.

- a) Identification of the system's changing and uncertain parameters.
- b) Definition of updating requirements for system components.
- c) Incorporation of surrogate models for model updating.
- d) Specification of updating algorithms.
- e) Optimization of dataset retrieval frequency and system refreshing rate.

6.6. Refreshing/updating rate of DTs

In the proposed framework, for each sequential data stream, an adaptive updating rate is recommended based on these tasks:

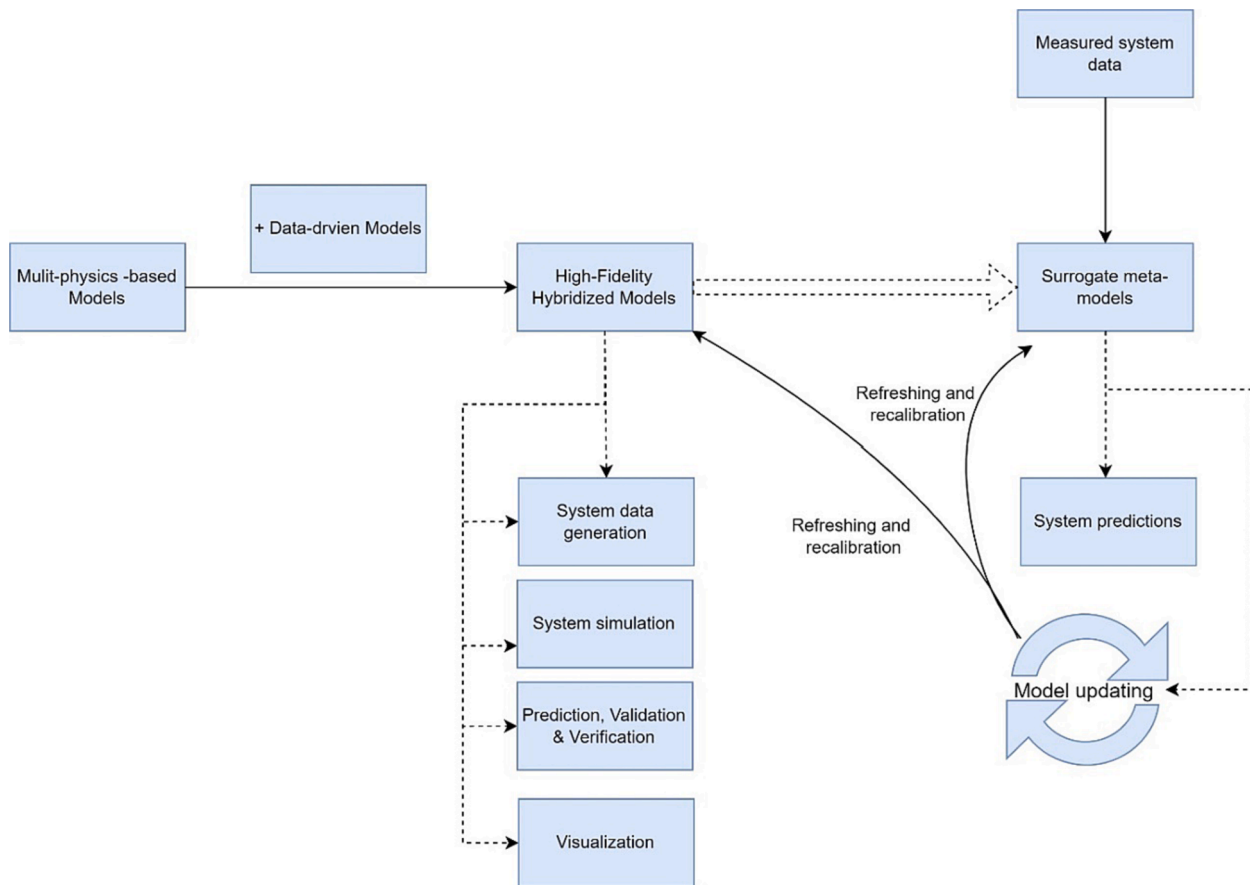


Fig. 4. The interaction between the various models, modeling levels and modeling techniques.

- a) Extraction of useful responses and information from the data.
- b) Assessment of model refreshing needs based on changes and level of changes in data streams.
- c) Adaptive updating of the data retrieval rate, and the system refreshing rate, based on a defined divergence criterion.
- d) Implementation of the analytics and control components for decision-making and control actions.

The processes and tasks involved in the proposed adaptive updating/refreshing for DTs are detailed in Fig. 5.

6.7. Simulations

The various aspects of simulation required in DTs could include:

- a) Simulation for training data-driven models on unobserved system characteristics, unmeasurable data, and extreme events.
- b) Simulation for prediction.
- c) Simulation for inference and re-adaptation.
- d) Simulation for visualization.

6.8. Cognition, semantics, and ontology

To manage the complexity of the ARTS-DT, ontology and semantics are used to design knowledge graph models for coordinating the activities of the DT including:

- a) Interactions between DTs of different levels.
- b) General system decision making, and analytics.
- c) Interactions between different system DTs of complex systems.

6.9. Accessibility, user-interface, and feedback

DT outcomes should be user-friendly and easily understandable by non-experts, through clear visualizations, simplified summaries, and explicit feedback loops. This involves:

- a) Graphical simulation of the system’s behavior in real-time.
- b) Visualization of dynamic charts and notifications.
- c) Incorporation of human-centered software for control actions.
- d) Incorporation of the online-based platform for easy access.

A flowchart detailing the proposed conceptual framework for ARTS-DT is presented in Fig. 6.

7. Other aspects of advanced rail transit with high potential for DT

As rail transport is becoming increasingly digitalized, the role of digital technology in all aspects of the rail sector is growing, along with the benefits.

7.1. Smart city and smart transportation

As an evolving strategy for city planning and integration, the market for smart city technologies is projected to worth around 165.8 billion USD by 2025 [208]. City-wide DTs also enhance effective planning, transportation, and comfortable urban living literature [209–211].

7.2. Train movement, journey scheduling, and other scheduling tasks

DT can also be applicable to train movements [212] and automation

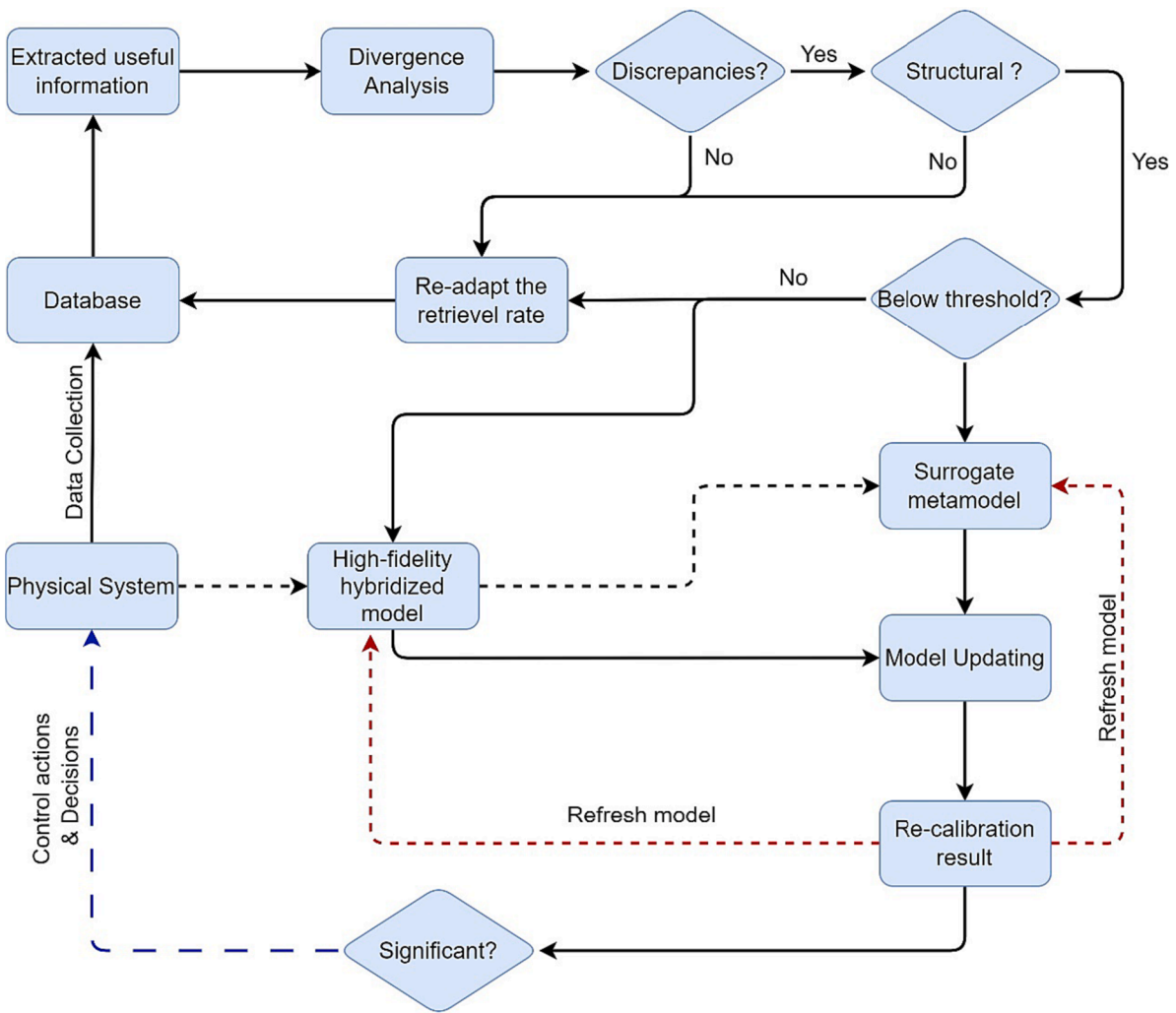


Fig. 5. The steps involved in the proposed adaptive refreshing algorithm.

of passenger movement and ticketing [146]. Negri et al. [213] have demonstrated the strong prospect of DT in scheduling tasks, and enhancing efficiency.

7.3. Smart construction and lifetime control

Gu et al. [214] demonstrated the ability of DT to facilitate ancient building protection, emergency rescue, and general construction practices including environmental quality monitoring, thermal comfort, and energy consumption.

7.4. Smart manufacturing of rail infrastructure

DTs can enhance decision-making during the design phase of a structure/infrastructure, construction, and its operational life [8,215].

7.5. Infrastructure asset management

DTs will help seamlessly manage railway infrastructure assets throughout their entire service life, even for remote assets.

7.6. Stations management and crowd control

DTs can facilitate interactions with customer behavior in stations, platforms, and trains in the railway industry [27], helping passengers to passengers can make informed decisions.

7.7. Enhanced passengers experience

DTs can provide insights into passengers' behavior and can help improve customer experience and services [216] by analyzing factors like ride comfort, such as temperature and noise levels [212].

7.8. Safety

DT has enormous potential in the safety planning and coordination of railway industry activities, including evacuations during unusual events and construction [217,218].

7.9. Sustainability and resilience and green ecosystem

DTs enable the use of decision support tools to improve asset management sustainability, optimize resource utilization and reduce the life cycle costs of assets [219].

7.10. Others

Studies such as Parviainen et al. [220] and Marcucci et al. [221] identified that DTs enhance efficiency and the creation of new opportunities, thus impacting urban transport policymaking.

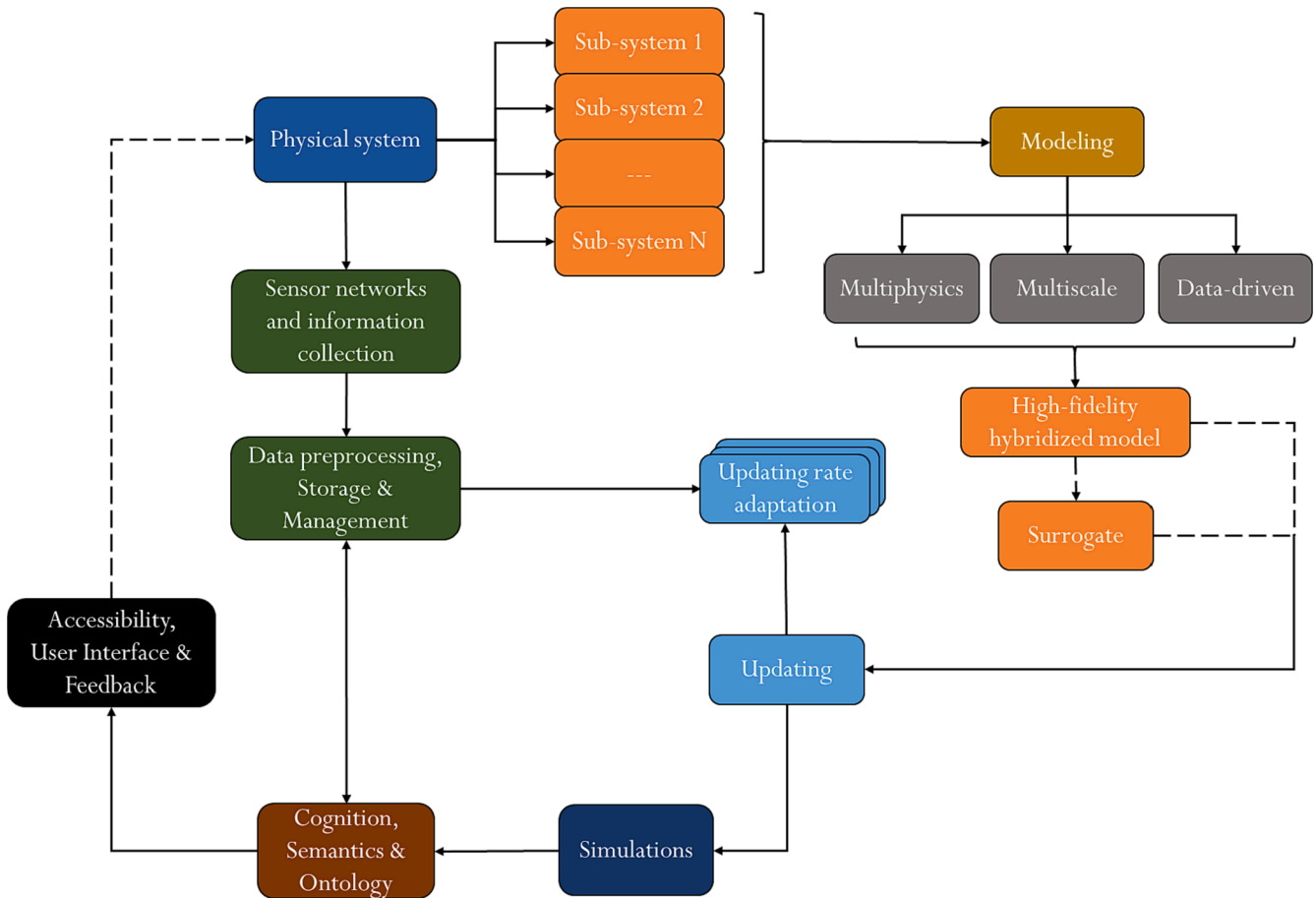


Fig. 6. Overall representation of the proposed framework.

8. Challenges and future works on SHM-DT for advanced rail transit

8.1. Current challenges

- a) Practical challenges, e.g., sensor installations, data volume, and advanced sensing networks may be required in areas with peculiarities.
- b) The necessity for organizational and perspective changes of key players poses a significant challenge for the railway industry.
- c) The skepticism of infrastructure managers towards SHM, and preference for experience-based decisions.
- d) Threats in security and policy also pose a significant barrier to the implementation of DT.
- e) Ownership, ethical and copyright concerns arise when dealing with the vast amount of data collected in DTs.
- f) The scale, complexity, and governance of data related to multi-modal rail journeys, which are influenced by various parties.
- g) The need for effective collaboration and teamwork among DTs practitioners/end users to address the variety, complexity, and scale.
- h) The complexity and need for aggregating several DTs from different systems, and key players poses a huge threat.
- i) Potential heterogeneity of architectures due to the lack of unified design, platforms, and tools.
- j) The challenge of disparate information systems resulting from data fragmentation.

8.2. Future works

Future works on solving some of the issues raised in the previous

section include:

- a) Modularization, decentralization, and integration of DTs.
- b) Full implementation of DTs for a modern rail transit system, rather than conceptual.
- c) Incorporation of enhanced cognitive, management, and security components to DTs.
- d) Development of standardized methodologies and frameworks.
- e) Efficient integration of more advanced cyber-physical immersions.
- f) Advancements in sensor technology.

9. Conclusion

The rapid advancement of rail transit systems has brought numerous benefits and challenges in terms of safety and maintenance. To address these challenges, the concept of DTs has emerged as a powerful tool, leveraging Industry 4.0 technologies and virtualization concepts. DTs and DSs have been increasingly applied in various processes, including maintenance and SHM, with promising outcomes. This paper has provided an explorative review of the literature on DTs' and SHM, as well as highlighted DTs' main features, enablers, and potentials in advanced railway SHM. The distinguishing characteristics of DTs have been clarified, highlighting the core requirements. However, it is noted that the literature still lacks comprehensive implementations of DTs in the rail industry, particularly for ARTS. Many studies mislabel concepts similar to DTs; or focus only on specific rail systems or infrastructure components.

To this effect, this paper aims to answer the question of how DTs can be applied to enhance the SHM of ARTS. It argued that DTs are a promising technology that can overcome the limitations of traditional

SHM methods and provide more accurate, reliable, and timely information about the health and performance of rail systems. Hence, a framework for implementing digital twin based-SHM in ARTS is proposed.

The proposed framework provides a systematic approach to leverage Industry 4.0 and 5.0 technologies as well as virtualization concepts in several sectors of the railway industry. The contributions of the proposed framework can be quantified through several key metrics. Firstly, it offers a comprehensive integration of data collection, storage, integration, management, and analytics, enabling real-time monitoring and proactive maintenance based on both the system history and the prevailing system condition. This leads to a significant reduction in downtime and maintenance costs. The framework also facilitates proactive decision-making by providing accurate and timely information on the health and performance of rail transit systems, without the necessity of an expert for interpretation of results as in conventional SHM. Additionally, the framework acknowledges and addresses the challenges specific to ARTS by considering their unique characteristics and requirements. By leveraging DTs, it enables a paradigmatic shift from traditional methods based on digital models and digital shadows to dynamic, automated, and interactive representations of rail transit systems. This shift fosters a deeper understanding of system behavior and enables more effective maintenance strategies.

While the proposed framework contributes to the field of ARTS and SHM, it is essential to acknowledge the existing gaps and challenges that need further exploration, such as addressing data volume management, ensuring data security and privacy, and establishing industry standards for DT implementation in the rail sector. The paper also acknowledged the limitations of this study, such as the lack of empirical validation, and the need to consider the specific characteristics and requirements of different rail systems and components.

In summary, the developed framework for DT-based SHM in ARTS presents a significant step towards revolutionizing the monitoring, optimization, planning, and control of rail transit systems. By highlighting its contributions in terms of reduced downtime, cost savings, and improved decision-making, the framework provides a practical and valuable solution for the rail industry. There is however a need for future research focusing on the development, refinement, implementation, and performance evaluation of the DT framework in high-speed rails and maglev trains, while concurrently addressing the identified challenges. Through these efforts, the integration of DTs in ARTS will drive the digitalization and interconnectivity agenda to new heights, ultimately enhancing the safety, efficiency, and performance of rail transit systems.

CRediT authorship contribution statement

Mujib Olamide Adeagbo: Writing – original draft. **Su-Mei Wang:** Writing – original draft. **Yi-Qing Ni:** Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Yi-Qing Ni reports financial support was provided by Research Grants Council of the Hong Kong Special Administrative Region (SAR). Yi-Qing Ni reports financial support was provided by Innovation and Technology Commission of Hong Kong SAR Government.

Data availability

No data was used for the research described in the article.

Acknowledgments

This work was supported in part by the National Natural Science Foundation of China (Grant No. U1934209 and 52302481), in part by

Wuyi University's Hong Kong and Macao Joint Research and Development Fund (Grants No. 2019WGalH15, 2019WGalH17 and 2021WGalH15), in part by the Innovation and Technology Commission of Hong Kong SAR Government, China (Grant No. K-BBY1), and by the Hong Kong Polytechnic University Hong Kong S.A.R. under the Postdoc Matching Fund Scheme (1-W272).

References

- [1] J. Vieira, J. Clara, H. Patrício, N. Almeida, J.P. Martins, Digital Twins in Asset Management: Potential Application Use Cases in Rail and Road Infrastructures, in: J.O.P. et al. Pinto (Ed.), Lect. Notes Mech. Eng. 15th WCEAM Proc., Springer Science and Business Media Deutschland GmbH, 2022: pp. 250–260. https://doi.org/10.1007/978-3-030-96794-9_23.
- [2] M. Ikeda, Recent research and development activities in maintenance technologies for electric railway power supply systems, Q. Rep. RTRI (Railw. Tech. Res. Institute) 61 (2020) 6–10, <https://doi.org/10.2219/rtrigr.61.1.6>.
- [3] J. hui Li, D. feng Zhou, J. Li, G. Zhang, P. chang Yu, Modeling and simulation of CMS04 maglev train with active controller, J. Cent. South Univ. 22 (2015) 1366–1377. <https://doi.org/10.1007/S11771-015-2654-Z/METRICS>.
- [4] J. Ding, X. Yang, Z. Long, N. Dang, Three-dimensional numerical analysis and optimization of electromagnetic suspension system for 200 km/h maglev train considering eddy current effect, IEEE Access 6 (2018) 61547–61555, <https://doi.org/10.1109/ACCESS.2018.2876599>.
- [5] Y. Cao, J. Wen, L. Ma, Tracking and collision avoidance of virtual coupling train control system, Alexandria Eng. J. 60 (2021) 2115–2125, <https://doi.org/10.1016/J.AEJ.2020.12.010>.
- [6] H.W. Lee, K.C. Kim, J. Lee, Review of Maglev train technologies, IEEE Trans. Magn. 42 (2006) 1917–1925, <https://doi.org/10.1109/TMAG.2006.875842>.
- [7] H. Dang, M. Tatipamula, H.X. Nguyen, Cloud-based digital twinning for structural health monitoring using deep learning, IEEE Trans. Ind. Informatics. 18 (2022) 3820–3830, <https://doi.org/10.1109/TII.2021.3115119>.
- [8] M.F. Bado, D. Tonelli, F. Poli, D. Zonta, J.R. Casas, Digital Twin for Civil Engineering Systems: An Exploratory Review for Distributed Sensing Updating, Sensors 2022, Vol. 22, Page 3168. 22 (2022) 3168. <https://doi.org/10.3390/S22093168>.
- [9] G.W. Housner, L.A. Bergman, T.K. Caughey, A.G. Chassiakos, R.O. Claus, S. F. Masri, R.E. Skelton, T.T. Soong, B.F. Spencer, J.T.P. Yao, Structural control: Past, present, and future, J. Eng. Mech. 123 (1997) 897–971, [https://doi.org/10.1061/\(ASCE\)0733-9399\(1997\)123:9\(897\)](https://doi.org/10.1061/(ASCE)0733-9399(1997)123:9(897)).
- [10] J.M. López-Higuera, L.R. Cobo, A.Q. Incera, A. Cobo, Fiber optic sensors in structural health monitoring, J. Light. Technol. 29 (2011) 587–608, <https://doi.org/10.1109/JLT.2011.2106479>.
- [11] P. Cawley, Structural health monitoring: Closing the gap between research and industrial deployment, Struct. Heal. Monit. 17 (2018) 1225–1244, https://doi.org/10.1177/1475921717750047/ASSET/IMAGES/LARGE/10.1177_1475921717750047-FIG4.JPEG.
- [12] A. Barrias, J.R. Casas, S. Villalba, A review of distributed optical fiber sensors for civil engineering applications, Sensors (Switzerland) 16 (2016), <https://doi.org/10.3390/s16050748>.
- [13] J. Ren, W. Jin, Y. Wu, Z. Sun, L. Li, Research on Performance Degradation Estimation of Key Components of High-Speed Train Bogie Based on Multi-Task Learning, Entropy 2023, Vol. 25, Page 696. 25 (2023) 696. <https://doi.org/10.3390/E25040696>.
- [14] Y. Cao, P. Li, Y. Zhang, Parallel processing algorithm for railway signal fault diagnosis data based on cloud computing, Futur. Gener. Comput. Syst. 88 (2018) 279–283, <https://doi.org/10.1016/J.FUTURE.2018.05.038>.
- [15] D. Zhou, P. Yu, L. Wang, J. Li, An adaptive vibration control method to suppress the vibration of the maglev train caused by track irregularities, J. Sound Vib. 408 (2017) 331–350, <https://doi.org/10.1016/J.JSV.2017.07.037>.
- [16] S. Wang, Y. Wang, Y. Ni, Y. Lu, Technology Innovation in Developing the Health Monitoring Cloud Platform for Maglev Vehicle- Suspension-Guideway Coupling System, in: Proc. 14th Int. Work. Struct. Heal. Monit., Stanford, CA, 2023.
- [17] M.F. Bado, J.R. Casas, A review of recent distributed optical fiber sensors applications for civil engineering structural health monitoring, Sensors 21 (2021) 1–83, <https://doi.org/10.3390/s21051818>.
- [18] B. Glišić, D. Hubbell, D.H. Sigurdardottir, Y. Yao, Damage detection and characterization using long-gauge and distributed fiber optic sensors, Opt. Eng. 52 (2013) 087101, <https://doi.org/10.1117/1.OE.52.8.087101>.
- [19] M. Kor, I. Yitmen, S. Alizadehsalehi, An investigation for integration of deep learning and digital twins towards Construction 4.0, Smart Sustain. Built Environ. (2022), <https://doi.org/10.1108/SASBE-08-2021-0148>.
- [20] S. Qahtan, H.A. Alsattar, A.A. Zaidan, D. Pamucar, M. Devenci, Integrated sustainable transportation modelling approaches for electronic passenger vehicle in the context of industry 5.0, J. Innov. Knowl. 7 (2022) 100277, <https://doi.org/10.1016/J.JIK.2022.100277>.
- [21] D. Mourtzis, E. Vlachou, V. Zogopoulos, X. Fotini, Integrated production and maintenance scheduling through machine monitoring and augmented reality: An industry 4.0 approach, IFIP Adv. Inf. Commun. Technol. 513 (2017) 354–362, https://doi.org/10.1007/978-3-319-66923-6_42/FIGURES/3.
- [22] M.G. Juarez, V.J. Botti, A.S. Giret, Digital twins: Review and challenges, J. Comput. Inf. Sci. Eng. 21 (2021) 1–23, <https://doi.org/10.1115/1.4050244>.

- [23] M. Shafto, M.C. Rich, D.E. Glaessgen, C. Kemp, J. Lemoigne, L. Wang, Modeling, simulation, information technology & processing roadmap: Technology area 11, *Natl. Aeronaut. Sp. Adm.* (2010) 1–38.
- [24] W. Kritzinger, M. Karner, G. Traar, J. Henjes, W. Sihn, Digital Twin in manufacturing: A categorical literature review and classification, *IFAC-PapersOnLine* 51 (2018) 1016–1022, <https://doi.org/10.1016/j.ifacol.2018.08.474>.
- [25] Gemma Nicholson, Digital Twins and the Railway: One Framework Many Implementations, *Rail Saf. Stand. Board Blog*. (2019). <https://www.rssb.co.uk/what-we-do/insights-and-news/blogs/digital-twins-and-the-railway-one-framework-many-implementations> (accessed May 27, 2023).
- [26] Peter El Hajj, Using Digital Twins to Improve Customer Experience, *Rail Saf. Stand. Board Blog*. (2020). <https://www.rssb.co.uk/en/what-we-do/insights-and-news/blogs/using-digital-twins-to-improve-customer-experience> (accessed May 29, 2023).
- [27] Luisa Moisiso, Clive Roberts, Digital Twins for Rail - Going Beyond the Buzzword, *Rail Saf. Stand. Board Blog*. (2020). <https://www.rssb.co.uk/what-we-do/insights-and-news/blogs/digital-twins-for-rail-going-beyond-the-buzzword> (accessed May 27, 2023).
- [28] S. Aheleroff, X. Xu, R.Y. Zhong, Y. Lu, Digital Twin as a Service (DTaaS) in industry 4.0: An architecture reference model, *Adv. Eng. Informatics* 47 (2021) 101225, <https://doi.org/10.1016/j.aei.2020.101225>.
- [29] B.R. Barricelli, E. Casiraghi, D. Fogli, A survey on digital twin: Definitions, characteristics, applications, and design implications, *IEEE Access* 7 (2019) 167653–167671, <https://doi.org/10.1109/ACCESS.2019.2953499>.
- [30] K.Y.H. Lim, P. Zheng, C.H. Chen, A state-of-the-art survey of Digital Twin: techniques, engineering product lifecycle management and business innovation perspectives, *J. Intell. Manuf.* 31 (2020) 1313–1337, <https://doi.org/10.1007/S10845-019-01512-W>.
- [31] X. Zheng, J. Lu, D. Kiritsis, The emergence of cognitive digital twin: vision, challenges and opportunities, *Int. J. Prod. Res.* 60 (2022) 7610–7632, <https://doi.org/10.1080/00207543.2021.2014591>.
- [32] D. Jones, C. Snider, A. Nassehi, J. Yon, B. Hicks, Characterising the Digital Twin: A systematic literature review, *CIRP J. Manuf. Sci. Technol.* 29 (2020) 36–52.
- [33] J. Wu, Y. Yang, X.U.N. Cheng, H. Zuo, Z. Cheng, The Development of Digital Twin Technology Review, in: *Proc. - 2020 Chinese Autom. Congr. CAC 2020*, Institute of Electrical and Electronics Engineers Inc., 2020: pp. 4901–4906. <https://doi.org/10.1109/CAC51589.2020.9327756>.
- [34] D.M. Botín-Sanabria, S. Mihaita, R.E. Peimbert-García, M.A. Ramírez-Moreno, R. A. Ramírez-Mendoza, J. de J. Lozoya-Santos, Digital Twin Technology Challenges and Applications: A Comprehensive Review, *Remote Sens.* 14 (2022) 1335. <https://doi.org/10.3390/rs14061335>.
- [35] X. Fang, H. Wang, G. Liu, X. Tian, G. Ding, H. Zhang, Industry application of digital twin: from concept to implementation, *Int. J. Adv. Manuf. Technol.* 121 (2022) 4289–4312, <https://doi.org/10.1007/s00170-022-09632-z>.
- [36] M. Perno, L. Hvam, A. Haug, Implementation of digital twins in the process industry: A systematic literature review of enablers and barriers, *Comput. Ind.* 134 (2022), <https://doi.org/10.1016/j.compind.2021.103558>.
- [37] A. Fuller, S. Member, Z. Fan, C. Day, C. Barlow, Digital twin: Enabling technologies, challenges and open research, *IEEE Access* 8 (2020) 108952–108971, <https://doi.org/10.1109/ACCESS.2020.2998358>.
- [38] D.G. Broo, J. Schooling, Digital twins in infrastructure: definitions, current practices, challenges and strategies, *Int. J. Constr. Manag.* 23 (2021) 1254–1263, <https://doi.org/10.1080/15623599.2021.1966980>.
- [39] C. Boje, A. Guerriero, S. Kubicki, Y. Rezgui, Towards a semantic Construction Digital Twin: Directions for future research, *Autom. Constr.* 114 (2020).
- [40] J.M. Davila Delgado, L. Oyedele, Digital Twins for the built environment: learning from conceptual and process models in manufacturing, *Adv. Eng. Informatics* 49 (2021), <https://doi.org/10.1016/j.aei.2021.101332>.
- [41] R. Al-Sehrawy, B. Kumar, Digital twins in architecture, engineering, construction and operations. A brief review and analysis, *Lect. Notes Civ. Eng.* 98 (2021) 924–939, https://doi.org/10.1007/978-3-030-51295-8_64/FIGURES/3.
- [42] F. Jiang, L. Ma, T. Broyd, K. Chen, Digital twin and its implementations in the civil engineering sector, *Autom. Constr.* 130 (2021), <https://doi.org/10.1016/j.autcon.2021.103838>.
- [43] M. Mashaly, Connecting the twins: A review on digital twin technology & its networking requirements, *Procedia Comput. Sci.*, Elsevier B.V. (2021) 299–305, <https://doi.org/10.1016/j.procs.2021.03.039>.
- [44] E. Shahat, C.T. Hyun, C. Yeom, City digital twin potentials: A review and research agenda, *Sustain.* 13 (2021), <https://doi.org/10.3390/su13063386>.
- [45] J. Ferré-Bigorra, M. Casals, M. Gangoellets, The adoption of urban digital twins, *Cities* 131 (2022) 103905, <https://doi.org/10.1016/j.cities.2022.103905>.
- [46] C.R. Corrado, S.M. DeLong, E.G. Holt, E.Y. Hua, A. Tolk, Combining green metrics and digital twins for sustainability planning and governance of smart buildings and cities, *Sustain.* 14 (2022), <https://doi.org/10.3390/SU142012988>.
- [47] I. Errandonea, S. Beltrán, S. Arrizabalaga, Digital Twin for maintenance: A literature review, *Comput. Ind.* 123 (2020), <https://doi.org/10.1016/j.compind.2020.103316>.
- [48] D. Yu, Z. He, Digital twin-driven intelligence disaster prevention and mitigation for infrastructure: advances, challenges, and opportunities, *Nat. Hazards* 112 (2022) 1–36, <https://doi.org/10.1007/S11069-021-05190-X>.
- [49] R. Dirmfeld, L. De Donato, F. Flammini, M.S. Azari, V. Vittorini, Railway Digital Twins and Artificial Intelligence: Challenges and Design Guidelines, *Commun. Comput. Inf. Sci.* 1656 CCIS (2022) 102–113. https://link.springer.com/chapter/10.1007/978-3-031-16245-9_8 (accessed May 5, 2023).
- [50] Y.K. Liu, S.K. Ong, A.Y.C. Nee, State-of-the-art survey on digital twin implementations, *Adv. Manuf.* 10 (2022) 1–23, <https://doi.org/10.1007/s40436-021-00375-w>.
- [51] M.M. Rathore, S.A. Shah, D. Shukla, E. Bentafat, S. Bakiras, The role of AI, machine learning, and big data in digital twinning: A systematic literature review, challenges, and opportunities, *IEEE Access* 9 (2021) 32030–32052, <https://doi.org/10.1109/ACCESS.2021.3060863>.
- [52] C.R. Farrar, K. Worden, An introduction to structural health monitoring, *CISM Int. Cent. Mech. Sci. Courses Lect.* 520 (2010) 1–17, https://doi.org/10.1007/978-3-7091-0399-9_1/COVER.
- [53] V.R. Gharebaghi, E. Noroozinejad Farsangi, M. Noori, T.Y. Yang, S. Li, A. Nguyen, C. Málaga-Chuquitaype, P. Gardoni, S. Mirjalili, A Critical Review on Structural Health Monitoring: Definitions, Methods, and Perspectives, *Arch. Comput. Methods Eng.* 29 (2022) 2209–2235. <https://doi.org/10.1007/s11831-021-09665-9>.
- [54] A. Kampczyk, K. Dybel, The fundamental approach of the digital twin application in railway turnouts with innovative monitoring of weather conditions, *Sensors* 21 (2021), <https://doi.org/10.3390/s21175757>.
- [55] J.W. Han, J.D. Kim, S.Y. Song, Fatigue strength evaluation of a bogie frame for urban maglev train with fatigue test on full-scale test rig, *Eng. Fail. Anal.* 31 (2013) 412–420, <https://doi.org/10.1016/j.engfailanal.2013.01.009>.
- [56] H.S. Han, B.H. Yim, N.J. Lee, Y.C. Hur, S.S. Kim, Effects of the guideway's vibrational characteristics on the dynamics of a Maglev vehicle, *Veh. Syst. Dyn.* 47 (2009) 309–324, <https://doi.org/10.1080/00423110802054342>.
- [57] D. Zhou, J. Li, C.H. Hansen, Suppression of the stationary maglev vehicle-bridge coupled resonance using a tuned mass damper, *JVC/J. Vib. Control* 19 (2013) 191–203, https://doi.org/10.1177/1077546311430716/ASSET/IMAGES/LARGE/10.1177_1077546311430716-FIG12.JPG.
- [58] X. Wu, W. Lian, M. Zhou, H. Song, H. Dong, A Digital twin based fault diagnosis framework for bogies of high-speed trains, *IEEE J. Radio Freq. Identif. PP* (2022). <https://doi.org/10.1109/JRFID.2022.3216331>.
- [59] F.F. Manggapi, O.G.D. Cruz, Structural health monitoring: A review on its application in historical structure, *Lect. Notes Civ. Eng.* 243 (2022) 29–37, https://doi.org/10.1007/978-3-030-99979-7_4/TABLES/2.
- [60] F.N. Catbas, T. Kijewski-Correa, Structural identification of constructed systems: Collective effort toward an integrated approach that reduces barriers to adoption, *J. Struct. Eng.* 139 (2013) 1648–1652, [https://doi.org/10.1061/\(ASCE\)ST.1943-541X.0000682](https://doi.org/10.1061/(ASCE)ST.1943-541X.0000682).
- [61] J.M.W. Brownjohn, A. de Stefano, Y.L. Xu, H. Wenzel, A.E. Aktan, Vibration-based monitoring of civil infrastructure: Challenges and successes, *J. Civ. Struct. Heal. Monit.* 1 (2011) 79–95, <https://doi.org/10.1007/S13349-011-0009-5>.
- [62] H. Seo, Monitoring of CFA pile test using three dimensional laser scanning and distributed fiber optic sensors, *Opt. Lasers Eng.* 130 (2020) 106089, <https://doi.org/10.1016/j.optlaseng.2020.106089>.
- [63] J.H. Park, H.S. Kim, W.T. Kim, DM-MQTT: An efficient MQTT based on SDN multicast for massive IoT communications, *Sensors (Switzerland)* 18 (2018) 3071, <https://doi.org/10.3390/s18093071>.
- [64] C.B. Yun, J. Min, Smart sensing, monitoring, and damage detection for civil infrastructures, *KSCIE J. Civ. Eng.* 15 (2011) 1–14, <https://doi.org/10.1007/s12205-011-0001-y>.
- [65] M. Callcut, J.P. Cerceau Agliozzo, L. Varga, L. McMillan, Digital Twins in Civil Infrastructure Systems, *Sustain.* 2021, Vol. 13, Page 11549. 13 (2021) 11549. <https://doi.org/10.3390/SU132011549>.
- [66] M. Liu, S. Fang, H. Dong, C. Xu, Review of digital twin about concepts, technologies, and industrial applications, *J. Manuf. Syst.* 58 (2021) 346–361, <https://doi.org/10.1016/j.jmsys.2020.06.017>.
- [67] F. Tao, J. Cheng, Q. Qi, M. Zhang, H. Zhang, F. Sui, Digital twin-driven product design, manufacturing and service with big data, *Int. J. Adv. Manuf. Technol.* 94 (2018) 3563–3576, <https://doi.org/10.1007/s00170-017-0233-1>.
- [68] J. Lee, E. Lapira, B. Bagheri, H. an Kao, Recent advances and trends in predictive manufacturing systems in big data environment, *Manuf. Lett.* 1 (2013) 38–41. <https://doi.org/10.1016/j.mfglet.2013.09.005>.
- [69] J. Autiosalo, J. Vepsäläinen, R. Viitala, K. Tammi, A feature-based framework for structuring industrial digital twins, *IEEE Access* 8 (2020) 1193–1208, <https://doi.org/10.1109/ACCESS.2019.2950507>.
- [70] M. Singh, E. Fuenmayor, E.P. Hinchy, Y. Qiao, N. Murray, D. Devine, Digital twin: Origin to future, *Appl. Syst. Innov.* 4 (2021), <https://doi.org/10.3390/ASI4020036>.
- [71] M. Batty, Digital twins, *Environ. Plan. B Urban Anal. City Sci.* 45 (2018) 817–820, <https://doi.org/10.1177/239808318796416>.
- [72] J. Lubell, S.P. Frechette, R.R. Lipman, F.M. Proctor, J.A. Horst, M. Carlisle, P.J. Huang, Model-Based Enterprise Summit Report, 2013. <https://doi.org/https://doi.org/10.6028/NIST.TN.1820>.
- [73] M. Helu, T. Hedberg, Enabling smart manufacturing research and development using a product lifecycle test bed, *Procedia Manuf.* 1 (2015) 86–97, <https://doi.org/10.1016/J.PROMFG.2015.09.066>.
- [74] BS EN ISO 19650-1 Concepts and principles, Organization and digitization of information about buildings and civil engineering works, including building information modelling (BIM) - Information management using building information modelling. UK: BSI Standards Publication, p.6., UK: BSI Standards Publication, 2018. <https://www.citethisforme.com/topic-ideas/other/BIM Coursework - 2-102116732> (accessed May 26, 2023).
- [75] H. Hosamo, M.H. Hosamo, H.K. Nielsen, P.R. Svennevig, K. Svigt, Digital Twin of HVAC system (HVACDT) for multiobjective optimization of energy consumption and thermal comfort based on BIM framework with ANN-MOGA, *Adv. Build. Energy Res.* (2022), <https://doi.org/10.1080/17512549.2022.2136240>.

- [76] C.S. Shim, N.S. Dang, S. Lon, C.H. Jeon, Development of a bridge maintenance system for prestressed concrete bridges using 3D digital twin model, *Struct. Infrastruct. Eng.* 15 (2019) 1319–1332, <https://doi.org/10.1080/15732479.2019.1620789>.
- [77] A. Bolton, D.B. Blackwell, I. Dabson, M. Enzer, M. Evans, T. Fenemore, F. Harradence, E. Keaney, A. Kemp, A. Luck, N. Pawsey, S. Saville, J. Schooling, M. Sharp, T. Smith, J. Tennison, J. Whyte, A. Wilson, *The Gemini Principles: Guiding values for the national digital twin and information management framework*, Cambridge, UK, 2018. <https://doi.org/10.17863/CAM.32260>.
- [78] Y. Tchana, G. Ducellier, S. Remy, Designing a unique Digital Twin for linear infrastructures lifecycle management, *Procedia CIRP* 84 (2019) 545–549.
- [79] E.P. Hinchy, N.P. O'Dowd, C.T. McCarthy, Using open-source microcontrollers to enable digital twin communication for smart manufacturing, *Procedia Manuf.* 38 (2019) 1213–1219, <https://doi.org/10.1016/J.PROMFG.2020.01.212>.
- [80] S. Yun, J.H. Park, W.T. Kim, Data-centric middleware based digital twin platform for dependable cyber-physical systems, *Int. Conf. Ubiquitous Futur. Networks, ICUFN* (2017) 922–926, <https://doi.org/10.1109/ICUFN.2017.7993933>.
- [81] K.Y.H. Lim, P. Zheng, C.H. Chen, L. Huang, A digital twin-enhanced system for engineering product family design and optimization, *J. Manuf. Syst.* 57 (2020) 82–93, <https://doi.org/10.1016/J.JMSY.2020.08.011>.
- [82] R. Ward, P. Soulatiantork, S. Finneran, R. Hughes, A. Tiwari, Real-time vision-based multiple object tracking of a production process: Industrial digital twin case study, *Proc. Inst. Mech. Eng. Part B J. Eng. Manuf.* 235 (2021) 1861–1872, <https://doi.org/10.1177/09544054211002464>.
- [83] G.N. Schroeder, C. Steinmetz, C.E. Pereira, D.B. Espindola, Digital twin data modeling with AutomationML and a communication methodology for data exchange, *IFAC-PapersOnLine* 49 (2016) 12–17, <https://doi.org/10.1016/J.IFACOL.2016.11.115>.
- [84] R. Morimoto, Estimating the benefits of effectively and proactively maintaining infrastructure with the innovative Smart Infrastructure sensor system, *Socioecon. Plann. Sci.* 44 (2010) 247–257, <https://doi.org/10.1016/J.JSEPS.2010.07.005>.
- [85] E. Negri, L. Fumagalli, M. Macchi, A review of the roles of digital twin in CPS-based production systems, *Procedia Manuf.* 11 (2017) 939–948, <https://doi.org/10.1016/J.PROMFG.2017.07.198>.
- [86] Industrial Internet Consortium (IIC), *Digital Twins for Industrial Applications: Definition, Business Values, Design Aspects, Standards and Use Cases*, 2020. http://www.iiconsortium.org/pdf/IIC_Digital_Twins_Industrial_Apps_White_Paper_2020-02-18.pdf (accessed May 29, 2023).
- [87] Michael Grieves, *Digital Twin: Manufacturing Excellence through Virtual Factory Replication*, White Pap. (2014). https://www.researchgate.net/publication/275211047_Digital_Twin_Manufacturing_Excellence_through_Virtual_Factory_Replication (accessed May 27, 2023).
- [88] A. Consilvio, C. Crovetto, B. Guyot, A. Kirwan, N. Mazzino, F. Papa, Towards an intelligent and automated platform for railway Asset Management, *Proc. 7th Transp. Res. Arena, TRA*. (2018). <https://doi.org/10.5281/ZENODO.1441166>.
- [89] R. Sacks, I. Brilakis, E. Piskas, H.S. Xie, M. Girolami, Construction with digital twin information systems, *Data-Centric Eng.* 1 (2020), <https://doi.org/10.1017/DCE.2020.16>.
- [90] M. Ahmadi, H.J. Kaleybar, M. Brenna, F. Castelli-Dezza, M.S. Carmeli, Adapting Digital Twin Technology in Electric Railway Power Systems, in: 2021 12th Power Electron. Drive Syst. Technol. Conf. PEDSTC 2021, Institute of Electrical and Electronics Engineers Inc., 2021: pp. 1–6. <https://doi.org/10.1109/PEDSTC52094.2021.9405876>.
- [91] P. Moutis, O. Alizadeh-Mousavi, Digital twin of distribution power transformer for real-time monitoring of medium voltage from low voltage measurements, *IEEE Trans. Power Deliv.* 36 (2021) 1952–1963, <https://doi.org/10.1109/TPWRD.2020.3017355>.
- [92] M. Zhou, J. Yan, A new solution architecture for online power system analysis, *CSEE J. Power Energy Syst.* 4 (2018) 250–256, <https://doi.org/10.17775/CSEEJPES.2017.00430>.
- [93] Y. Fathy, M. Jaber, Z. Nadeem, Digital twin-driven decision making and planning for energy consumption, *J. Sens. Actuator Networks* 10 (2021), <https://doi.org/10.3390/JSAN10020037>.
- [94] K.H. Soon, V.H.S. Khoo, Citygml modelling for Singapore 3D national mapping, in: *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. - ISPRS Arch.*, International Society for Photogrammetry and Remote Sensing, 2017: pp. 37–42. <https://doi.org/10.5194/isprs-archives-XLII-4-W7-37-2017>.
- [95] F. Dembski, U. Wössner, M. Letzgus, M. Ruddat, C. Yamu, Urban digital twins for smart cities and citizens: The case study of herrenberg, germany, *Sustain.* 12 (2020), <https://doi.org/10.3390/SU12062307>.
- [96] G. Schrotter, C. Hürzeler, The digital twin of the city of Zurich for urban planning, *PFG - J. Photogramm. Remote Sens. Geoinf. Sci.* 88 (2020) 99–112, <https://doi.org/10.1007/s41064-020-00092-2>.
- [97] U. Dahmen, J. Rossmann, Experimentable Digital Twins for a Modeling and Simulation-based Engineering Approach, in: 4th IEEE Int. Symp. Syst. Eng. ISSE 2018 - Proc., Institute of Electrical and Electronics Engineers Inc., 2018. <https://doi.org/10.1109/SysEng.2018.8544383>.
- [98] A. Werner, N. Zimmermann, J. Lentes, Approach for a holistic predictive maintenance strategy by incorporating a digital twin, *Procedia Manuf.* 39 (2019) 1743–1751, <https://doi.org/10.1016/J.PROMFG.2020.01.265>.
- [99] F. Xiang, Z. Zhang, Y. Zuo, F. Tao, Digital twin driven green material optimal-selection towards sustainable manufacturing, *Procedia CIRP* 81 (2019) 1290–1294, <https://doi.org/10.1016/J.PROCIR.2019.04.015>.
- [100] Y. Zheng, S. Yang, H. Cheng, An application framework of digital twin and its case study, *J. Ambient Intell. Humaniz. Comput.* 10 (2019) 1141–1153, <https://doi.org/10.1007/S12652-018-0911-3>.
- [101] Q. Qi, F. Tao, Y. Zuo, D. Zhao, Digital twin service towards smart manufacturing, *Procedia CIRP* 72 (2018) 237–242, <https://doi.org/10.1016/J.PROCIR.2018.03.103>.
- [102] A. Almalki, D. Downing, B. Lozanovski, R. Tino, A. Du Plessis, M. Qian, M. Brandt, M. Leary, A digital-twin methodology for the non-destructive certification of lattice structures, *JOM* 74 (2022) 1784–1797, <https://doi.org/10.1007/s11837-021-05144-5>.
- [103] T. Hoebert, W. Lepuschitz, E. List, M. Merdan, Cloud-Based Digital Twin for Industrial Robotics, *Lect. Notes Comput. Sci. (Including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*. 11710 LNAI (2019) 105–116. https://doi.org/10.1007/978-3-030-27878-6_9.
- [104] Q. Wei, Y. Liu, Y. Dong, T. Li, W. Li, A digital twin framework for real-time ship routing considering decarbonization regulatory compliance, *Ocean Eng.* 278 (2023), <https://doi.org/10.1016/j.oceaneng.2023.114407>.
- [105] L. Wei, D. Pu, M. Huang, Q. Miao, Applications of digital twins to offshore oil/gas exploitation: From visualization to evaluation, *IFAC-PapersOnLine* 53 (2020) 738–743, <https://doi.org/10.1016/J.IFACOL.2021.04.166>.
- [106] F. Laamarti, H.F. Badawi, Y. Ding, F. Arafsha, B. Hafidh, A. El Saddik, An ISO/IEE 11073 standardized digital twin framework for health and well-being in smart cities, *IEEE Access* 8 (2020) 105950–105961, <https://doi.org/10.1109/ACCESS.2020.2999871>.
- [107] C. Quilodrán-Casas, V.L.S. Silva, R. Arcucci, C.E. Heaney, Y.K. Guo, C.C. Pain, Digital twins based on bidirectional LSTM and GAN for modelling the COVID-19 pandemic, *Neurocomputing* 470 (2022) 11–28, <https://doi.org/10.1016/j.neucom.2021.10.043>.
- [108] N.K. Chakshu, J. Carson, I. Sazonov, P. Nithiarasu, A semi-active human digital twin model for detecting severity of carotid stenoses from head vibration—A coupled computational mechanics and computer vision method, *Int. J. Numer. Method. Biomed. Eng.* 35 (2019), <https://doi.org/10.1002/CNM.3180>.
- [109] H. Laaki, Y. Miche, K. Tammi, Prototyping a digital twin for real time remote control over mobile networks: Application of remote surgery, *IEEE Access* 7 (2019) 20235–20336, <https://doi.org/10.1109/ACCESS.2019.2897018>.
- [110] Y. Liu, L. Zhang, Y. Yang, L. Zhou, L. Ren, F. Wang, R. Liu, Z. Pang, M.J. Deen, A novel cloud-based framework for the elderly healthcare services using digital twin, *IEEE Access* 7 (2019) 49088–49101, <https://doi.org/10.1109/access.2019.2909828>.
- [111] R. Bernini, A. Minardo, S. Ciaramella, V. Minutolo, L. Zeni, F. Soldovieri, Distributed strain measurement along a concrete beam via stimulated Brillouin scattering in optical fibers, *Int. J. Geophys.* 2011 (2011), <https://doi.org/10.1155/2011/710941>.
- [112] H.N. Li, D.S. Li, G.B. Song, Recent applications of fiber optic sensors to health monitoring in civil engineering, *Eng. Struct.* 26 (2004) 1647–1657, <https://doi.org/10.1016/J.ENGSTRUCT.2004.05.018>.
- [113] P. Ferdinand, The evolution of optical fiber sensors technologies during the 35 last years and their applications in structural health monitoring, in: 7th Eur. Work. Struct. Heal. Monit. EWSHM 2014 - 2nd Eur. Conf. Progn. Heal. Manag. Soc., 2014: pp. 914–929. <https://inria.hal.science/hal-01021251> (accessed May 27, 2023).
- [114] R. Sienko, M. Zych, Ł. Bednarski, T. Howiacki, Strain and crack analysis within concrete members using distributed fibre optic sensors, *Struct. Heal. Monit.* 18 (2019) 1510–1526, <https://doi.org/10.1177/1475921718804466>.
- [115] A. Rasheed, O. San, T. Kvamsdal, Digital twin: Values, challenges and enablers from a modeling perspective, *IEEE Access* 8 (2020) 21980–22012, <https://doi.org/10.1109/ACCESS.2020.2970143>.
- [116] Z. Liu, C. Jin, W. Jin, J. Lee, Z. Zhang, C. Peng, G. Xu, Industrial AI enabled prognostics for high-speed railway systems, 2018 IEEE Int. Conf. Progn. Heal. Manag. ICPHM 2018 (2018), <https://doi.org/10.1109/ICPHM.2018.8448431>.
- [117] R. Spigolon, L. Oneto, D. Anastasovski, N. Fabrizio, M. Swiatek, R. Canepa, D. Anguita, Improving Railway Maintenance Actions with Big Data and Distributed Ledger Technologies, (2020) 120–125. https://doi.org/10.1007/978-3-030-16841-4_12.
- [118] A. Consilvio, J. Solís-Hernández, N. Jiménez-Redondo, P. Sanetti, F. Papa, I. Mingolarra-Garzaiz, On applying machine learning and simulative approaches to railway asset management: The earthworks and track circuits case studies, *Sustain.* 12 (2020), <https://doi.org/10.3390/SU12062544>.
- [119] M.M. Najafabadi, F. Villanustre, T.M. Khoshgoftar, N. Seliya, R. Wald, E. Muharemagic, Deep learning applications and challenges in big data analytics, *J. Big Data* 2 (2015), <https://doi.org/10.1186/S40537-014-0007-7>.
- [120] S. Hochreiter, J. Schmidhuber, Long short-term memory, *Neural Comput.* 9 (1997) 1735–1780, <https://doi.org/10.1162/NECO.1997.9.8.1735>.
- [121] M. Ghita, B. Siham, Digital Twins Development Architectures and Deployment Technologies: Moroccan use Case, *IJACSA Int. J. Adv. Comput. Sci. Appl.* 11 (2020). www.ijacsa.thesai.org (accessed May 8, 2023).
- [122] J. Yang, Y. Sun, Y. Cao, X. Hu, Predictive maintenance for switch machine based on digital twins, *Inf.* 12 (2021), <https://doi.org/10.3390/INFO12110485>.
- [123] R. Kour, P. Tretten, R. Karim, EMaintenance solution through online data analysis for railway maintenance decision-making, *J. Qual. Maint. Eng.* 20 (2014) 262–275, <https://doi.org/10.1108/JQME-05-2014-0026-FULL/PDF>.
- [124] A. Thaduri, M. Aljumaili, R. Kour, R. Karim, Cybersecurity for eMaintenance in railway infrastructure: risks and consequences, *Int. J. Syst. Assur. Eng. Manag.* 10 (2019) 149–159, <https://doi.org/10.1007/S13198-019-00778-W/TABLES/2>.
- [125] Z. Zhu, C. Liu, X. Xu, Visualisation of the digital twin data in manufacturing by using augmented reality, *Procedia CIRP* 81 (2019) 898–903, <https://doi.org/10.1016/J.PROCIR.2019.03.223>.
- [126] F. Tao, Y. Cheng, J. Cheng, M. Zhang, W. Xu, Q. Qi, Theories and technologies for cyber-physical fusion in digital twin shop-floor, *Jisuanji Jicheng Zhizao Xitong/*

- Comput. Integr. Manuf. Syst. CIMS. 23 (2017) 1603–1611, <https://doi.org/10.13196/j.cims.2017.08.001>.
- [127] S. Singh, M. Weeber, K.P. Birke, Advancing digital twin implementation: A toolbox for modelling and simulation, *Procedia CIRP*, Elsevier B.V. (2021) 567–572, <https://doi.org/10.1016/j.procir.2021.03.078>.
- [128] R. Ward, R. Choudhary, A. Gregory, M. Jans-Singh, M. Girolami, Continuous calibration of a digital twin: comparison of particle filter and Bayesian calibration approaches, *Data-Centric Eng.* 2 (2021), <https://doi.org/10.1017/dce.2021.12>.
- [129] E.J. Tuegel, A.R. Ingraffea, T.G. Eason, S.M. Spottswood, Reengineering aircraft structural life prediction using a digital twin, (2011). <https://doi.org/10.1155/2011/154798>.
- [130] M. Schwabacher, K. Goebel, A survey of artificial intelligence for prognostics, in: AAAI Fall Symp. - Tech. Rep., 2007: pp. 107–114. <https://aaai.org/papers/0016-a-survey-of-artificial-intelligence-for-prognostics/> (accessed May 27, 2023).
- [131] P.A. Vikhar, Evolutionary algorithms: A critical review and its future prospects, *Proc. - Int. Conf. Glob. Trends Signal Process. Inf. Comput. Commun. ICGTSPICC 2016*. (2017) 261–265. <https://doi.org/10.1109/ICGTSPICC.2016.7955308>.
- [132] D.J. Wagg, K. Worden, R.J. Barthorpe, P. Gardner, Digital twins: State-of-the-art and future directions for modeling and simulation in engineering dynamics applications, *ASCE-ASME J. Risk Uncertain. Eng. Syst. Part B Mech. Eng.* 6 (2020), <https://doi.org/10.1115/1.4046739>.
- [133] Y.C. Zhu, D. Wagg, E. Cross, R. Barthorpe, Real-Time Digital Twin Updating Strategy Based on Structural Health Monitoring Systems, in: Z. Mao (Ed.), *Conf. Proc. Soc. Exp. Mech. Ser.*, Springer, 2020: pp. 55–64. https://doi.org/10.1007/978-3-030-47638-0_6.
- [134] A. Choudhary, J.F. Lindner, E.G. Holliday, S.T. Miller, S. Sinha, W.L. Ditto, Physics-enhanced neural networks learn order and chaos, *Phys. Rev. E* 101 (2020) 062207, <https://doi.org/10.1103/PHYSREVE.101.062207>/FIGURES/10/MEDIUM.
- [135] L. Wright, S. Davidson, How to tell the difference between a model and a digital twin, *Adv. Model. Simul. Eng. Sci.* 7 (2020), <https://doi.org/10.1186/S40323-020-00147-4>.
- [136] M. Gonzalez, O. Salgado, J. Croes, B. Plumeyers, W. Desmet, A digital twin for operational evaluation of vertical transportation systems, *IEEE Access* 8 (2020) 114389–114400, <https://doi.org/10.1109/ACCESS.2020.3001686>.
- [137] R. Magargle, L. Johnson, P. Mandloi, P. Davoudabadi, O. Keskar, S. Krishnaswamy, J. Batteh, A. Pitchaikani, A Simulation-Based Digital Twin for Model-Driven Health Monitoring and Predictive Maintenance of an Automotive Braking System, in: *Proc. 12th Int. Model. Conf. Prague, Czech Republic, May 15–17, 2017*, Linköping University Electronic Press, 2017: pp. 35–46. <https://doi.org/10.3384/ecp1713235>.
- [138] A.E. Bondoc, M. Tayefeh, A. Barari, Employing LIVE digital twin in prognostic and health management: Identifying location of the sensors, *IFAC-PapersOnline*, Elsevier B.V. (2022) 138–143, <https://doi.org/10.1016/j.ifacol.2022.04.183>.
- [139] A.E. Bondoc, M. Tayefeh, A. Barari, LIVE Digital Twin: Developing a Sensor Network to Monitor the Health of Belt Conveyor System, in: *IFAC-PapersOnline*, Elsevier B.V., 2022: pp. 49–54. <https://doi.org/10.1016/j.ifacol.2022.09.182>.
- [140] R. Carvalho, A.R. da Silva, Sustainability requirements of digital twin-based systems: A meta systematic literature review, *Appl. Sci.* 11 (2021), <https://doi.org/10.3390/app11125519>.
- [141] S. Yu, D. Li, J. Ou, Digital twin-based structure health hybrid monitoring and fatigue evaluation of orthotropic steel deck in cable-stayed bridge, *Struct. Control Heal. Monit.* 29 (2022) e2976, <https://doi.org/10.1002/STC.2976>.
- [142] E. Bernal, Q. Wu, M. Spiryagin, C. Cole, Augmented digital twin for railway systems, (2023). <https://doi.org/10.1080/00423114.2023.2194543>.
- [143] A.M. Madni, C.C. Madni, S.D. Lucero, Leveraging digital twin technology in model-based systems engineering, *Systems* 7 (2019), <https://doi.org/10.3390/SYSTEMS7010007>.
- [144] D. Niermann, T. Doernbach, C. Petzoldt, M. Isken, M. Freitag, Software framework concept with visual programming and digital twin for intuitive process creation with multiple robotic systems, *Robot. Comput. Integr. Manuf.* 82 (2023), <https://doi.org/10.1016/j.rcim.2023.102536>.
- [145] J. Lu, X. Zheng, L. Schweiger, D. Kiritzis, A Cognitive Approach to Manage the Complexity of Digital Twin Systems, in: S. West Al. (Eds.), *Smart Serv. Summit, Proc. IS*, 2021: pp. 105–115. https://doi.org/10.1007/978-3-030-72090-2_10.
- [146] R. Sahal, S.H. Alsamhi, K.N. Brown, D. O'shea, C. McCarthy, M. Guizani, Blockchain-empowered digital twins collaboration: Smart transportation use case, *Machines* 9 (2021), <https://doi.org/10.3390/MACHINES9090193>.
- [147] E. Negri, L. Fumagalli, C. Cimino, M. MacChi, FMU-supported simulation for CPS digital twin, *Procedia Manuf.* 28 (2019) 201–206, <https://doi.org/10.1016/J.PROMFG.2018.12.033>.
- [148] M.J. Pratt, Introduction to ISO 10303—the STEP standard for product data exchange, *J. Comput. Inf. Sci. Eng.* 1 (2001) 102–103, <https://doi.org/10.1115/1.1354995>.
- [149] Q. Lu, A.K. Parlikad, P. Woodall, G.D. Ransinghe, X. Xie, Z. Liang, E. Konstantinou, J. Heaton, J. Schooling, Developing a digital twin at building and city levels: Case study of West Cambridge Campus, *J. Manag. Eng.* 36 (2020) 05020004, [https://doi.org/10.1061/\(ASCE\)ME.1943-5479.0000763](https://doi.org/10.1061/(ASCE)ME.1943-5479.0000763).
- [150] Z. Liu, N. Meyendorf, N. Mrad, The role of data fusion in predictive maintenance using digital twin, 1949 020023, <https://doi.org/10.1063/1.5031520>.
- [151] I. Yaqoob, K. Salah, M. Uddin, R. Jayaraman, M. Omar, M. Imran, Blockchain for digital twins: Recent advances and future research challenges, *IEEE Netw.* 34 (2020) 290–298, <https://doi.org/10.1109/MNET.001.1900661>.
- [152] Frank Schmieke, Thomas Kuhn, Building the Industry 4.0 IT Infrastructure for Digital Twins - Blog des Fraunhofer IESE, Blog Des Fraunhofer-Institut Für Exp. Softw. Eng. - Fraunhofer Inst. Exp. Softw. Eng. Blog. (2020). <https://www.iese.fr/aunhofer.de/blog/industry-4-0-it-infrastructure-for-digital-twins/> (accessed May 27, 2023).
- [153] C. Zhang, W. Xu, J. Liu, Z. Liu, Z. Zhou, D.T. Pham, A reconfigurable modeling approach for digital twin-based manufacturing system, *Procedia CIRP* 83 (2019) 118–125, <https://doi.org/10.1016/J.PROCIR.2019.03.141>.
- [154] L. Zhang, L. Zhou, B.K.P. Horn, Building a right digital twin with model engineering, *J. Manuf. Syst.* 59 (2021) 151–164, <https://doi.org/10.1016/j.jmsy.2021.02.009>.
- [155] A. Fuller, Z. Fan, C. Day, C. Barlow, Digital twin: a state-of-the-art review of its enabling technologies, applications and challenges, *J. Intell. Manuf. Spec. Equip.* 8 (2021) 108952–108971, <https://doi.org/10.1109/access.2020.2998358>.
- [156] M. Ayani, M. Ganebäck, A.H.C. Ng, Digital Twin: Applying emulation for machine reconditioning, *Procedia CIRP* 72 (2018) 243–248, <https://doi.org/10.1016/J.PROCIR.2018.03.139>.
- [157] V. Gorodetsky, P. Skobelev, V. Marik, System engineering view on multi-agent technology for industrial applications: Barriers and prospects, *Cybern. Phys.* 9 (2020) 13–30, <https://doi.org/10.35470/2226-4116-2020-9-1-3-30>.
- [158] N. Metropolis, A.W. Rosenbluth, M.N. Rosenbluth, A.H. Teller, E. Teller, Equation of state calculations by fast computing machines, *J. Chem. Phys.* 21 (1953) 1087–1092, <https://doi.org/10.1063/1.1699114>.
- [159] M.O. Adeagbo, H.-F. Lam, Y.-J. Chu, Bayesian system identification of rail-sleeper-ballast system in time and modal domains: Comparative study, *ASCE-ASME J. Risk Uncertain. Eng. Syst. Part A Civ. Eng.* 8 (2022) 04022020, <https://doi.org/10.1061/AJRUA6.0001242>.
- [160] M.O. Adeagbo, H.F. Lam, Y.Q. Ni, A Bayesian methodology for detection of railway ballast damage using the modified Ludwik nonlinear model, *Eng. Struct.* 236 (2021) 112047, <https://doi.org/10.1016/J.ENGSTRUCT.2021.112047>.
- [161] D. Heckerman, A tutorial on learning with Bayesian networks, *Stud. Comput. Intell.* 156 (2008) 33–82, https://doi.org/10.1007/978-3-540-85066-3_3.
- [162] C. Li, S. MahaDeVan, Y. Ling, S. Choze, L. Wang, Dynamic Bayesian network for aircraft wing health monitoring digital twin, *AIAA J.* 55 (2017) 930–941, <https://doi.org/10.2514/1.J055201>.
- [163] R. Rosen, S. Boschert, A. Sohr, Next generation digital twin, *ATP Mag.* 60 (2018) 86–96, <https://doi.org/10.17560/atp.v60i10.2371>.
- [164] R. van Dinter, B. Tekinerdogan, C. Catal, Predictive maintenance using digital twins: A systematic literature review, *Inf. Softw. Technol.* 151 (2022), <https://doi.org/10.1016/j.infsof.2022.107008>.
- [165] H.-F. Lam, M.O. Adeagbo, Y.-B. Yang, Time-domain Markov chain Monte Carlo-based Bayesian damage detection of ballasted tracks using nonlinear ballast stiffness model, *Struct. Heal. Monit.* (2020) 147592172096695, <https://doi.org/10.1177/1475921720966950>.
- [166] J. Wang, X.Z. Liu, Y.Q. Ni, A Bayesian probabilistic approach for acoustic emission-based rail condition assessment, *Comput. Civ. Infrastruct. Eng.* 33 (2018) 21–34, <https://doi.org/10.1111/MICE.12316>.
- [167] Q.A. Wang, C. Zhang, Z.G. Ma, J. Huang, Y.Q. Ni, C. Zhang, SHM deformation monitoring for high-speed rail track slabs and Bayesian change point detection for the measurements, *Constr. Build. Mater.* 300 (2021) 124337, <https://doi.org/10.1016/J.CONBUILDMAT.2021.124337>.
- [168] Y.T. Ke, C.C. Cheng, Y.C. Lin, Y.Q. Ni, K.T. Hsu, T.T. Wai, Preliminary Study on Assessing Delaminated Cracks in Cement Asphalt Mortar Layer of High-Speed Rail Track Using Traditional and Normalized Impact-Echo Methods, *Sensors* 2020, Vol. 20, Page 3022. 20 (2020) 3022. <https://doi.org/10.3390/S20113022>.
- [169] S.X. Chen, L. Zhou, Y.Q. Ni, Wheel condition assessment of high-speed trains under various operational conditions using semi-supervised adversarial domain adaptation, *Mech. Syst. Signal Process.* 170 (2022) 108853, <https://doi.org/10.1016/J.YMSSP.2022.108853>.
- [170] X.Z. Liu, Y.Q. Ni, Wheel tread defect detection for high-speed trains using FBG-based online monitoring techniques, *Smart Struct. Syst.* 21 (2018) 687–694, <https://doi.org/10.12989/SSS.2018.21.5.687>.
- [171] K. Lin, Y.L. Xu, X. Lu, Z. Guan, J. Li, Digital twin-based collapse fragility assessment of a long-span cable-stayed bridge under strong earthquakes, *Autom. Constr.* 123 (2021), <https://doi.org/10.1016/j.autcon.2020.103547>.
- [172] Y. Sun, H. Qiang, J. Xu, G. Lin, Internet of things-based online condition monitor and improved adaptive fuzzy control for a medium-low-speed maglev train system, *IEEE Trans. Ind. Informatics* 16 (2020) 2629–2639, <https://doi.org/10.1109/TII.2019.2938145>.
- [173] X. Sun, C. Guo, L. Yuan, Q. Kong, Y. Ni, Diffuse Ultrasonic Wave-Based Damage Detection of Railway Tracks Using PZT/FBG Hybrid Sensing System, *Sensors* 2022, Vol. 22, Page 2504. 22 (2022) 2504. <https://doi.org/10.3390/S22072504>.
- [174] D.Z. Dang, C.C. Lai, Y.Q. Ni, Q. Zhao, B. Su, Q.F. Zhou, Image classification-based defect detection of railway tracks using fiber bragg grating ultrasonic sensors, *Appl. Sci.* 13 (2023) 384, <https://doi.org/10.3390/app13010384>.
- [175] S.X. Chen, L. Zhou, Y.Q. Ni, X.Z. Liu, An acoustic-homologous transfer learning approach for acoustic emission-based rail condition evaluation, *Struct. Heal. Monit.* 20 (2021) 2161–2181, <https://doi.org/10.1177/1475921720976941/FORMAT/EPUB>.
- [176] P. Aivaliotis, K. Georgoulas, Z. Arkouli, S. Makris, Methodology for enabling digital twin using advanced physics-based modelling in predictive maintenance, *Procedia CIRP* 81 (2019) 417–422, <https://doi.org/10.1016/J.PROCIR.2019.03.072>.
- [177] J. Wang, L. Ye, R.X. Gao, C. Li, L. Zhang, Digital Twin for rotating machinery fault diagnosis in smart manufacturing, *Int. J. Prod. Res.* 57 (2019) 3920–3934, <https://doi.org/10.1080/00207543.2018.1552032>.
- [178] D. Gürdür Broo, M. Bravo-Haro, J. Schooling, Design and implementation of a smart infrastructure digital twin, *Autom. Constr.* 136 (2022) 104171, <https://doi.org/10.1016/j.autcon.2022.104171>.

- [179] N.S. Dang, C.S. Shim, Bridge assessment for PSC girder bridge using digital twins model, *Lect. Notes Civ. Eng.* 54 (2020) 1241–1246, https://doi.org/10.1007/978-981-15-0802-8_199.
- [180] C. Zhou, D. Xiao, J. Hu, Y. Yang, B. Li, S. Hu, C. Demartino, M. Butala, An Example of Digital Twins for Bridge Monitoring and Maintenance: Preliminary Results, *Lect. Notes Civ. Eng.* 200 LNCE (2022) 1134–1143. https://doi.org/10.1007/978-3-030-91877-4_129/FIGURES/11.
- [181] Z. Liu, W. Bai, X. Du, A. Zhang, Z. Xing, A. Jiang, Digital twin-based safety evaluation of prestressed steel structure, *Adv. Civ. Eng.* 2020 (2020), <https://doi.org/10.1155/2020/8888876>.
- [182] S. Venkatesan, K. Manickavasagam, N. Tengenka, N. Vijayalakshmi, Health monitoring and prognosis of electric vehicle motor using intelligent-digital twin, *IET Electr. Power Appl.* 13 (2019) 1328–1335, <https://doi.org/10.1049/iet-epa.2018.5732>.
- [183] E. Febrianto, L. Butler, M. Girolami, F. Cirak, Digital twinning of self-sensing structures using the statistical finite element method, *Data-Centric Eng.* 3 (2022) e31.
- [184] D. Efanov, A.S. Shilenko, V. V. Khoroshev, Digital Modeling in Railway Infrastructure and Rolling Stock Objects at all Stages Life Cycle: Features, *Proc. - 2020 Int. Russ. Autom. Conf. RusAutoCon 2020.* (2020) 29–34. <https://doi.org/10.1109/RUSAUTOCON49822.2020.9208088>.
- [185] R. Ferdousi, F. Laamarti, C. Yang, A. El Saddik, RailTwin: A Digital Twin Framework For Railway, in: *IEEE Int. Conf. Autom. Sci. Eng., IEEE Computer Society, 2022*: pp. 1767–1772. <https://doi.org/10.1109/CASE49997.2022.9926529>.
- [186] B. Rodriguez, E. Sanjurjo, M. Tranchero, C. Romano, F. Gonzalez, Thermal parameter and state estimation for digital twins of E-powertrain components, *IEEE Access* 9 (2021) 97384–97400, <https://doi.org/10.1109/ACCESS.2021.3094312>.
- [187] H. Zheng, Research and analysis on the application of digital twin technology in urban rail transit, in: *Proc. IEEE Asia-Pacific Conf. Image Process. Electron. Comput. IPEC 2021, Institute of Electrical and Electronics Engineers Inc., 2021*: pp. 1067–1070. <https://doi.org/10.1109/IPEC51340.2021.9421186>.
- [188] A. Morant, P.O. Larsson-Kräik, U. Kumar, Data-driven model for maintenance decision support: A case study of railway signalling systems, *Http://Dx.Doi.Org/10.1177/0954409714533680.* 230 (2014) 220–234. <https://doi.org/10.1177/0954409714533680>.
- [189] L. Yang, T. Xu, Z. Wang, Agent based heterogeneous data integration and maintenance decision support for high-speed railway signal system, *2014 17th IEEE Int. Conf. Intell. Transp. Syst. ITSC 2014* (2014) 1976–1981, <https://doi.org/10.1109/ITSC.2014.6957995>.
- [190] A. Nunez, J. Hendriks, Z. Li, B. De Schutter, R. Dollevoet, Facilitating maintenance decisions on the Dutch railways using big data: The ABA case study, *Proc. - 2014 IEEE Int. Conf. Big Data, IEEE Big Data 2014.* (2015) 48–53. <https://doi.org/10.1109/BIGDATA.2014.7004431>.
- [191] A. Jamshidi, S. Hajizadeh, Z. Su, M. Naeimi, A. Núñez, R. Dollevoet, B. De Schutter, Z. Li, A decision support approach for condition-based maintenance of rails based on big data analysis, *Transp. Res. Part C Emerg. Technol.* 95 (2018) 185–206, <https://doi.org/10.1016/j.trc.2018.07.007>.
- [192] A. Consilvio, M. Iorani, V. Iovane, M. Sciutto, G. Sciutto, Real-time monitoring of the longitudinal strain of Continuous Welded Rail for safety improvement, *Proc. Inst. Mech. Eng. Part F J. Rail Rapid Transit.* 234 (2020) 1238–1252, <https://doi.org/10.1177/0954409719890166>.
- [193] R. Jiang, W. Wang, Y. Xie, X. Yin, Research and design of infrastructure monitoring platform of intelligent high speed railway, *IEEE 6th Inf. Technol. Mechatron. Eng. Conf. ITOEC 2022* (2022) 2096–2099, <https://doi.org/10.1109/ItoEC53115.2022.9734553>.
- [194] W. Du, T. Zhang, G. Zhang, J. Wang, A digital twin framework and an implementation method for urban rail transit, *2021 Glob. Reliab. Progn. Heal. Manag. PHM-Nanjing 2021* (2021), <https://doi.org/10.1109/PHM-NANJING52125.2021.9612933>.
- [195] I. Errandonea, J. Goya, U. Alvarado, S. Beltron, S. Arrizabalaga, IoT Approach for Intelligent Data Acquisition for Enabling Digital Twins in the Railway Sector, *Proc. - 2021 Int. Symp. Comput. Sci. Intell. Control. ISCSIC 2021.* (2021) 164–168. <https://doi.org/10.1109/ISCSIC54682.2021.00039>.
- [196] S. Kaewunruen, N. Xu, Digital twin for sustainability evaluation of railway station buildings, *Front. Built Environ.* 4 (2018), <https://doi.org/10.3389/FBUIL.2018.00077>.
- [197] S. Kaewunruen, Q. Lian, Digital twin aided sustainability-based lifecycle management for railway turnout systems, *J. Clean. Prod.* 228 (2019) 1537–1551, <https://doi.org/10.1016/j.jclepro.2019.04.156>.
- [198] J. Neves, S. Sampaio, M. Vilela, A Case Study of BIM Implementation in Rail Track Rehabilitation, *Infrastructures* 2019, Vol. 4, Page 8. 4 (2019) 8. <https://doi.org/10.3390/INFRASTRUCTURES4010008>.
- [199] M. Hamarat, M. Papaalias, S. Kaewunruen, Fatigue damage assessment of complex railway turnout crossings via Peridynamics-based digital twin, *Sci. Rep.* 12 (2022), <https://doi.org/10.1038/s41598-022-18452-w>.
- [200] C.A. Avizzano, G. Scivoletto, P. Tripicchio, Robust image stitching and reconstruction of rolling stocks using a novel Kalman filter with a multiple-hypothesis measurement model, *IEEE Access* 9 (2021) 154011–154021, <https://doi.org/10.1109/ACCESS.2021.3128564>.
- [201] Y.Q. Ni, Q.H. Zhang, A Bayesian machine learning approach for online detection of railway wheel defects using track-side monitoring, *Struct. Heal. Monit.* 20 (2021) 1536–1550, https://doi.org/10.1177/1475921720921772/ASSET/IMAGES/10.1177_1475921720921772-IMG1.PNG.
- [202] A. Guclu, H. Yilboga, O.F. Eker, F. Camci, I. Jennions, Prognostics with autoregressive moving average for railway turnouts, *Annu. Conf. PHM Soc.* 2 (2010), <https://doi.org/10.36001/PHMCONF.2010.V211.1901>.
- [203] P. Li, R. Goodall, V. Kadirkamanathan, Parameter estimation of railway vehicle dynamic model using rao-blackwellised particle filter, *Eur. Control Conf. ECC 2003* (2003) 2384–2389, <https://doi.org/10.23919/ECC.2003.7085323>.
- [204] L.H. Zhang, Y.W. Wang, Y.Q. Ni, S.K. Lai, Online condition assessment of high-speed trains based on Bayesian forecasting approach and time series analysis, *Smart Struct. Syst.* 21 (2018) 705–713, <https://doi.org/10.12989/SSS.2018.21.5.705>.
- [205] G.C. Doubell, K. Kruger, A.H. Basson, P. Conradie, The potential for digital twin applications in railway infrastructure management, *Lect. Notes Mech. Eng.* (2022) 241–249, https://doi.org/10.1007/978-3-030-96794-9_22/FIGURES/1.
- [206] A. Kumari, S. Tanwar, S. Tyagi, N. Kumar, R.M. Parizi, K.K.R. Choo, Fog data analytics: A taxonomy and process model, *J. Netw. Comput. Appl.* 128 (2019) 90–104, <https://doi.org/10.1016/j.jnca.2018.12.013>.
- [207] A. Thelen, X. Zhang, O. Fink, Y. Lu, S. Ghosh, B.D. Youn, M.D. Todd, S. Mahadevan, C. Hu, Z. Hu, A comprehensive review of digital twin—part 2: roles of uncertainty quantification and optimization, a battery digital twin, and perspectives, *Struct. Multidiscip. Optim.* 66 (2023), <https://doi.org/10.1007/s00158-022-03410-x>.
- [208] Statista, Projected revenue generated by companies in the global smart city from 2020 to 2028*(in billion U.S. dollars), (2023). <https://www.statista.com/statistics/1111626/worldwide-smart-city-market-revenue/> (accessed May 29, 2023).
- [209] Dassault Systèmes, Virtual Singapore, *Cust. Stories.* (n.d.). <https://www.3ds.com/insights/customer-stories/virtual-singapore> (accessed May 29, 2023).
- [210] Smart Nation and Digital Government Office, Smart Nation Singapore, (2023). <https://www.smartnation.gov.sg/> (accessed May 29, 2023).
- [211] S. Wei, Is human digital twin possible? *Comput. Methods Programs Biomed. Updat.* 1 (2021) 100014 <https://doi.org/10.1016/j.cmpbup.2021.100014>.
- [212] T. Ambra, C. MacHarris, Agent-Based Digital Twins (ABM-Dt) in Synchronomodal Transport and Logistics: The Fusion of Virtual and Physical Spaces, *Proc. - Winter Simul. Conf. 2020-December* (2020) 159–169. <https://doi.org/10.1109/WSC48552.2020.9383955>.
- [213] E. Negri, H.D. Ardakani, L. Cattaneo, J. Singh, M. MacChi, J. Lee, A digital twin-based scheduling framework including equipment health index and genetic algorithms, *IFAC-PapersOnLine, Elsevier B.V.* (2019) 43–48, <https://doi.org/10.1016/j.ifacol.2019.10.024>.
- [214] S. Gu, B. Liu, X. Yin, H. Li, Research on Application of Digital Twin in Railway Construction, in: *Lect. Notes Electr. Eng., 2022*: pp. 467–475. https://doi.org/10.1007/978-981-16-9909-2_50.
- [215] I. Ricondo, A. Porto, M. Ugarte, A digital twin framework for the simulation and optimization of production systems, *Procedia CIRP, Elsevier B.V.* (2021) 762–767, <https://doi.org/10.1016/j.procir.2021.11.128>.
- [216] L. Oliveira, C. Bruen, S. Birrell, R. Cain, What passengers really want: Assessing the value of rail innovation to improve experiences, *Transp. Res. Interdiscip. Perspect.* 1 (2019) 100014, <https://doi.org/10.1016/j.trip.2019.100014>.
- [217] J. Guo, Q. Wu, K. Guo, S. Xiong, W. Feng, J. Xue, Study on the construction and application of digital twins on high voltage transmission line live working scenes, *IEEE Access* 9 (2021) 111587–111594, <https://doi.org/10.1109/ACCESS.2021.3097179>.
- [218] N.M. Levine, B.F. Spencer, Post-earthquake building evaluation using UAVs: A BIM-based digital twin framework, *Sensors* 22 (2022), <https://doi.org/10.3390/S22030873>.
- [219] K. Van Breugel, Societal burden and engineering challenges of ageing infrastructure, *Procedia Eng.* 171 (2017) 53–63, <https://doi.org/10.1016/J.PROENG.2017.01.309>.
- [220] P. Parviainen, M. Tihinen, J. Kääriäinen, S. Teppola, Tackling the digitalization challenge: How to benefit from digitalization in practice, *Int. J. Inf. Syst. Proj. Manag.* 5 (2017) 63–77, <https://doi.org/10.12821/IJSPM050104>.
- [221] E. Marcucci, V. Gatta, M. Le Pira, L. Hansson, S. Bråthen, Digital twins: A critical discussion on their potential for supporting policy-making and planning in urban logistics, *Sustain.* 12 (2020) 1–15, <https://doi.org/10.3390/SU122410623>.