A Survey on Large-span Steel Structure Health Monitoring and Advanced Technologies

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Abstract

This survey paper explores the integration of advanced technologies in structural health monitoring (SHM) for large-span steel structures. It emphasizes the significance of real-time sensor networks, digital twins, Building Information Modeling (BIM), and advanced data analytics in enhancing structural safety and performance. The paper highlights the critical role of SHM in ensuring the integrity of steel structures, particularly during construction phases, and underscores the benefits of integrating IoT-based solutions despite existing adoption barriers. Advanced methodologies, including deep learning and multi-physics simulations, are discussed as pivotal in improving monitoring accuracy and operational efficiency. The survey further examines the synergy between BIM and digital twins, illustrating how these technologies enhance decision-making and risk management. Challenges in traditional SHM methods, such as manual inspections and high implementation costs, are contrasted with the innovative solutions offered by integrated digital frameworks. Additionally, the paper delves into the applications of multi-physics simulations in structural design and optimization, demonstrating their role in advancing engineering practices. The integration of advanced data analytics with digital twins and BIM is presented as a transformative approach, providing comprehensive insights and facilitating proactive maintenance strategies. The paper concludes by identifying future research directions, emphasizing the potential of these technologies to revolutionize SHM practices, improve safety, and promote sustainability in civil engineering.

1 Introduction

1.1 Significance of SHM for Large-span Steel Structures

Structural health monitoring (SHM) is crucial for ensuring the safety and integrity of large-span steel structures throughout their lifecycle. In particular, the construction phase of large-span steel pipe truss structures requires meticulous monitoring to ensure safety and durability [1]. SHM systems provide vital insights for maintaining structural integrity, especially given the prevalence of deficient or functionally obsolete steel bridges in the U.S. [2].

Beyond construction, SHM plays a significant role in assessing ongoing structural conditions, such as vehicle-induced fatigue damage in steel bridges [3] and detecting anomalies that could compromise safety [4]. Additionally, these systems are essential for understanding the thermal behavior of structures under solar radiation, further emphasizing their role in maintaining structural integrity [5].

Despite their advantages, the adoption of SHM technologies encounters challenges, particularly in integrating IoT-based solutions for improved safety management on construction sites [6]. Overcoming these barriers is essential for maximizing SHM's potential in enhancing occupational health and safety, an area marked by high injury and fatality rates [7].

Advanced SHM methodologies, including deep learning approaches, are increasingly being utilized to improve monitoring accuracy and efficiency [8]. These innovations enhance the reliability of

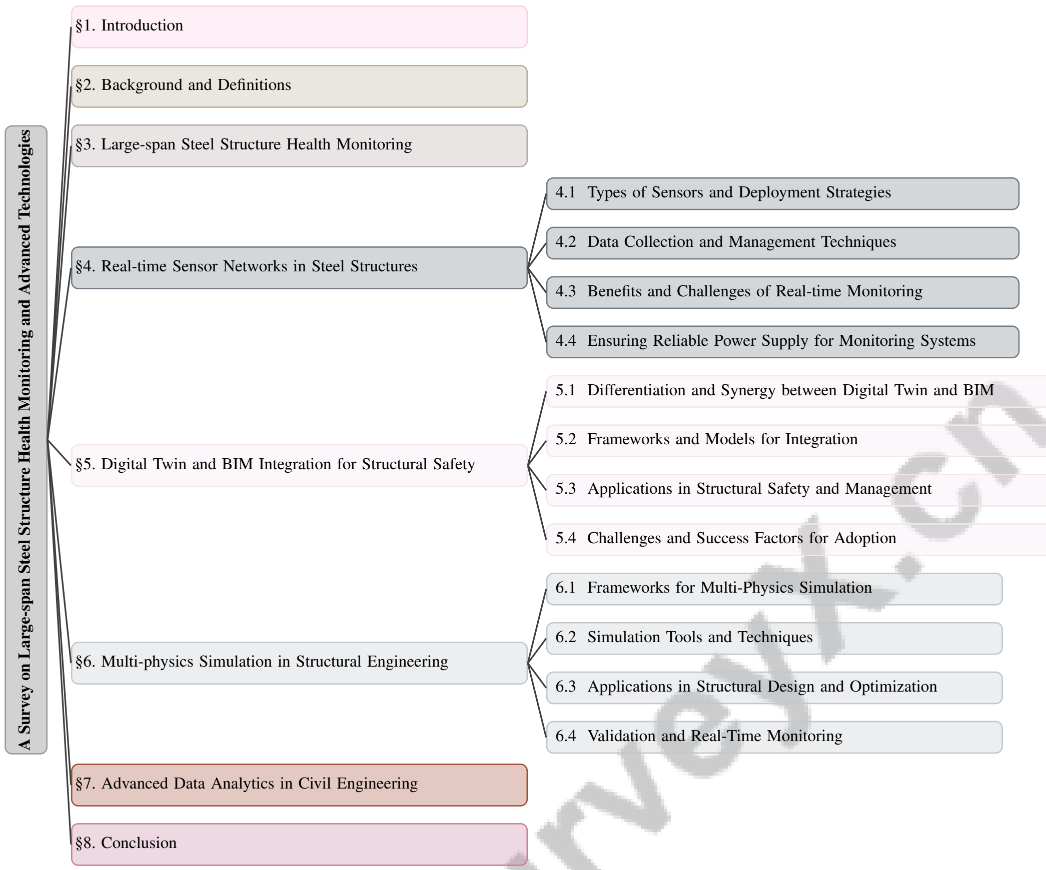

Figure 1: chapter structure

SHM systems and contribute to the cost and time efficiency of monitoring processes, highlighting the necessity for innovative solutions that bolster the resilience of large-span steel structures against potential failures.

1.2 Role of Advanced Technologies

The integration of advanced technologies such as Building Information Modeling (BIM), Digital Twins (DT), and the Internet of Things (IoT) significantly enhances SHM practices for large-span steel structures. These technologies collectively establish a robust framework for construction progress monitoring and safety management [9]. The synergy between BIM and digital twin technologies is pivotal for improving decision-making and risk management, offering a comprehensive approach to structural safety and operational efficiency.

BIM, despite its low adoption rates in the construction industry, holds substantial potential for streamlining processes and enhancing decision-making [10]. Its integration with IoT and sensor technologies facilitates real-time data acquisition and analysis, thereby augmenting the predictive and preventive capabilities of SHM systems [11]. Frameworks assessing BIM-DT adoption readiness further underscore the significance of these technologies in sustainable construction practices [12].

Digital twins provide a dynamic platform for monitoring the structural integrity of steel structures, offering a virtual representation that enhances risk-based inspection and maintenance, particularly under extreme weather conditions [13]. Their implementation alongside real-time sensor networks enables continuous monitoring and assessment, improving the accuracy and reliability of SHM systems [1]. The integration of Wireless Sensor Networks (WSN) with BIM technologies is proposed as a breakthrough for enhancing real-time monitoring and safety management [14].

Advanced sensor technologies, including augmented reality and mobile equipment tracking, further enhance SHM practices by improving labor and supply chain management, as well as safety manage-

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ment [15]. Wireless sensor networks offer scalable and cost-effective solutions for real-time condition assessment, advancing the efficacy of SHM practices [16].

Deep learning techniques, particularly convolutional neural networks (CNNs), have introduced innovative frameworks for automating feature extraction and enhancing the accuracy of both vibration-based and vision-based monitoring systems [8]. These advancements in artificial intelligence contribute to the development of sophisticated SHM systems capable of real-time anomaly detection and predictive maintenance.

The integration of advanced technologies, especially deep learning applications and CNNs, is transforming SHM by providing innovative solutions that significantly enhance structural safety, operational efficiency, and predictive maintenance throughout the lifecycle of large-span steel structures. These technologies facilitate automated inspections, precise identification of structural defects, and effective monitoring of safety conditions, thereby addressing inefficiencies and high costs associated with traditional SHM methods in the architecture, engineering, and construction (AEC) industry [17, 8].

1.3 Structure of the Survey

This survey is organized to comprehensively explore the integration of advanced technologies in SHM for large-span steel structures, emphasizing the synergy between digital twins and other innovative methodologies for enhanced safety management [18]. The paper is divided into several key sections, each addressing distinct aspects of SHM and associated technologies.

The survey begins by highlighting the importance of SHM for large-span steel structures, discussing the role of advanced technologies such as sensor networks, digital twins, and BIM in enhancing structural safety and performance. This is followed by a background section that provides definitions and an overview of key concepts, including the integration of real-time sensor networks and multi-physics simulations.

Subsequent sections delve into specific challenges and requirements of SHM for large-span steel structures, focusing on real-time data acquisition and analysis. The paper then examines the deployment of sensor networks in steel structures, discussing the types of sensors used, data collection methods, and the benefits and challenges of real-time monitoring.

A thorough analysis of the integration of digital twin technology with BIM for enhancing structural safety in the construction industry follows, focusing on the development of frameworks and models that facilitate this integration. The discussion encompasses practical applications of the combined technologies, such as real-time health monitoring and predictive analysis for risk management, while addressing the challenges faced in their implementation within the architecture, engineering, and construction sectors [19, 20, 21, 22, 23]. The survey also addresses the role of multi-physics simulations in structural engineering, emphasizing their contributions to design, analysis, and optimization.

Finally, the survey explores the application of advanced data analytics in civil engineering, particularly in processing and interpreting data from SHM systems. The paper categorizes current methods into stages of design, construction, and maintenance, illustrating how digital twins can facilitate processes at each stage through enhanced data management and analysis [24]. The conclusion summarizes key findings and suggests future research directions, underscoring the potential of integrating advanced technologies to improve the safety and performance of large-span steel structures.The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Large-span Steel Structures and Health Monitoring

Large-span steel structures, integral to modern infrastructure like bridges and stadiums, require robust structural health monitoring (SHM) systems to ensure safety and integrity throughout their lifecycle [2]. The construction phase is particularly vulnerable to risks, necessitating effective management to prevent accidents [25]. Accurate SHM methods are crucial for addressing challenges such as vehicle-induced fatigue [3], anomaly detection [8], and thermal behavior monitoring under solar exposure [5].

Advanced technologies enhance SHM practices by integrating Building Information Modeling (BIM) and digital twins, providing a comprehensive monitoring framework [23]. However, the disconnect between static BIM data and dynamic IoT sensor data poses challenges, impeding effective management [11]. Synergizing these technologies with real-time sensor networks enables continuous data acquisition, essential for assessing structural conditions and preemptively identifying potential issues [26].

Construction sites' dynamic nature, with numerous interacting risk factors, complicates safety management. Integrating wireless sensor networks (WSN) with BIM enhances real-time environmental monitoring and safety management, especially beneficial in developing countries where BIM and digital twins are emerging [14, 7]. Monitoring low-amplitude vibrations and sudden events in large-scale infrastructures further underscores the need for effective SHM systems. Advances in data analytics, particularly deep learning, offer promising solutions for improving damage detection accuracy and efficiency in civil infrastructure [8].

2.2 Challenges in Traditional SHM Methods

Traditional SHM methods face limitations that hinder their effectiveness in ensuring the safety of large-span steel structures. Manual inspections are labor-intensive, hazardous, and prone to variability, leading to inconsistent structural health assessments [8]. The high costs and complexities of traditional wired systems further complicate these methods, particularly in remote locations [5].

Wireless sensor networks (WSNs) provide a promising alternative but are limited by the operational lifetime of battery-powered nodes, requiring frequent replacements, especially in remote monitoring scenarios [7]. Traditional wireless nodes may also lack the sensitivity needed for detecting ambient vibrations and subtle structural changes [8].

Integrating advanced technologies like BIM and Digital Twins (DT) into SHM is often hindered by high implementation costs, regulatory ambiguities, and cultural resistance within the construction industry [23]. Industry fragmentation leads to data silos, obstructing effective data sharing and collaboration among stakeholders [23]. In developing countries, BIM-DT integration is further limited by inadequate evaluations of influencing factors [7].

Traditional SHM methods also struggle with the complexity and computational costs of developing finite element (FE) models, essential for accurate structural analysis but expensive and time-consuming to maintain [8]. The lack of real-time data sharing and timely updates results in inefficiencies in facility management and decision-making processes [5]. Environmental factors, such as temperature fluctuations, complicate anomaly detection in large-span bridges, limiting traditional SHM effectiveness [5]. Current studies often overlook IoT adoption's broader implications and lack comprehensive evaluations of barriers, restricting potential enhancements to SHM practices [7].

These challenges, including inefficiency and high costs, underscore the need for innovative solutions utilizing advanced technologies like deep learning, which can enhance safety and performance in large-span steel structures through automated inspections, defect identification, and workforce behavior monitoring. While deep learning applications are emerging, gaps in their implementation within SHM and jobsite safety management (JSM) sectors highlight the necessity for further exploration and development [17, 1].

In recent years, the study of structural health monitoring has gained significant traction, particularly in the context of large-span steel structures. This paper explores various methodologies and technologies that contribute to effective health monitoring practices. Figure 2 illustrates the hierarchical structure of large-span steel structure health monitoring, emphasizing the importance of real-time data acquisition and the integration of advanced monitoring technologies. Key components depicted in the figure include technological tools, integration methods, and advancements in real-time data usage. Furthermore, the role of digital twin technology and Building Information Modeling (BIM) is highlighted, showcasing how these innovations enhance structural health management. By examining these elements, we can better understand the complexities and necessities of maintaining the integrity of large-span structures in a dynamic environment.

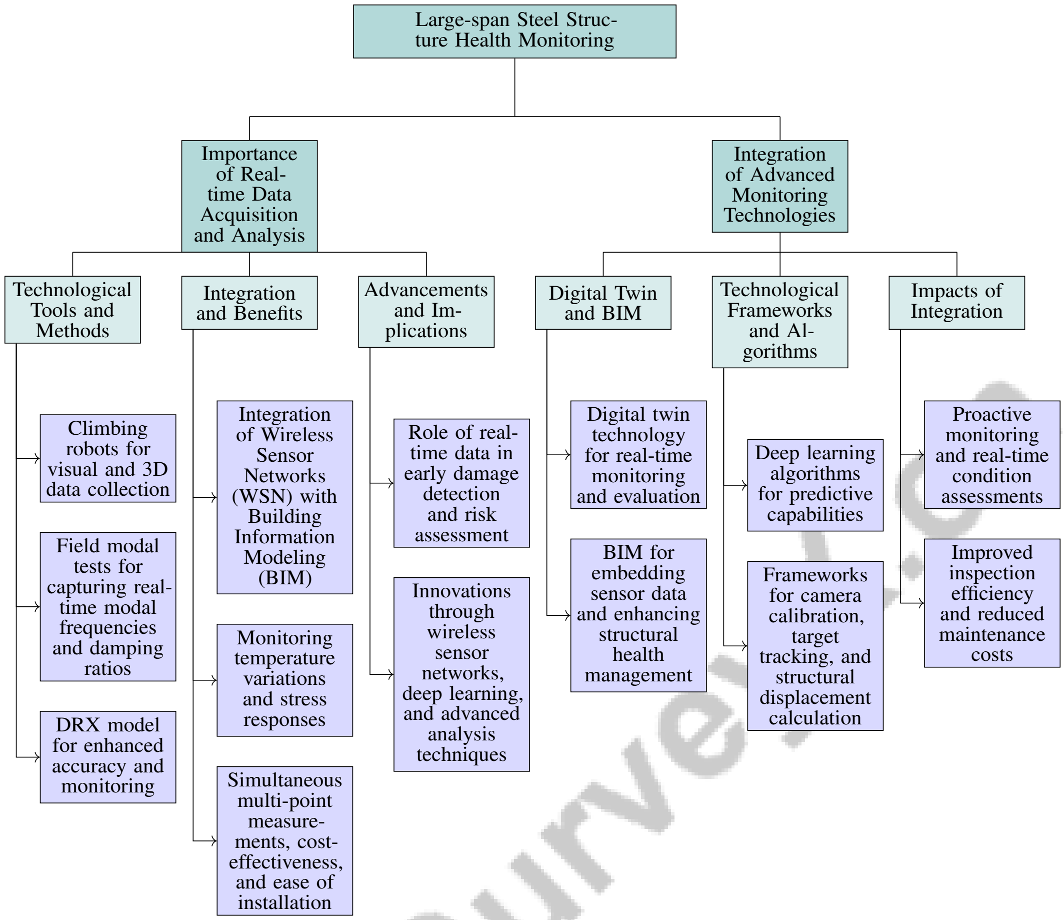

Figure 2: This figure illustrates the hierarchical structure of large-span steel structure health monitoring, emphasizing the importance of real-time data acquisition and the integration of advanced monitoring technologies. Key components include technological tools, integration methods, and advancements in real-time data usage, alongside the role of digital twin technology and Building Information Modeling (BIM) in enhancing structural health management.

3 Large-span Steel Structure Health Monitoring

3.1 Importance of Real-time Data Acquisition and Analysis

Real-time data acquisition and analysis are essential for effective structural health monitoring (SHM) in large-span steel structures, allowing for continuous oversight and early detection of potential issues throughout construction and operation [27]. Advanced technologies, such as climbing robots for visual and 3D data collection, underscore the necessity of real-time data for timely structural assessments [2]. Field modal tests, such as those conducted on the Yingzhou Bridge, highlight the importance of capturing real-time modal frequencies and damping ratios for effective SHM [3].

Frameworks like the DRX model enhance SHM accuracy and real-time monitoring capabilities, promoting better stakeholder communication and informed decision-making [25]. The integration of Wireless Sensor Networks (WSN) with Building Information Modeling (BIM) creates a dynamic platform that visually represents safety status and autonomously responds to hazards, thereby enhancing real-time monitoring [14]. Monitoring temperature variations and stress responses is crucial, as these factors significantly impact structural integrity [5]. Research highlights the advantages of real-time data, including simultaneous multi-point measurements, cost-effectiveness, and ease of installation [26], and emphasizes its role in adapting anomaly detection thresholds for prompt issue resolution [4].

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Recent advancements in SHM underscore the critical role of real-time data acquisition and analysis in maintaining the integrity and safety of large-span steel structures. Innovations driven by wireless sensor networks, deep learning, and advanced analysis techniques necessitate continuous monitoring systems that support timely, data-driven decision-making. These systems are vital for early damage detection and risk assessment, enhancing the longevity and safety of civil infrastructures vulnerable to material deterioration and environmental stresses [24, 28, 16, 1, 17].

3.2 Integration of Advanced Monitoring Technologies

Integrating advanced monitoring technologies into SHM systems for large-span steel structures is crucial for improving operational efficiency and safety. Digital twin technology plays a pivotal role by enabling real-time monitoring and evaluation of structural performance, consolidating various data sources to enhance decision-making processes [21]. This integration allows for continuous assessment of structural conditions and timely interventions through a cohesive digital representation.

As illustrated in Figure 3, the integration of advanced monitoring technologies in structural health monitoring (SHM) systems highlights the roles of digital twin technology, building information modeling, and deep learning algorithms in enhancing operational efficiency, safety, and predictive capabilities. Building Information Modeling (BIM) is integral to this integration, providing a dynamic platform that embeds sensor data into a comprehensive model, displaying real-time information about structural conditions and enhancing structural health management [29]. The synergy between BIM and sensor networks is illustrated by frameworks that incorporate sensor-based technologies into construction safety management, offering a structured approach to operationalizing these technologies within safety practices [30].

Advanced monitoring technologies also utilize deep learning algorithms to enhance the predictive capabilities of SHM systems. By extracting high-level features from raw data, these algorithms improve predictions related to structural performance, such as building cooling loads, thereby refining maintenance and operational strategies [31]. Research categorizes the integration of technologies into a framework encompassing camera calibration, target tracking, and structural displacement calculation, collectively enhancing SHM system precision and reliability [26].

Ongoing advancements in deep learning, wireless sensor networks, and BIM underscore their transformative potential for SHM practices. These innovations provide comprehensive, data-driven solutions that enhance safety and longevity through proactive monitoring, real-time condition assessments, and defect and deterioration pattern identification. Consequently, these technologies improve inspection efficiency and significantly reduce infrastructure maintenance costs, contributing to safer built environments [24, 28, 8, 16, 17].

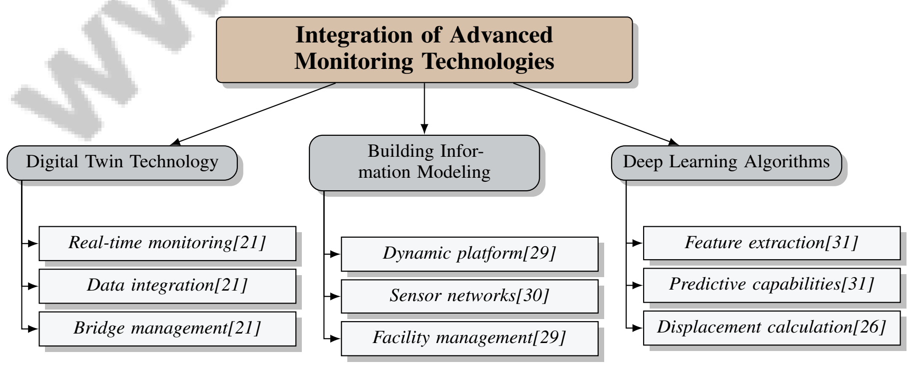

Figure 3: This figure illustrates the integration of advanced monitoring technologies in structural health monitoring (SHM) systems, highlighting the roles of digital twin technology, building information modeling, and deep learning algorithms in enhancing operational efficiency, safety, and predictive capabilities.

Category	Feature	Method
Types of Sensors and Deployment Strategies	Deployment Strategies	ARMI[2], BIM-WSN[14]
Data Collection and Management Techniques	Continuous Data Collection	DTC[19], CMS[1]
Benefits and Challenges of Real-time Monitoring	Renewable Energy Solutions Advanced Evaluation Techniques	WSHMS[27] RFCE[32]
Ensuring Reliable Power Supply for Monitoring Systems	Renewable Energy Solutions	WSSN-SHM[16], SEH-WSN[33]

Table 1: This table summarizes the various methods and techniques employed in real-time sensor networks for large-span steel structures. It categorizes these methods into four key areas: types of sensors and deployment strategies, data collection and management techniques, benefits and challenges of real-time monitoring, and ensuring reliable power supply for monitoring systems. The table highlights specific features and methods within each category, providing a comprehensive overview of the current advancements in structural health monitoring (SHM).

4 Real-time Sensor Networks in Steel Structures

The integration of real-time sensor networks within steel structures marks a significant leap in structural health monitoring (SHM), enhancing evaluations of structural integrity and performance. Table 1 provides a comprehensive summary of the methods and techniques utilized in the integration of real-time sensor networks within steel structures, highlighting their significance in enhancing structural health monitoring (SHM) systems. Additionally, Table 4 offers a detailed comparison of the different methods and technologies utilized in the integration of real-time sensor networks within steel structures, underscoring their critical role in advancing structural health monitoring systems. This section explores the various sensor types and deployment strategies that optimize functionality, which are crucial for ensuring the safety and reliability of large-span steel structures.

4.1 Types of Sensors and Deployment Strategies

Method Name	**Sensor Types**	**Deployment Strategies**	**Technological Integration**
WSHMS[27]	Strain, Temperature	Critical Monitoring Points	Wireless Sensor Network
RFCE[32]	Stress And Deformation	Critical Points	Fuzzy Logic
WSSN-SHM[16]	Mems Accelerometers	Deploy Sensors	Wireless Communication Technologies
BIM-WSN[14]	Sensor Nodes	Various Locations	Wireless Sensor Networks
SEH-WSN[33]	Low-power Sensor	Install Solar Panels	Solar Energy Harvesting
ARMI[2]	Visual And 3D	Robot Climbs	Climbing Robot

Table 2: Overview of sensor types, deployment strategies, and technological integration in Structural Health Monitoring (SHM) systems. The table summarizes various methods, highlighting the diversity in sensor applications and integration techniques essential for effective monitoring of large-span steel structures.

Deploying sensor networks in steel structures is vital for real-time data acquisition, ensuring structural safety and integrity. Key sensor types include strain and temperature sensors, essential for measuring stress and thermal conditions [27]. During the West Stand roof construction, strategically placed stress and deformation sensors provided crucial data on structural behavior [32]. Sensor technologies are categorized into vibration-based and vision-based methods. Vibration-based SHM utilizes MEMS accelerometers for detecting subtle structural changes [16], while vision-based SHM employs cameras and UAVs for innovative data acquisition [28]. Effective deployment strategies are crucial for maximizing sensor performance. Wireless sensor nodes monitor environmental conditions and hazardous gases, offering comprehensive risk coverage [14]. Solar-powered wireless sensor networks (SEH-WSN) enable continuous monitoring without frequent battery replacements [33]. Climbing robots automate data collection and image capture, enhancing SHM efficiency and accuracy [2]. These strategies highlight the importance of selecting appropriate sensor types and deployment methods to optimize SHM systems in large-span steel structures. Table 2 provides a comprehensive summary of different sensor types, deployment strategies, and technological integrations employed in Structural Health Monitoring (SHM) systems for steel structures.

4.2 Data Collection and Management Techniques

Robust data collection and management are pivotal for SHM systems in large-span steel structures. Solar-powered wireless sensor networks ensure a sustainable power supply for continuous monitoring

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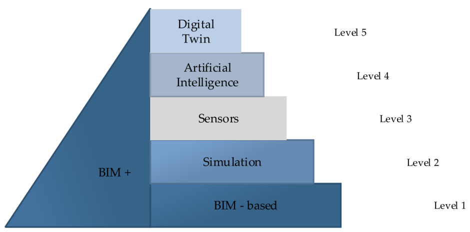
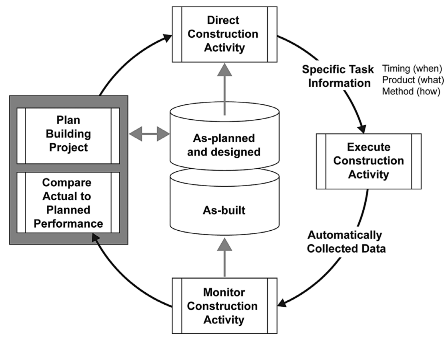
[33]. Integrating finite element simulation with real-time monitoring through strain sensors allows comprehensive assessments of structural integrity across construction stages [1]. Data management techniques involve advanced algorithms and software tools to process and analyze large datasets, utilizing machine learning to identify patterns and anomalies for timely interventions [4, 15, 7, 34, 23]. Cloud-based platforms enhance data management by providing scalable storage solutions and enabling remote data access, improving stakeholder collaboration. The integration of these advanced techniques is vital for enhancing SHM system performance and reliability, enabling timely detection of structural anomalies and deterioration, ensuring the safety and longevity of critical infrastructures [16, 1, 4, 17, 35].



(a) The image represents a pyramid diagram illustrating the levels of digitalization in construction projects.[20]



(b) The image depicts a flowchart illustrating the process of monitoring and controlling construction activities.[19]

Figure 4: Examples of Data Collection and Management Techniques

As depicted in Figure 4, the integration of real-time sensor networks in steel structures signifies a major advancement in construction technology, particularly concerning data collection and management techniques. The pyramid diagram illustrates the structured levels of digitalization in construction, starting from 'BIM +'—encompassing Building Information Modeling—and extending to digital twins, artificial intelligence, sensors, and simulation technologies. This foundation supports sophisticated data collection systems crucial for real-time monitoring. The flowchart highlights the process of monitoring and controlling construction activities, emphasizing the cyclical nature of task execution based on collected data, optimizing resource utilization and enhancing project outcomes [20, 19].

4.3 Benefits and Challenges of Real-time Monitoring

Method Name	Technological Integration	Operational Challenges	Cost Implications
WSHMS[27]	Wireless Sensor Networks	Sensor Installation Errors	High Initial Deployment
RFCE[32]	Real-time Monitoring	Sensor Readings Inaccuracies	-
SEH-WSN[33]	Solar-powered Wireless	Hardware And Software	Reduced Maintenance Costs
WSSN-SHM[16]	Wireless Sensor Networks	Synchronization OF Nodes	Lower Costs

Table 3: Summary of methods for real-time structural health monitoring (SHM) in large-span steel structures, highlighting their technological integration, operational challenges, and cost implications. The table compares different approaches, focusing on wireless sensor networks and solar-powered solutions, and discusses the trade-offs between deployment costs and operational efficiencies.

Real-time monitoring systems in large-span steel structures offer significant advantages, enhancing SHM practices' reliability and efficiency. They adapt well to complex construction environments, ensuring continuous safety assessments and timely interventions [27]. The integration of advanced monitoring technologies bolsters safety evaluations during construction, enhancing structural safety [32]. A key benefit is reduced power consumption and maintenance costs. Solar-powered wireless sensor networks eliminate frequent battery replacements by leveraging renewable energy [33]. This reduces operational costs and enhances environmental sustainability. The sensitivity and cost-effectiveness of wireless sensor networks make them suitable for large-scale applications [16]. However, challenges include productivity reductions linked to wearable sensors, the need for specialized technical training, and continuous monitoring requirements. Hardware and software limitations,

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lack of standardization, and safety hazards complicate adopting advanced technologies in construction safety management [6, 15, 7]. The integration of diverse sensor technologies and ensuring interoperability present significant hurdles, necessitating sophisticated data management and processing capabilities. Initial deployment costs and technical expertise required for operation and maintenance can impede widespread adoption, particularly in resource-limited regions. The reliability of real-time monitoring systems hinges on robust data transmission infrastructure. Effective communication between sensor nodes and central monitoring systems is essential for rapid identification and management of structural anomalies, enhancing civil infrastructures' safety and longevity through timely interventions [4, 16]. Addressing these challenges is crucial for maximizing real-time monitoring benefits and ensuring the long-term safety and performance of large-span steel structures. Table 3 provides a comprehensive comparison of various real-time monitoring methods used in structural health monitoring (SHM), detailing their technological integration, operational challenges, and cost implications.

4.4 Ensuring Reliable Power Supply for Monitoring Systems

A reliable power supply is essential for the continuous operation of SHM systems in large-span steel structures, ensuring real-time data acquisition and monitoring capabilities critical for timely structural anomaly detection. Traditional monitoring systems often rely on battery-powered sensors, limited by short operational lifespans and requiring frequent maintenance [33]. Innovative solutions like solar-powered wireless sensor networks (WSN) provide a sustainable alternative by harnessing renewable energy to power sensor nodes. These systems collect energy via solar panels, stored in supercapacitors or rechargeable batteries, ensuring continuous power supply even in remote locations [33]. This approach reduces reliance on conventional power sources and minimizes the environmental impact of monitoring systems, aligning with civil engineering sustainability goals. Implementing energy-efficient technologies enhances power supply reliability. Integrating low-power consumption sensors and energy-harvesting techniques extends sensor node operational lifespans and reduces maintenance frequency [16]. Such advancements are crucial for large-scale applications, where maintaining extensive sensor networks can be logistically challenging. Advanced smart power management strategies, like adaptive power allocation and load balancing, maximize energy resource utilization across sensor networks, particularly in Internet-of-Things (IoT) applications. These strategies ensure low-power sensor nodes, dependent on limited battery life or renewable energy, operate effectively and continuously, enhancing the reliability and performance of real-time environmental monitoring systems [36, 33, 37]. These strategies improve monitoring systems' resilience to power fluctuations, ensuring critical monitoring functions under varying environmental conditions. Integrating diverse research approaches underscores the importance of reliable power supply systems in maintaining SHM systems' uninterrupted functionality. This highlights the urgent need for innovative and sustainable solutions that enhance large-span steel structures' safety and performance while addressing maintenance and operational reliability challenges. Effective SHM can significantly extend structures' service life, like bridges and gymnasiums, by enabling timely maintenance interventions based on real-time data analysis. Advanced monitoring technologies, like wireless smart sensor networks, facilitate precise condition assessments and anomaly detection, reinforcing these vital infrastructures' structural integrity [16, 1, 4, 17, 35].

Feature	Types of Sensors and Deployment Strategies	Data Collection and Management Techniques	Benefits and Challenges of Real-time Monitoring
Sensor Type	Strain, Temperature	Strain, Various	Wireless, Wearable
Deployment Strategy	Wireless, Solar-powered	Cloud-based, Remote	Diverse, Interoperable
Power Supply	Solar Energy	Sustainable, Continuous	Solar-powered

Table 4: This table provides a comparative analysis of various sensor types, deployment strategies, and power supply methods employed in real-time sensor networks for structural health monitoring (SHM) systems in steel structures. It highlights the integration of wireless, solar-powered, and wearable technologies, alongside cloud-based and remote data management techniques, emphasizing their benefits and challenges in enhancing SHM efficiency and reliability.

5 Digital Twin and BIM Integration for Structural Safety

The integration of Building Information Modeling (BIM) and Digital Twin (DT) technologies marks a significant advancement in the construction industry, enhancing structural safety and operational efficiency. This section explores the distinct yet complementary roles of these technologies and their synergistic potential. Understanding their interplay is crucial for optimizing structural health monitoring and management in modern construction projects.

5.1 Differentiation and Synergy between Digital Twin and BIM

BIM and DT technologies, while distinct, offer complementary advantages that enhance structural health monitoring (SHM) and management of large-span steel structures. BIM is primarily utilized during the design and construction phases, providing detailed digital representations for planning, visualization, and stakeholder coordination [10]. It serves as a foundational platform for creating comprehensive models essential for effective collaboration.

Conversely, Digital Twins excel in the operational phase, offering real-time monitoring and predictive maintenance capabilities by maintaining an interactive model reflecting the current state of a structure [38]. This integration fosters enhanced maintenance practices, reducing costs and greenhouse gas emissions. The synergy between BIM and DT is evident in frameworks that integrate real-time sensor data with BIM models, creating dynamic digital twins for proactive management and operational efficiency [29, 11].

Innovative models, such as the Digital Twin-based Reality Capture to Extended Reality (DRX) progress monitoring management model, automate construction progress monitoring by merging BIM, reality capture technologies, digital twins, and extended reality [25]. Despite these advantages, challenges like slow adoption of advanced technologies and the need for effective integration with existing systems persist [39]. Addressing these challenges requires systematic frameworks, especially in heritage conservation, where comparisons between digital twin and heritage building information modeling (HBIM) are essential [40].

The differentiation and synergy between BIM and DT underscore their transformative potential in the construction industry. Integrating advanced technologies such as deep learning, sensor-based systems, and digital twin methodologies enhances structural safety, operational efficiency, and sustainability within the architecture, engineering, and construction (AEC) industry. These technologies facilitate automated structural inspections, real-time data collection, and dynamic simulations for continuous monitoring and optimization of structural performance [24, 30, 17, 7, 23].

5.2 Frameworks and Models for Integration

The integration of BIM and DT technologies is supported by frameworks and models that highlight their complementary roles and synergies. A proposed framework categorizes existing research on DT and BIM, emphasizing their distinct functions and collaborative potential [20]. Integration often progresses from enhanced BIM models to semantic platforms for data flow and ultimately to AI-enabled agents for data analysis [41].

The Digital Twin Construction (DTC) concept exemplifies a comprehensive approach combining BIM, lean construction principles, and AI to optimize construction processes [19]. This approach enhances efficiency, real-time monitoring, and decision-making, improving project outcomes. Research progresses from conventional BIM to integrating digital twins with real-time monitoring and advanced technologies like AI and deep learning [42]. This highlights the transformative potential of integrating digital models with real-time data.

Digital twins' operationalization is examined from a theoretical perspective, emphasizing their evolution alongside architectural projects [43]. Adoption is structured into phases of the construction project lifecycle, including design, construction, facilities management, and restoration [23]. Proposed frameworks often use structural equation modeling to elucidate relationships between key success factors and sustainable parameters, enhancing understanding of BIM-DT adoption [44].

The integration of BIM and DT technologies enhances safety, efficiency, and sustainability in construction projects. These technologies address challenges such as low productivity and poor adoption of advancements, providing innovative, data-driven solutions for sustainable practices. By leveraging real-time data and advanced analytics, BIM and DT facilitate improved building design, construction processes, and project performance, supporting the industry's transformation towards sustainable construction methods [20, 44, 12, 19].

5.3 Applications in Structural Safety and Management

The integration of BIM and DT technologies has revolutionized structural safety and management, particularly in large-span steel structures. By merging real-time data from SHM systems with BIM models, these technologies enhance structural evaluations' precision and efficiency. Their application is evident in advanced simulation techniques combined with wireless monitoring systems, providing a comprehensive framework for assessing structural health beyond traditional methods [5].

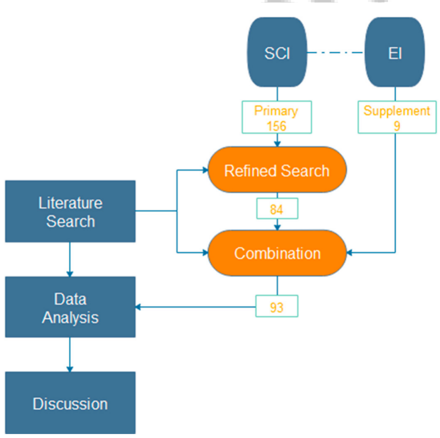
In bridge maintenance, the synergy between real-time monitored data and reliability assessment techniques facilitates informed decision-making and proactive maintenance strategies, enhancing structural safety [23]. The DTC model exemplifies these technologies' potential by improving situational awareness and decision-making through diverse data streams and monitoring technologies [39].

The deployment of low-power wireless sensors, coupled with sophisticated data management capabilities, enables precise and timely assessments of structural health, offering a cost-effective solution for large-scale infrastructure monitoring [8]. This approach supports proactive safety planning and management solutions, as demonstrated by a BIM-based digital twin framework for effective risk management in construction projects [23].

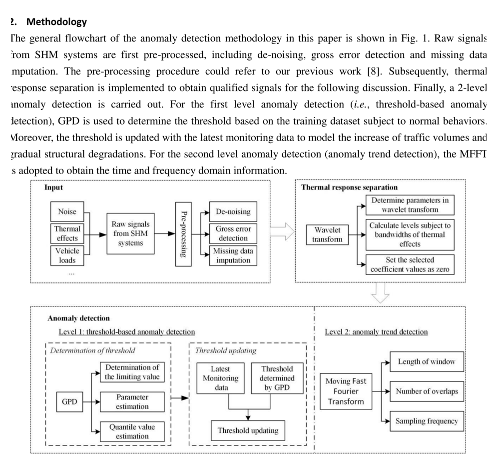
Despite these advantages, the adoption of BIM and DT technologies faces challenges, including the need for cross-disciplinary collaboration and practical methodologies for effective implementation [39]. The BIM + Bridge Risk Inspection Model addresses these challenges by improving bridge inspections and maintenance planning efficiency, providing a robust framework for managing risks associated with aging infrastructures [8].

Moreover, digital twins can transform the architectural design process by enhancing data integration and scenario planning, improving overall safety and management of construction projects [5]. Successful adoption of BIM-DT technologies relies on key success factors, such as organizational support, technological infrastructure, and financial considerations, which significantly influence readiness for adoption [23].

The integration of BIM and DT technologies represents a significant advancement in the AEC industries, enhancing structural safety and management. These technologies optimize the design and performance of large-span steel structures while improving resilience and sustainability. By leveraging real-time data and advanced analysis techniques, stakeholders can achieve more accurate monitoring, maintenance, and safety management, leading to safer and more efficient construction practices [20, 21, 17, 24].



(a) Literature Search and Data Analysis Flowchart[30]


2. Methodology

The general flowchart of the anomaly detection methodology in this paper is shown in Fig. 1. Raw signals from SHM systems are first pre-processed, including de-noising, gross error detection and missing data imputation. The pre-processing procedure could refer to our previous work [8]. Subsequently, thermal response separation is implemented to obtain qualified signals for the following discussion. Finally, a 2-level anomaly detection is carried out. For the first level anomaly detection (*i.e.*, threshold-based anomaly detection), GPD is used to determine the threshold based on the training dataset subject to normal behaviors. Moreover, the threshold is updated with the latest monitoring data to model the increase of traffic volumes and gradual structural degradations. For the second level anomaly detection (anomaly trend detection), the MFFT is adopted to obtain the time and frequency domain information.

(b) The methodology for anomaly detection in SHM systems[4]

Figure 5: Examples of Applications in Structural Safety and Management

As shown in Figure 5, the integration of Digital Twin and BIM technologies presents a transformative approach to enhancing structural integrity and operational efficiency in structural safety and management. The figures exemplify key methodologies within this domain, illustrating processes involved in literature search and data analysis, as well as anomaly detection in SHM systems. The "Literature Search and Data Analysis Flowchart" outlines a systematic approach to identifying and refining relevant scientific literature, essential for informed research and development in structural safety applications. Concurrently, the "Methodology for Anomaly Detection in SHM Systems" highlights critical stages of input management, thermal response separation, and anomaly detection, emphasizing the importance of addressing noise, thermal effects, and vehicle loads to ensure accurate anomaly detection, thereby safeguarding structural health. Together, these examples underscore the pivotal role of advanced methodologies and technologies in fortifying structural safety and management [30, 4].

5.4 Challenges and Success Factors for Adoption

The adoption of BIM and DT technologies in the construction industry faces various challenges and success factors that must be addressed to fully realize their potential benefits. A primary challenge is the seamless integration of physical and digital systems, often hindered by technical limitations and high implementation costs associated with these advanced technologies [42]. Data processing complexity at scale, coupled with concerns regarding data security and privacy, complicates the adoption process, necessitating robust frameworks for effective management [42].

Interoperability issues remain a critical barrier, as fragmented adoption of Digital Twin technologies and a lack of standardized guidelines impede effective collaboration and data sharing among stakeholders. This fragmentation is exacerbated by variability in environmental conditions, such as lighting and background changes, impacting measurement accuracy and data reliability from sensor networks [26].

Furthermore, the absence of comprehensive guidelines and examples of successful Digital Twin implementations across the AEC sector limits practitioners' ability to adopt and integrate these technologies effectively [45]. Empirical validation of proposed frameworks is crucial to address unpredictable aspects in practical applications and ensure their effectiveness in real-world scenarios [39].

Success factors for effective adoption of BIM and DT technologies include developing interoperable frameworks accommodating diverse data types and enhancing collaboration among stakeholders. Establishing standardized definitions and robust datasets to support model training and validation is essential for overcoming technical limitations and improving model generalization [42]. Additionally, fostering a better understanding of Digital Twin concepts among practitioners and enhancing digital skills within facility management teams will be vital for successful implementation [39].

To fully harness the transformative potential of BIM and DT technologies, the construction industry must effectively address existing challenges and capitalize on key success factors. This integration is essential for achieving significant improvements in structural safety, operational efficiency, and sustainability, as recent studies emphasize the importance of organizational readiness, cost optimization, and resource management in the successful adoption of these advanced digital technologies. By fostering a collaborative framework that combines BIM and DT, the industry can enhance project outcomes and contribute to the overarching goals of sustainable development [20, 23, 44, 12].

6 Multi-physics Simulation in Structural Engineering

As structural engineering increasingly addresses multi-physics interactions, understanding the frameworks that facilitate these simulations becomes essential. This section explores various frameworks for multi-physics simulation, underscoring their significance in analyzing and designing large-span steel structures. By examining these frameworks, we can grasp the methodologies that enhance effective multi-physics modeling and their implications for engineering practices.

6.1 Frameworks for Multi-Physics Simulation

Robust frameworks for multi-physics simulations are crucial in structural engineering, especially for large-span steel structures, as they integrate various physical phenomena to provide a comprehensive understanding of complex interactions. The OpenFOAM-preCICE adapter allows OpenFOAM solvers to interact with other simulation codes via the preCICE library without modifying the original solver code, enhancing multi-physics simulation capabilities [46]. ALE3D employs a hybrid finite element and finite volume formulation, effectively simulating complex interactions within steel structures and addressing dynamic behaviors [47]. Its dual handling of finite element and finite volume aspects captures intricate structural responses under various loading conditions.

The benchmark by McMurray et al. introduces a multi-physics modeling framework integrating thermodynamic models with real-time data, offering insights into molten salts in reactors that surpass previous benchmarks [48]. This integration is crucial for capturing transient phenomena and enhancing predictive accuracy. Avramova et al. categorize multi-physics simulation methods into traditional and novel high-fidelity approaches, highlighting the evolution from conventional techniques to advanced simulations leveraging computational advancements for more accurate insights [49]. The incorporation of deep learning techniques further enhances these frameworks by identifying complex data patterns, improving simulation accuracy and reliability [31].

These frameworks signify a substantial advancement in multi-physics simulations, providing innovative solutions that enhance the understanding and management of large-span steel structures. By integrating advanced analysis techniques, real-time data collection methods, and Building Information Modeling (BIM), engineers gain deeper insights into structural behaviors, ensuring more realistic and reliable design and verification processes [24, 5].

6.2 Simulation Tools and Techniques

The tools and techniques employed in multi-physics simulations are crucial for modeling complex interactions within large-span steel structures. The OpenFOAM-preCICE adapter enables peer-to-peer communication between solvers, effectively mitigating bottlenecks associated with central processes and enhancing scalability across numerous compute cores, which is essential for high-fidelity simulations [46]. Current methodologies in multi-physics modeling and simulation (MS) are categorized into traditional and novel high-fidelity approaches, with traditional MS focusing on assembly or channel scales and novel high-fidelity MS operating on pin or sub-pin scales, distinguished by spatial resolution and coupling complexity [49]. This distinction underscores the evolution from conventional techniques to advanced methods leveraging increased computational capabilities for greater accuracy.

Integrating advanced analytical tools, computational modeling, and BIM techniques enhances the understanding of structural dynamics, allowing effective simulation of intricate phenomena such as thermal-fluid interactions and stress distributions. Coupling software platforms, such as OpenFOAM with specialized solvers, broadens the analysis scope for bespoke structural systems in engineering applications [24, 8, 46, 50]. By utilizing advanced simulation frameworks and high-performance computing resources, multi-physics simulations yield invaluable insights that inform the design, analysis, and optimization of large-span steel structures.

6.3 Applications in Structural Design and Optimization

Integrating multi-physics simulations into the structural design and optimization of large-span steel structures is vital for enhancing performance and safety by enabling comprehensive analyses of physical phenomena, such as thermal behavior under solar radiation and stress distribution during construction, thus ensuring design requirements are met and potential issues proactively addressed [49, 1, 5]. These simulations provide a framework for understanding complex interactions, empowering engineers to make informed decisions during design and optimization.

Tools like OpenFOAM and preCICE facilitate advanced simulations involving conjugate heat transfer and fluid-structure interactions, which are critical for validating design assumptions and optimizing structural components [46]. ALE3D's mesh relaxation and advection techniques further enhance simulation accuracy, enabling detailed analyses of structural responses to dynamic loads [47]. Incorporating solar energy harvesting with low-power sensor electronics creates a self-sufficient sensor network, crucial for continuous monitoring and optimization of structural performance [33]. This integration supports the development of sustainable monitoring systems that contribute to long-term optimization of structural health.

Advancements in multi-physics simulations have led to more accurate safety assessments and operational predictions, particularly in complex systems like nuclear reactors, with direct applicability to optimizing large-span steel structures [49]. The use of convolutional neural networks (CNNs) alongside multi-physics simulations offers significant potential for optimizing structural performance through improved damage detection and condition assessment [8]. By leveraging machine learning techniques, engineers can enhance simulation model predictive capabilities, leading to more effective design and optimization strategies.

Overall, integrating multi-physics simulations in designing and optimizing large-span steel structures enhances safety, efficiency, and sustainability by providing a comprehensive understanding of thermal behavior under varying environmental conditions. This advanced modeling approach allows accurate predictions of structural performance and reliability throughout their lifecycle, as demonstrated by studies emphasizing the importance of temperature distribution and mechanical responses in components sensitive to thermal loads. Additionally, structural health monitoring and digital twinning technologies support continuous assessment and improvement of these structures, ensuring they meet design requirements and perform optimally over time [24, 1, 3, 49, 5].

6.4 Validation and Real-Time Monitoring

Validation and real-time monitoring are pivotal in the simulation processes of large-span steel structures, ensuring the accuracy and reliability of structural health monitoring (SHM) systems. Integrating real-time data collection with methodologies like fuzzy logic enhances structural safety assessments by addressing uncertainties inherent in monitoring processes [32], fostering a nuanced understanding of structural conditions and enabling proactive maintenance and risk management strategies.

Advanced simulation tools, such as the OpenFOAM-preCICE adapter, exemplify the importance of validation in multi-physics simulations by providing accurate coupling capabilities that enhance collaborative potential within the simulation community and enable precise modeling of complex interactions within steel structures [46]. Likewise, ALE3D's capability to manage mesh distortions significantly contributes to validation and real-time monitoring processes, ensuring the fidelity of simulation results [47].

Real-time monitoring systems, as demonstrated by the SHM system developed by Navabian et al., showcase high sensitivity and reliability, validating their effectiveness in continuously monitoring civil infrastructures [16]. These systems offer critical insights into structural health, allowing timely interventions that mitigate risks and enhance structural longevity. The Digital Twin methodology, evaluated in a collaborative Living Lab environment, highlights the potential of integrating real-time monitoring with digital models to provide comprehensive insights into structural conditions [36]. This approach not only improves condition assessment accuracy but also facilitates proactive maintenance strategy implementation.

Despite advancements, challenges such as sensor node power supply dependency remain, impacting operational reliability in remote areas [14]. Future research should address these limitations by developing robust power solutions and exploring IoT integration with other technologies to enhance construction safety [6]. Additionally, developing better validation benchmarks and integrating data science techniques, including machine-learning models, hold significant potential for advancing multi-physics simulations [49]. These efforts will be crucial in enhancing the accuracy and applicability of simulation models, ensuring effective management and safety of large-span steel structures.

7 Advanced Data Analytics in Civil Engineering

7.1 Integration of Advanced Data Analytics with Digital Twins and BIM

The integration of advanced data analytics with Digital Twins (DT) and Building Information Modeling (BIM) is transforming civil engineering by enhancing insights from structural health monitoring (SHM) systems. Machine learning and data mining techniques facilitate the analysis of extensive sensor network data, enabling more accurate and timely decision-making [31]. By merging real-time data with predictive analytics, engineers create comprehensive digital models that represent both current and future structural performance.

Digital Twins act as dynamic counterparts to physical structures, utilizing data analytics to simulate scenarios and anticipate structural issues, critical for large-span steel structures where early anomaly detection is essential [36]. This synergy fosters a proactive maintenance approach, optimizing resources and reducing costs.

BIM provides a robust platform for data analytics integration, offering detailed digital representations of a facility's physical and functional characteristics. This integration enhances complex dataset visualization, improving structural behavior understanding and supporting informed decision-making [25]. Cloud-based platforms further enhance this integration by offering scalable storage and enabling remote data access, improving stakeholder collaboration [39].

Machine learning algorithms within BIM and DT frameworks automate data analysis, improving prediction accuracy regarding structural performance and facilitating real-time digital model updates. This integration enhances SHM predictive capabilities and contributes to the development of more resilient and sustainable structures [31]. It also addresses data fragmentation and interoperability challenges, ensuring seamless data flow and boosting construction and maintenance efficiency [20].

7.2 Machine Learning Techniques in Structural Health Monitoring

Machine learning (ML), particularly deep learning (DL), has revolutionized structural health monitoring (SHM) by improving damage detection precision and automation. Advances in sensor technology, cloud computing, and data-driven methodologies have facilitated ML adoption in SHM, enhancing structural defect identification and deterioration pattern recognition. This is crucial for aging infrastructure in the United States, where many bridges require urgent attention. Convolutional neural networks (CNNs) are favored for their effectiveness in processing complex data, streamlining inspections, and reducing traditional monitoring costs [26, 17, 28, 8]. These deep learning approaches outperform conventional methods, offering enhanced capabilities for anomaly detection and damage identification in civil infrastructure.

Deep learning research in SHM encompasses diverse applications, including vision-based damage detection and unsafe behavior identification on job sites [17]. This diversity highlights ML techniques' broad applicability in SHM, enabling comprehensive monitoring systems addressing structural and safety concerns.

ML techniques, such as neural networks and support vector machines, effectively extract insights from large datasets, as evidenced by comparative analyses [37]. These techniques facilitate complex data processing, allowing for the identification of previously undetected patterns and trends.

Integrating ML with digital twin technologies presents a promising research avenue, enhancing data analysis methodologies and exploring economic viability [42]. This integration could further improve SHM systems by providing real-time updates and predictive insights, enhancing decision-making and structural safety.

Key considerations in ML application in SHM include improving model interpretability and robust data handling and validation [34]. Addressing these challenges is essential for maximizing ML techniques' effectiveness in SHM applications.

Incorporating machine learning, particularly deep learning, into SHM signifies a transformative advancement, offering innovative solutions that enhance the safety, reliability, and efficiency of large-span steel structures. These developments facilitate automated inspections and real-time structural integrity monitoring, identifying defects, deterioration patterns, and unsafe behaviors, thereby bridging critical gaps in traditional methods and bolstering infrastructure resilience [17, 28, 8].

7.3 Real-time Data Processing and Decision-Making

Real-time data processing is essential for effective structural health monitoring (SHM) systems, especially for large-span steel structures. Analyzing data in real-time enables timely decision-making, facilitating proactive maintenance and risk mitigation strategies. Advanced data analytics, employing machine learning algorithms, extract actionable insights from extensive sensor network data [31]. These insights are crucial for identifying patterns and anomalies indicative of structural issues, allowing immediate interventions to maintain safety and integrity.

Integrating cloud-based platforms with SHM systems enhances real-time data processing by providing scalable storage and enabling remote data access [39]. This integration supports continuous structural condition monitoring and fosters stakeholder collaboration, ensuring decision-makers have access to the latest information. Moreover, cloud computing enables complex data processing algorithms capable of analyzing large datasets in real-time, yielding more accurate and reliable structural health assessments.

Machine learning techniques, including neural networks and deep learning models, automate real-time data analysis, enhancing prediction accuracy related to structural performance and safety [8]. These techniques facilitate predictive maintenance strategies, allowing early detection of potential issues and reducing catastrophic failure risks. Furthermore, machine learning enhances scenario simulation capabilities and intervention impact evaluation, supporting informed decision-making.

The synergy between Digital Twins (DT) and real-time data analytics improves decision-making by providing dynamic digital representations of physical structures [36]. This integration allows continuous digital model updates with real-time data, enabling more accurate structural behavior predictions and optimizing maintenance and operational strategies.

Despite these advancements, challenges persist in ensuring real-time data processing system reliability, particularly in remote or harsh environments where sensors face power limitations [33]. Addressing these challenges requires developing robust power solutions and exploring alternative energy sources, such as solar power, to maintain continuous monitoring system operation.

8 Conclusion

8.1 Innovative Solutions and Future Directions

The convergence of advanced technologies like Building Information Modeling (BIM), Digital Twins (DT), and the Internet of Things (IoT) is reshaping structural health monitoring (SHM) for large-span steel structures. Future research should aim to develop standardized frameworks for DT implementation and enhance AI and IoT integration to refine decision-making processes in the Architecture, Engineering, Construction, and Operations (AECO) sector. Increasing data interoperability and exploring AI applications in construction will optimize SHM practices, offering novel solutions for improved safety and efficiency.

Emerging trends highlight the potential of integrating BIM with web technologies and augmented reality, providing innovative solutions for real-time monitoring and data collection. The development of robust deep learning models promises to enhance monitoring accuracy and automate data analysis. Moreover, rapid modeling techniques are expected to facilitate wider BIM adoption in bridge management, thus strengthening structural safety protocols.

Exploring the potential of BIM-based digital twins in safety management through comprehensive analysis and real-world project integration is crucial for addressing existing gaps and enhancing safety protocols. Prototyping to quantify the benefits of Digital Twins and examining trends in data integration and AI applications will further advance SHM methodologies. Assessing the applicability of BIM-DT frameworks across diverse cultural contexts and establishing sustainability metrics will be essential for evaluating their impact on construction performance.

Incorporating real-time weather data into Digital Twin models can significantly improve maintenance strategies, particularly in sectors like railways where environmental conditions impact structural integrity. Enhancing synchronization techniques and integrating additional sensors will expand SHM systems' monitoring capabilities, ensuring comprehensive coverage and timely interventions. Future research should focus on improving sensor accuracy and exploring advanced data analytics integration to enhance monitoring capabilities.

Investigating non-contact methods and evaluating measurement uncertainty under various environmental conditions can improve tracking robustness and accuracy. Developing cooperative inspection strategies involving multiple robots presents a promising avenue for advancing localization techniques in structural health monitoring.

These innovative solutions and research directions underscore the transformative potential of advanced technologies in SHM, promising significant enhancements in the safety, efficiency, and sustainability of large-span steel structures. As the construction industry evolves, these advancements will be pivotal in shaping the future of infrastructure management and safety.

8.2 Emerging Trends and Future Directions

Emerging trends in integrating advanced technologies within the construction industry highlight the transformative potential of Digital Twins (DT) in enhancing project efficiency and stakeholder collaboration. Recent studies demonstrate that DTs significantly improve construction processes by enabling real-time monitoring and predictive maintenance, which are vital for enhancing project outcomes and operational efficiency. The adoption of DTs is expected to revolutionize traditional construction practices by providing comprehensive digital representations of physical assets, thereby facilitating improved decision-making and risk management.

The integration of Building Information Modeling (BIM) with Digital Twin technologies marks a critical shift towards more intelligent and automated construction management systems. This synergy allows seamless information flow across various project lifecycle stages, from design and construction to maintenance and operation. By leveraging real-time data analytics and machine learning algorithms, these technologies can significantly enhance the accuracy of structural health monitoring (SHM) systems, enabling proactive maintenance strategies and reducing the risk of structural failures.

Moreover, incorporating the Internet of Things (IoT) into construction practices is poised to enhance SHM systems' capabilities. IoT-enabled sensor networks provide continuous data streams feeding into digital models, offering real-time insights into structural performance and environmental conditions. This connectivity fosters the development of smart infrastructure that can adapt to changing conditions and optimize resource allocation, thereby improving sustainability and resilience.

The construction industry is increasingly prioritizing sustainability and environmental considerations, with advanced technologies playing a crucial role in achieving these objectives. Integrating renewable energy sources, such as solar power, with sensor networks ensures sustainable monitoring solutions that align with global sustainability initiatives. Additionally, utilizing advanced data analytics to optimize energy consumption and minimize carbon footprints is becoming increasingly important in the design and operation of large-span steel structures.

As these emerging trends continue to shape the construction industry, their potential impact on project delivery, operational efficiency, and environmental sustainability is profound. Future research should address challenges associated with the widespread adoption of these technologies, such as interoperability issues and the need for standardized frameworks. By overcoming these barriers, the construction industry can fully leverage the benefits of advanced technologies, leading to safer, more efficient, and sustainable infrastructure solutions.

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