Technium Vol. 3, Issue 10 pp.109-121 (2021)
ISSN: 2668-778X
www.techniumscience.com

BUILDING HEALTH MONITORING OF HOSPITAL FACILITIES SUPPORTED BY DIGITAL TWINS MODELS

Mohammad Amin Oyarhossein

University of Aveiro, Portugal

Abstract. Emerging Building Information Modelling (BIM) tools and technologies have gradually changed how information about our built environment is created, stored, and exchanged between involved stakeholders. This paper elaborates on viable ways of crossing from a BIM world view with its existing knowledge domain and specific technologies towards a Digital Twin (DT) world view, which promises more significant potential at the intersection of IoT and AI through semantic models. This should address the challenge of changing from its static, closed data with recursive interoperability issues towards a linked data paradigm. The building product can be fully represented in the form of a Digital Twin. The present thesis proposal intends to develop a building health monitoring (BHM) system applied in hospital assets using digital twin concepts based on an optimized method of optimally sensor networks supported by a digital twin. The sensors' initial location will be determined by their ability to detect structural and non-structural influencing parameters, like, temperature, strains or deflections, and dynamic properties, among other paraments base on an initial building model. A digital twin model will receive the sensors network's information, update the building model, and evaluate the building response under the climate actions and extreme events. In the end, the framework will be able to predict the building behavior and the operation and maintenance needs. In this study, by using neural network hierarchy and innovating in damage index as neural network input, the damage detection technique has high efficiency for detecting failures in hospital constructive elements.

Keywords: ***Digital Twin Building, Building health monitoring, Building Life cycle, Performance and maintenance prediction***

Introduction:

The structure's health can identify the behavioral characteristics and detect a possible failure of structures during their useful life. Structural health is a process in which various issues such as damage detection and location in structures are addressed. In the structural health system, a network of sensors is used to inform the structure's behavior. Since the installation of sensors, the information related to it is the recording and processing of data. As a result, it receives an essential process in monitoring, lack of data causes incorrect or insufficient effects, and there are additional cases of confusion in the analysis. Data is analyzed and processed. Also, increasing the number of sensors increases the cost of the monitor. Using the sensor network's optimal design means that the correct use of the type sensors, type, number, and locations is critical.

For this purpose, in this research, a method is employed to optimally design the sensor network for a health system in light construction structures made of cold-rolled steel sheets. The optimal location of sensors is due to their ability to detect modal parameters. In this research, the start of use and the optimal location of the sensors are adjusted using different optimization algorithms and the proposed differential completion algorithm that has been modified. Then, using the finite element structural model and pressure analysis of the instrument, the failure characteristics are recruited from the sensors' optimal location. With the help of the neural network hierarchy, the possible failures are discharged.

Definition of product digital twin model, Considering the evolution process and related explanations of the existing product digital twin model, the author defines the product digital twin model: the product digital twin model refers to the full-element reconstruction and digitized mapping of the physical entity's working state and work progress in the information space, and is an integrated multiphysics, multiscale, hyperrealistic, dynamic probability simulation model that can be used for simulating, monitoring, diagnosing, predicting, and controlling

the formation process, state, and behavior of physical entities in the real world. Product digital twin model generated by the product model based on the product design stage. During the following product manufacturing and service stage, with the product data and information interaction between physical entities, it continually improves their integrity and accuracy, finishing a complete and accurate product physical entity description. Some scholars have also interpreted the digital twin model as a digital mirror, digital mapping, digital twins, etc.

It can be seen from the definition of the product digital twin model that: (1) the product digital twin model is a simulation model in which product physical entities are integrated into the information space, a digital file of the entire lifecycle of product physical entities, and the integrated management of the product lifecycle data and complete value chain data; (2) the product digital twin model is perfected by continuous data and information interaction with the physical entity of the product; (3) the final representation of the product digital twin models is a complete and accurate digital description of the physical entity of the product; and (4) product digital twin model can be used to simulate, monitor, diagnose, predict, and control the formation process and status of physical entities in a physical environment.

The product's digital twin model is far beyond the digital prototype category (or virtual prototype) and digital product definition. The product digital twin model includes describing the product geometry, function, performance, and story of the formation process and states of the whole life cycle, such as product manufacturing or maintenance. A Digital prototype, also called a virtual prototype, is a digital description of a mechanical product or a subsystem with independent functions. It reflects the product object's geometric properties and demonstrates its process and performance in at least one domain. Digital prototype is formed in the product design stage. It can be applied to the whole lifecycle of products, including engineering design, manufacturing, assembly, inspection, sales, use, after-sale, recovery, and other links. The digital product definition refers to digitizing the function, performance, and physical properties of mechanical products. From the connotation of the digital prototype (or virtual prototype) and digital product definition, they mainly focus on the description of the product geometry, function, and performance in the product design stage and does not involve the story of the formation process and state of other entire life cycle stages such as product manufacturing or maintenance process.

The various parts of a SIIM system consist of sensors and their accessories as follows:

Data Sampling, this section provides a map for sensors to receive information of absolute values or changes in one or more of the following parameters: strain, displacement, acceleration, temperature, humidity, time, Electrical potential, load, and other structural issues

Transferring data from the receiving location like sensors to the processing site to collect data. The processing place can be another place or place, depending on the type and importance of monitoring. Intelligent data processing, To correctly interpret the collected data, the data must be cleared and processed. When multiple sensors are installed on the structure, all sensors' data are usually stored in a row without separation from each other, in which case data processing is necessary.

Stored processed data: After the data has been cleared and processed in the previous step, it should be stored appropriately and understandably to be accessed in the future without any problem in understanding the data. Diagnoses: The most crucial part of SHIM is the recognition or interpretation of processed data. In this section, the data is converted into values that deal directly with the structural response. For example, the measured values for displacement can be related to flexural stiffness, strains to stresses, and accelerations to the frequency diagram versus spectral density. Data Recovery, Data stored in the future can be recovered as needed.

Basic features of the product digital twin model: The product digital twin model has many characteristics: virtuality, uniqueness, multiphysics, multiscale, hierarchical, integrated, dynamic, super-realistic, computability, probability, and multidisciplinary.

1. Virtuality: the product digital twin model is a physical product in the digital mapping model. Information space is a virtual model belonging to the information space (or virtual space) and does not belong to the physical space.

2. Uniqueness: a physical product corresponds to a product digital twin model.

3. Multiphysical: the product digital twin model is based on the physical properties of the physical product digital mapping model; It is not only necessary to describe the geometric properties of the physical product (such as shape, size, tolerance, etc.), but also to describe the various physical properties of the physical product, including structural dynamics models, thermodynamic models, stress analysis models, fatigue damage models, and material properties of product composition materials (such as stiffness, strength, hardness, and fatigue strength).

4. Multiscale: the product digital twin model not only describes the macroscopic properties of the physical product, such as geometric dimensions, but also the microscopic properties of the physical product, such as the microstructure of the material, the surface roughness.

5. Hierarchical: the different components, parts, etc. that make up the final product can all have their corresponding digital twin models.

6. Integrated: the product digital twin model is a multiscale and multilevel integrated model of multiple physical structure models, geometric models, and material models conducive to the rapid simulation and analysis of its structural and mechanical properties.

7. Dynamic: the product digital twin model will continuously change and improve through the continuous interaction with the product entity during various stages of the whole lifecycle; for example, product manufacturing data (such as test data, the progress data) will be reflected in the digital twin model of the virtual space, and at the same time, based on the digital twin model, can realize the real-time, dynamic and visual monitoring of the manufacturing state and process of the product.

8. Super-realistic: the product's digital twin model and the physical product are identical in appearance, content, and nature, with a high degree of actuality, and can accurately reflect the actual state of the physical product.

9. Computability: based on the product digital twin model, simulations, calculations, and analysis can be used to simulate and reflect the status and behavior of the corresponding physical product in real-time.

10. Probability: the product digital twin model allows computation and simulation using probabilistic statistics.

The development of the Internet of Things (IoT) allows Digital Twin (DT) models to support new intelligent services to connect and interact with the physical object. The Industry 4.0 context requires a broad horizontal and vertical integration [1], e.g., including consolidating, analyzing, connecting data derived from sensors, processes and, the constructed facility itself. As introduced in [2], the Information Factory refers to this comprehensive interconnection of all critical information systems. It delivers expertise for the operator platforms of the future as a core environment for Industry 4.0 solutions. The Information Factory serves as an implementation and operation framework for DT.

The network used to interconnect SOs (intelligent objects) can be based on existing Internet standards [1]. This allows the simple integration of structural health monitoring (SHM) into more general systems such as intelligent buildings, smart cities, smart infrastructure, and intelligent industry. Moreover, the sensitivity of the detection of the damage and continuous monitoring [3] permits essential features to be achieved, such as the timely detection of dangerous states and the storing of monitoring information. These features can introduce the monitoring system's ability to implement criteria for providing tools to optimize the building's residual life's maintenance and prognosis. The exciting aspect about the introduction of the IoT paradigm in the BHM system [2] regards the applicative of scenarios that include bridge monitoring [4], historical masonry structures monitoring [5], foundation earth monitoring [6], or alteration of the structure materials [7]. The Information Factory's role for the representation of DT comprises different aspects [8-9], and BHM systems would form a significant establishment in damage detection, assessment, and failure prediction. On a continuous real-time basis, the integrity of constructive in-service elements (CE) is crucial for manufacturers, maintenance teams, and operators [10]. BHM is an area of growing interest and new and innovative approaches [11]. A typical BHM system requires constant data collection from sensors embedded within the CE [12]. The data can then be analyzed to detect any possible issues; moreover, the monitored system's remaining life can be estimated. With the advances in sensor technology and reducing its costs, the computational processing capacities turn to a wide range of sensors, resulting in significant work in real-time monitoring of CE [13-14].

The main goals and innovations of this research proposal are as follows:

- Develop a Valid Technique for Sensor Design Optimisation, taking advantage of the traditional BHM concepts and the DT models applied to Hospital Assets. In this research, different optimum sensor location techniques on structures are tested a new method is presented.

- Develop a Valid Technique for Damage Detection based on information collected from Optimized Sensors and stored and managed with DT.

In this research using neural network hierarchy and introducing failure index as an input of the neural network, the damage detection technique is highly efficient for detecting CE.

The emergence of the Internet of Things (IoT), which is the result of Moore's law that allowed powerful semiconductor chips to be produced at low prices [21], can impact every aspect of our economy [22], [23]. Developments such as cars that are connected and autonomous [24], toying robots [25], and intelligent houses [26] are all examples of either IoT being integrated into legacy systems or IoT enabling the creation of entirely new concepts. Intelligent buildings are emerging as the next frontier in the development cycle of architectural structures [27]. Embedding programmable services into the residential buildings is currently underway, including heating and cooling and the integration of household appliances. This collaboration occurs between the largest household appliance manufacturers and internet companies such as Amazon, Google, and Microsoft. A concept that is explored extensively in the literature and has been implemented in real-world construction projects around the world is building information modeling (BIM) [28]-[30].

BIM is a platform for keeping an accurate and interoperable record of building information to enhance planning, construction, and maintenance over a facility's life cycle [30], [31]. In particular, BIM has been developed for embedding the building's 3D computer-aided design (CAD) model with additional data related to building specification, schedule, cost estimation, and maintenance management (i.e., 4D, 5D, and 6D) [32]-[34] to reduce cost by preventing mistakes in the design and construction phase [35]. Currently, BIM is used in architecture, construction, engineering, and facility management (AEC/FM) for design visualization and consistency, clash detection, lean construction, cost and time estimation, and enhanced stakeholders' interoperability [30]. Efforts [36, p. 19] to ensure BIM Benefits from real-time data inputs (e.g., from sensors and IoT devices)

are underway [37]; these efforts, in turn, would Benefit the buildings that already have implemented BIM or are willing to undertake the action and cost of creating BIM documentation. More than 80% of facilities in Europe are constructed before 1990, and therefore do not have BIM [30], [38] [41].

There are significant obstacles to producing existing buildings without BIM documentation (i.e., the high effort required to create and update the BIM model and difficulties related to solving uncertain data and relationships in the BIM [30]). Existing buildings can benefit from implementing a digital twin, a known manufacturing concept [42], to enhance building operation and maintenance and a closed-loop design [43].

Wireless sensor network (WSN) integration and data analytics are two components required to create a digital twin [44]. Digital twin visualization for a building can rely on a 3D CAD model extracted from BIM or a custom 3D model. The digital twin of a building can utilize various sensor networks to create a real-time view of the asset. This dynamic view allows for real-time analytics, informed decision-making, building efficiency, and comfort enhancement. The first significant difference between a building's BIM and digital twin is that the former was designed to improve design and construction efficiency and is still used in these phases of the building life cycle [45].

In contrast, the latter is designed to monitor a physical asset, improve its operational efficiency, and enable predictive maintenance [46]. The second significant difference is that BIM was not intended to work with real-time data but is still used in the design, construction, maintenance tasks, and interoperability.

Which does not necessarily require real-time capability [47]; meanwhile, the digital twin is the digital counterpart of a physical asset and works contrary to the current BIM platform. Digital twin works specifically with real-time data fed by the sensor systems to record and analyze a physical asset's real-time structural and environmental parameters to perform highly accurate digital twin simulation and data analytics [46]. The third difference between the two concepts is related to the type of data required for each model's construction. While BIM is suitable for the integration of cost estimation and schedule data to enhance the efficiency of a construction project [28], [48], the digital twin is designed to integrate real-time sensor readings to analyze and improve the building's interaction with the environment and with users [49].

Damage detection

As mentioned in the previous section, civil structures are exposed to various failures of various origins during their lifetime. The cause of damage to the structure can be natural events such as earthquakes, the use of substandard materials or out-of-date, defects in execution, etc. If the damage is not detected in its early stages, it may lead to irreparable damage to the structure and even its collapse. To this end, identifying damage in the early stages of its occurrence is one of the essential issues that has attracted engineers' and researchers' attention today. There are various methods for identifying damage or failure, an integral part of a structural system's structural health monitoring process. These methods are divided into two main categories of destructive and non-destructive methods. Non-destructive methods are more popular today than violent methods due to damage detection without damaging the structural system, and destructive practices are not used except when necessary. There are many types of non-destructive methods. Several non-destructive methods are based on local observations, such as ultrasonic experiments, radiographs, etc., usually detecting small structures' failure and high loss levels. These types of damage detection methods, both ocular and local, need to be performed in the vicinity of the fault and require that the fault's location be somewhat known.

Only part of the structure is inspected. Due to these limitations, the mentioned methods can detect failure only near the surface of the structure. Time-consuming, high cost combined with the inefficiency of this group of non-destructive methods to detect damage in large structures and multiple costs has led to another category of damage detection methods that, unlike the previous way, comprehensively. The need for comprehensive damage detection methods that can be used in complex structures led to the development of techniques based on changes in the structure's vibrational characteristics. Thus, the discovery and identification of damage or defect in facilities by examining dynamic properties changes with structural responses are of great interest today. In this category of damage detection methods, fault detection is expressed as a general problem that examines the structure's general condition. Ideally, it is a fault detection method that can detect damage in the early stages. It is desirable to determine the damage's severity and location and finally estimate the structure's remaining life. The process of identifying the appropriate injury by Ritter (4) in 1993was described as follows: Level 1: Detection of the presence or absence of damage in the structure. Level 2: Identification of the location of the damage.Level 3: Identification of the severity of the damage. Level 4: Determining the remaining life of the structures

In damage detection problems, therefore, we are faced with an inverse problem that in the absence of data, a single answer can not be achieved (location and severity of the purchase. The form should be automated, not based on engineering judgment, and consider performance constraints. An appropriate approach is to develop a method in which non-damaged instruments are used as baseline values to compare with the properties needed to diagnose the damage. One of the most popular forms of fault detection is vibration-based detection of the structure. The main idea is that dynamic parameters (frequencies, mod shape, modal attenuation, etc.) are functions of the structure's physical properties (mass, Damping, and stiffness, so changes in material properties lead to changes in dynamic parameters. A general assumption in most damage detection methods mentioned in research is that the structure's mass does not change due to failure. This assumption is not valid for some structures, such as oil rigs, and is an essential feature of methods based on predefined models. Their ability to detect model data scatter due to modeling errors and data scatter due to structural failure. The linear failure position is the state in which the linear elastic structure remains linearly elastic after injury. The change in dynamic properties is due to a change in the material's geometry, but the structure's behavior is still modeled as linear motion equations. Nonlinear damage is defined as a condition in which a linear elastic structure behaves nonlinearly after injury. An example of nonlinear damage is fatigue cracks that open and close continuously under normal ambient vibration conditions.

Introducing the optimal design of the sensor network:

As mentioned, instruments' health monitoring is one of its goals: diagnosing and locating damage in mechanical, civil, and spatial structures, achieved by the complete and timely diagnosis of damage. To achieve an efficient and reliable SHM system, designing a suitable network of sensors that record the desired structure's required data in the first step is necessary. A good network of sensors means an appropriate set. It is one of the types of sensors located in the best structural places as much as possible to record information and structural parameters. Their number is optimal both in terms of price and performance. As a result, it can be said that the design of the sensor network includes determining the number, location, and type of sensors. In designing the sensor network, issues such as reliability and economy in the sensor network should be considered. Structural requirements determine the kind of sensors, available technology, and budget. A variety of accelerometers can be used in a health monitoring system when vibration-based damage detection is considered. However, determining the location and number of sensors requires an optimization process, which is discussed below. Sensor optimization is essential from 3 perspectives:

1- Structure control

2- System identification

3- Identification of failure

Over the last 30 years, system identification techniques based on laboratory responses or on-site responses to simulate structural behavior have grown exponentially. A key issue in using these techniques is access to a limited number of responses. This means that for economic reasons and especially the cost of data collection and analysis or practical reasons such as lack of access to some degrees of freedom, the answers are usually reported from several degrees of freedom more diminutive than the total degrees of structural freedom. As structural responses are collected and recorded by sensors, the location of a limited number of sensors in a structure is usually chosen. The reported reactions can use system identification techniques to give the best possible estimate of the parameters. Have a structure.

The most common structural parameters whose correct estimation helps identify the system and accurate modeling are modal parameters. Due to the many advances in structural monitoring and fault detection based on modal data in recent years, the determination of structural modal parameters using dynamic data measured by sensors has become more critical. This application is used in model updating, structural monitoring, and structural control. Due to the destructive effect of perturbation, only a limited number of males are correctly estimated. As a result, the determination of model parameters is limited to the dominant modes. The best places to weave information from sensors are places where the dominant modes respond to undeniable participation. In areas where the sensors are not located, men's modal involvement cannot be obtained directly. Therefore, expansion or interpolation must be applied to get the whole shape of the mode. Locating the sensors can be based on experience and knowledge of the structure's forces and vibration position but does not guarantee the recording of correct answers. Finding sensors based on experience is also difficult for structures that have been studied in the past. Besides, in many cases, more analysis is required on the sensors' measured data to obtain stresses, strains, and accelerations at points where the measurement has not been performed, thus ensuring reliability. Ensure that data is recorded from the appropriate locations. Therefore, it is necessary to place the sensors in optimal areas to obtain high-precision responses.

Malfunction index:

The failure index is a dynamic feature of the structure. By examining its changes, the structure's failure status can be understood, and the damage detection algorithm is the method of reviewing the relevant failure index. The leading indicators of failure are divided into the following:

1- Index based on natural frequency 2- Index based on attenuation 3- Index based on mode (direct or indirect) 4- Index based on frequency response function 5- Index based on the response in the time range

Objectives :

Attending to the considered current requirement in building monitoring importance assets, the present thesis proposal aims to develop an integrated platform for study the development of a sensors network and safe, fast, and cost-effective systems. The asset is installed on difficult access, monitoring methods, and numerical models to analyze the hospital facilities subjected to several actions during their lifetime. This tool will assist in the life cycle assessment and management, based on the conjugation of aspects related to the building behavior comprehension. the main pathologies and damages observed, monitoring results, numerical analysis, and estimation of the impact that a potential calamity can produce in human and economic terms.[15] Considering that severe damages can be identified early by the monitoring and numerical models prediction, the thesis will suggest the proper maintenance and strengthening works to prevent unnecessary interventions and reduce the building life cycle.[16-17] Using this innovative system based on monitoring the entire building in conjugation with a virtual model (DT) results in critical economic advantages since the need for significant and more expensive maintenance repair and strengthening works or rehabilitation can be avoided. For early damage detection, monitoring systems are required and combined with the building model, updating and upgrading them continuously with the measuring results [18]. The interaction of monitoring devices/systems with the building models is minimal. Consequently, numerical models do not always reflect the CE's actual condition regarding existing damage and behavior. Data acquisition is rarely made. When completed, it happens from time to time. The update and calibration of the numerical models with the monitored parameters are also made periodically, which could be overcome with the present thesis proposal [19].

Detailed description :

The topic covered with the preset proposal follows the EU-Vision document that establishes that infrastructure buildings, including hospitals, must be prepared to resist all kinds of risks without any damage. With climate changes, it is expected that with increasing humidity and air temperature in Europe combined with pollution, structural and non-structural degradation may occur more rapidly. To prevent early infrastructure deactivation, monitoring is a crucial issue. This work significantly contributes to achieving the 12 (12.1, 12.2, 12.5, 12.6, 12.7) and 13.1 UN 2030 sustainable goals and the 6.4, 7.3, 9.5, 11.6. The sensors that will be considered for digital twin technology include temperature, humidity, strain, corrosion, and accelerometers for BHM [20] to perform the damage assessment specially focused on hospitals' concrete structures. This will be achieved by DT's development, characterized by the two-way interactions between the digital and physical worlds. It can lead to many benefits as the physical product can be made more 'intelligent' to adjust its real-time behavior according to the 'recommendations' made by the virtual product.

Physical Alert System :

The main aim of Task 1 is a digital model development of a case study considering characteristics of the system from a variety of sources ranging from geometric data, material properties, inspection processes, operating status, operating and environmental conditions. Intelligent measurement techniques can measure the state of conservation of a physical system from three aspects.

(A) Geometric modeling: including details of project geometry, performance requirements across the life cycle, method of construction details, scheduling and consulting of installed systems and components, and maintenance requirements.

(B) Condition status: The healthy condition of a facilities` physical system is often revealed by its CE anomalies. Information collected from a variety of intelligent sensors for monitoring analysis conditions, such as electric current accelerometer sensors for vibration measurement, dynamometer for force measurement, temperature, humidity, corrosion sensors, and image capturing (e.g., Cloud Points; Surveys of inner services, Structural load tests, GeoRadar, building condition assessment).

(C) Service Record that describes past services performed and components replaced (Major/Minor Retrofitting and regular maintenance)

Digital twin model:

Resourcing BIM technology, the 3D model of the building will be developed as the basis of DT.

The digital twin model will be developed using physics-based models and data-driven analysis to detect damage. The DT model is made up of three main elements, including the BIM model (digital model), data analysis, and knowledge base:

(A) Digital Model: Describes the subsystem structure, subsets, and components and creates a unique model: The digital model simulates the normal or abnormal behaviors of CE or processes related to domain understanding (e.g., statistics, dynamics, multi-physics, etc.). Understanding the domain can help create virtual sensors in the digital model to increase model sensitivity.

(B) Data analysis: Supports health analysis and maintenance decisions using digital simulation and data-driven intelligence. Data analysis is used to describe, diagnose, predict, and prescribe physical system behavior for fault detection. Meanwhile, the data analysis results are also transferred to the facility system's digital model for updating the digital twin model.

The methodology applied for facility inspection and identification of potential damages:

To validate the developed method of assessing the facility's health, the CE will be inspected at a Hospital Building, examining the existing building and recording the potential conditions of the damage being made. In this case, the CE affected by the damage will be studied, and solutions for detecting the anomalies will be provided. The digital twin method allows concluding of the appropriate alternative. At the end of Task 3, a paper is submitted to an international scientific journal to validate Task 2 and 3 by international reviews (Output 3).

Database of CE preventive maintenance actions:

Study and collect information about preventive maintenance actions of building construction elements, their periodicity, and their cost for each component. Create a database that in the future allows the process of maintenance to be quick and consistent to encourage the user to do the facility management. This task will be a decisive contribution to the next one.

Maintenance and inspection models:

Numerical inspection and maintenance models with optimizing resources and buildings' durability for sustainability will be developed. The models will be created using the actual data stored and managed in the DT. Develop a dynamic decision model for maintenance planning.

Model Update Strategy:

Damaged elements under the influence of various operating and environmental conditions. Accordingly, the digital twin model is determined, and the answer must reflect the system's actual requirements. The discrepancy between the response of the primary system and the digital twin model becomes a solvable problem. Therefore, digital twins are a technical hurdle in updating the dynamic system model to adapt to the physical system response. At the end of this work, a turning point will be reached, and an article will be presented to the international journal to expand study and knowledge(Output 4).

Conclusion :

This paper provided an overview of the origins and definition of Digital Twin and briefly discussed some of the Digital Twin applications in manufacturing and logistics. The current state of Digital Twin in construction was then investigated via literature review, and an illustration of Digital Twin in Construction was proposed. This study's culminating effort is a framework for understanding the current state of Digital Twin implementation in the construction industry. The framework was developed by synthesizing the extant literature and dividing the digital-twin-related research into three subcategories: Digital Model, Digital Shadow, and Digital Twin. Digital Model has no automated links between the physical object and virtual representation (i.e., BIM). Digital Shadow is augmented on the Digital Model concept and has a one-directional link. Digital Twin represents the highest integration level using the bidirectional automated link. The framework analysis showed that although construction has made significant strides by going beyond Digital Model, Digital Twin's application is still not fully accomplished in the construction industry. However, it can be concluded that the focus of research is currently being shifted toward Digital Twin. The first step to achieving this shift is to have sufficient data collection and connection to BIM, including sensing data, by leveraging the Digital Shadow subcategory research.

References :

[1] Uhlemann. Lehmann. Steinhilper (2017) The Digital Twin: Realizing the Cyber-physical Production System for Industry 4.0. Procedia CIRP 61:335–340. 2017.
[2] Stark Damerau, Lindow (2018) Industrie 4.0 Digital Redesign of Product Creation and Production in Berlin as an Industrial Location Challenges and Solutions for Digital Transformation and Innovation. in Sendler U, (Ed.) The Internet of Things — Industrie 4.0 Unleashed, Springer.
[3] Anderl Haag, Schuetzer Zancul (2018) Digital Twin Technology and Approach for Industrie 4.0, de Gruyter.
[4] Abramovici G.öbel, Dang (2016) Semantic Data Management for the Development and Continuous Reconfiguration of Smart Products and Systems. CIRP Annals 65(1):185–188.
[5] Grieves Vickers (2017) Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior. in KahlenFlumerfeltAlvesComplex Systems, Transdisciplinary Perspectives on Complex Systems, Springer, Cham.

[6] Schleich Anwer, Mathieu Wartzack (2017) Shaping the Digital Twin for Design and Production Engineering. CIRP Annals Manufacturing Technology.
[7] Stark Kind, Neumeyer (2017) Innovations in Digital Modelling for Next Generation Manufacturing System Design. CIRP Annals 66(1):169–172.
[8] Tardieu Hall, Esteban Hahn, Beetz Lehmann-Brauns (2018) The Rise of Industrial Data Platforms.
[10] Boschert Rosen (2016) in Hehenberger al, (Ed.) Digital Twin the Simulation Aspect, Mechatronictronic Futures: Challenges and Solutions for MechatronicSystems and their Designers, Springer International Publishing, pp. 59–74.
[11] Davis Edgar, Porter Bernaden, Sarli (2012) Smart Manufacturing, Manufacturing Intelligence, and Demand-dynamic Performance. Computers & Chemical Engineering 47:145–156.
[12] K. Yokozeki, K. Watanabe, N. Sakata, N. Otsuki, Modeling of leaching from cementitious materials used in an underground environment, App. Clay Sci. 32 (2004) 293–308, https://doi.org/10.1016/j.clay.2003.12.027 [CrossRef]
[13] T.P. Lees, Chapter 2, in G.C. Mays (Ed.), Deterioration Mechanisms. The durability of Concrete Structures Investigation, Repair, Protection, E. & F. N. Spon Press, 1992, pp. 10–36, ISBN 978-0-419-15620-8.
[14] P. Chindaprasirt, P. Kanchanda, A. Sathonsaowaphak, H.T. Cao, Sulfate resistance of blended cement containing fly ash and rice husk ash, Constr. Build. Mater. 21 (6) (2007) 1356–1361, View at Publisher View at Google Scholar.
[15] P. Runcie, S. Mustapha, and T. Rakotoarivelo, "Advances in
structural health monitoring system architecture," in Proceedings of the Fourth International Symposium Life-Cycle Civil Engineering, IALCCE, vol. 14, pp. 1064–1071, 2014.
[16] W. Ostachowicz, R. Soman, and P. Malinowski, "Optimization of sensor placement for structural health monitoring: a review," Structural Health Monitoring, vol. 18, no. 3, pp. 963–988, 2019.
[17] P. Kumar Mehta, Sulfate Attack on Concrete: Separating Myth from Reality, Concrete International, Farmington Hills, Michigan, 2000.
[18] Keith Worden et al., Structural Health Monitoring: from Structures to Systems of- Structures, International Federation of Automatic Control, 2015.
[19] PED. Love, J. Smith, Unpacking the ambiguity of rework in construction: making sense of the literature, Civ. Eng. Environ. Syst. (2019), https://doi.org/10.1080/
10286608.2019.1577396.
[20] Z.-Z. Hu, P.-L. Tian, S.-W. Li, J.-P. Zhang, BIM-based integrated delivery technologies for intelligent MEP management in the operation and maintenance phase, Adv. Eng. Softw. 115 (2018) 1–16, https://doi.org/10.1016/j.advengsoft.2017.08. 007.
[21] M. Chui, M. Löf_er, and R. Roberts, *The Internet of Things*, vol. 2. New York, NY, USA: McKinsey, 2010, pp. 1_9.
[22] T. Baranwal and P. K. Pateriya, "Development of IoT based smart security and monitoring devices for agriculture," in *Proc. IEEE 6th Int. Conf. Cloud Syst. Big Data Eng. (Con_uence)*, Jan. 2016, pp. 597_602.
[23] S. Leminen, M. Westerlund, M. Rajahonka, and R. Siuruainen, "Towards IoT ecosystems and business models," in the *Internet of Things, Smart Spaces, and Next Generation Networking*. Berlin, Germany: Springer, 2012, pp. 15_26.
[24] M. Gerla, E.-K. Lee, G. Pau, and U. Lee, "Internet of vehicles: From intelligent grid to autonomous cars and vehicular clouds," in *Proc. IEEE World Forum Internet Things (WF-IoT)*, Mar. 2014, pp. 241_246.
[25] N. H. Motlagh, T. Taleb, and O. Arouk, "Low-altitude unmanned aerial vehicles-based Internet of Things services: Comprehensive survey and future perspectives," *IEEE Internet Things J.*, vol. 3, no. 6, pp. 899_922, Dec. 2016.

[26] M. Wang, G. Zhang, C. Zhang, J. Zhang, and C. Li, "An IoT-based appliance control system for smart homes," in *Proc. IEEE 4th Int. Conf. Intell. Control Inf. Process. (ICICIP)*, 2013, pp. 744_747.
[27] D. Minoli, K. Sohrabi, and B. Occhiogrosso, "IoT considerations, requirements, and architectures for smart buildings_Energy optimization and next-generation building management systems," *IEEE Internet Things J.*, vol. 4, no. 1, pp. 269_283, Feb. 2017.
[28] S. Azhar, "Building information modeling (BIM): Trends, bene_ts, risks, and challenges for the AEC industry," *Leadership Manage. Eng.*, vol. 11, no. 3, pp. 241_252, 2011.
[29] C. Eastman, P. Teicholz, R. Sacks, and K. Liston, *BIM Handbook: A Guide to Building Information Modeling for Owners, Managers, Designers, Engineers, and Contractors*. Hoboken, NJ, USA: Wiley, 2011.
[30] R. Volk, J. Stengel, and F. Schultmann, "Building Information Modeling (BIM) for existing buildings_Literature review and future needs," *Autom. Construct.*, vol. 38, pp. 109_127, Mar. 2014.
[31] P. Tang, D. Huber, B. Akinci, R. Lipman, and A. Lytle, "Automatic reconstruction of as-built building information models from laser-scanned point clouds: A review of related techniques," *Autom. Construct.*, vol. 19, no. 7, pp. 829_843, 2010.
[32] B. Succar, "Building information modeling framework: A research and delivery foundation for industry stakeholders," *Autom. Construct.*, vol. 18, no. 3, pp. 357_375, 2009.
[33] D. Bryde, M. Broquetas, and J. M. Volm, "The project bene_ts of building information modeling (BIM)," *Int. J. Project Manage.*, vol. 31, no. 7, pp. 971_980, 2013.
[34] K.Wong and Q. Fan, "Building information modeling (BIM) for sustainable building design," *Facilities*, vol. 31, nos. 3_4, pp. 138_157, 2013.
[35] H.W. Lee, H. Oh, Y. Kim, and K. Choi, "Quantitative analysis of warnings in building information modeling (BIM)," *Autom. Construct.*, vol. 51, pp. 23_31, Mar. 2015.
[36] R. Sacks, C. Eastman, G. Lee, and P. Teicholz, *BIM Handbook: A Guide to Building Information Modeling for Owners, Designers, Engineers, Contractors, and Facility Managers*. Hoboken, NJ, USA: Wiley, 2018.
[37] S. Tang, D. R. Shelden, C. M. Eastman, P. Pishdad-Bozorgi, and X. Gao, "A review of building information modeling (BIM) and the Internet of Things (IoT) devices integration: Present status and future trends," *Automat. Construct.*, vol. 101, pp. 127_139, May 2019.
[38] Y. Arayici, "Towards building information modeling for existing structures," *Struct. Surv.*, vol. 26, no. 3, pp. 210_222, 2008.
[39] J. Armesto, I. Lubowiecka, C. Ordóñez, and F. I. Rial, "FEM modeling of structures based on close-range digital photogrammetry," *Autom. Con- Struct.*, vol. 18, no. 5, pp. 559_569, 2009.
[40] J. Dickinson, A. Pardasani, S. Ahamed, and S. Kruithof, "A survey of automation technology for realizing as-built models of services," in *Proc. 1st Int. Conf. Improving Construct. Use Through Integr. Design Solutions*, 2009, pp. 365_381.
[41] R. Attar, V. Prabhu, M. Glueck, and A. Khan, "210 King Street: A dataset for integrated performance assessment," in *Proc. Spring Simulation Multiconf.*, 2010, Art. No. 177.
[42] B. Schleich, N. Anwer, L. Mathieu, and S. Wartzack, ``Shaping the digital twin for design and production engineering," *CIRP Ann.*, vol. 66, no. 1, pp. 141_144, 2017.
[43] Q. Qi, F. Tao, Y. Zuo, and D. Zhao, "Digital twin service towards smart manufacturing," in *Proc. CIRP*, vol. 72, 2018, pp. 237_242.
[44] F. Tao, J. Cheng, Q. Qi, M. Zhang, H. Zhang, and F. Sui, "Digital twin-driven product design, manufacturing and service with big data," *Int. J. Adv. Manuf. Technol.*, vol. 94, nos. 9_12, pp. 3563_3576, Feb. 2018.
[45] Y. Liu, S. van Nederveen, and M. Hertogh, "Understanding effects of BIM on collaborative design and construction: An empirical study in China," *Int. J. Project Manage.*, vol. 35, no. 4, pp. 686_698, 2017.

[46] Q. Qi and F. Tao, "Digital twin and big data towards smart manufacturing and industry 4.0: 360-degree comparison," *IEEE Access*, vol. 6, pp. 3585_3593, 2018.
[47] S. Bruno, M. De Fino, and F. Fatiguso, "Historic building information modeling: Performance assessment for diagnosis-aided information modeling and management," *Autom. Construct.*, vol. 86, pp. 256_276, Feb. 2018.
[48] S.-K. Lee, K.-R. Kim, and J.-H. Yu, "BIM and ontology-based approach for building cost estimation," *Autom. Construct.*, vol. 41, pp. 96_105, May 2014.
[49] F. Tao, F. Sui, A. Liu, Q. Qi, M. Zhang, B. Song, Z. Guo, S. C.-Y. Lu, and A. Nee, "Digital twin-driven product design framework," *Int. J. Prod. Res.*, vol. 57, no. 12, pp. 3935_3953, 2019.