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Reimagining Construction with Digital Twin Technology

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Abstract
A digital twin is made up of a system or physical item, a virtual model (or digital copy) of that system, and the information and connection that connects them, allowing for real-time data analysis and sharing. Through extensive systematic literature review, a suitable qualitative research questions constructed. The research questions have been addressed through the secondary data survey. A system or physical item, a virtual model (or digital copy) of that system, and the information and connection that connects them, allowing for real-time data analysis and sharing. To create a digital representation of real-world objects and systems, the development of digital twins employs a range of technologies, including cloud computing, artificial intelligence (AI), extended reality (XR), and the Internet of Things (IoT). In addition to difficulties with data quality, availability, and integration, digital twin research faces deficiencies in fundamental mathematics, statistics, and computation. Additionally, more advanced modeling and artificial intelligence techniques are required for dynamic updating and prediction. These topics, such as uncertainty quantification, data-driven and mechanistic model coupling, and interoperability among digital twin models, should be the focus of future study. In this digital era, entrepreneurs are very much interested to know how the asset will behave over an operational period. To understand this concept the entrepreneurs are initially preparing digital models and understanding the operational performance of the digital model. There after entrepreneurs constructing the real time asset and data is allowed to flow either one or bi directional to addressed the challenges if arises, if any. Digital twin simplifies in addressing the issue/problem of real time asset. From the study it is concluded that the digital twin is suitable for asset/s which are critical in running/operating condition under different dynamics and these dynamics, which are beyond human control as well as digital twin is suitable in attending performance failures, easily instead of attending every component through longer inspection time. But, the same/asset failure shall be studied from a digital twin and the same/asset failure performance failure and can be fixed smoothly, easily, less effort and over shorter duration/s. It may result in asset breakdown over shorter duration period.

Key Words: Artificial intelligence, Digital Twin, virtual model, Internet of Things, Extended reality

Introduction:

One of the essential components of a human advancement, that has changed dramatically throughout time is manufacturing. In the beginning, people used simple tools and methods to manufacture items. Better production techniques were, nonetheless, required as demand/s increased. The advent of digital twins improves the use of these models in a number of contexts and helps to improve the conventional methods for product design and development [2]. The concept of a digital twin was initially introduced by Dr. Michael Grieves from the University of Michigan in 2002. It was dubbed the "Conceptual Ideal for product lifecycle Management (PLM)" and represented the connection between real and virtual space, even though the conceptual and technical foundation for digital twins had been established for several decades. A digital twin is a digital representation of a physical asset that is connected to its physical counterpart via a data flow that allows the digital model to be updated in real time. Digital twins are valuable for monitoring, controlling, and predicting a product's performance throughout its entire lifecycle, from conception to disposal. Design and production are merging to allow for mass customization, which necessitates monitoring and enhancing the whole product lifetime.

Definition of digital twin: A digital twin, is a virtual version of an item or system that is updated in real time using information from its physical counterpart, enabling it to offer an accurate depiction over time. Three components can be used to define it: An object model; An object-related data collection that is always changing; also known as a digital thread and A way to update the model dynamically or modify it in response to the data.

Digital manufacturing has significantly impacted the industry by representing factories, resources, workforces, and skills, and simulating product and process development. Information and Communication Technology (ICTs) are accelerating the evolution of various sectors, including computer-aided design (CAD), computer-aided engineering (CAE), computer-aided manufacturing (CAM), finite element analysis (FEEA), product data management (PDM), big data, the internet of things (IoT), AI, cloud computing, edge computing, fifth generation (5G), and wireless sensor networks. These technologies present chances for blending the physical and digital realms, responding to the complexities and demands of the market. Nevertheless, the complete strategic benefit of this integration has not yet been fully utilized, and the process remains far from finished (Mengnan Liu, Shuiliang Fang, Huiyue Dong, Cunzhi Xu. 2021). Upon examining the life cycle of a product, as noted in the literature (C.K. Lo, C.H. Chen, Ray Y. Zhong; Concetta Semeraro, Mario Lezoche, Hervé Panetto, Michele Dassisti; Mengnan Liu, Shuiliang Fang, Huiyue Dong, Cunzhi Xu, 2021), it can be categorized into four distinct, sequential stages: The System creation/Design phase, the Manufacturing/Production phase, the Operational/Use phase, and the Disposal/End-of-life phase.

The fire doors are recommended in the construction industry to secure the life of the inhabitants of a working place. The performance of the door may be examined under various condition by assigning the possible various condition/s on the digital object, through which the performance of the product may enhanced by better product manufacturing an delivering the same in the market for users [36].

The digital twin can represent either the product that is being developed or the production system responsible for manufacturing the product, providing the user with varying information based on the application.

Classification of digital twins regarding their structural functions

The recent surge in the use of digital twins across various applications has resulted in a proliferation of definitions, making it challenging to organize and comprehend the existing literature. Some authors, like Adrian Dima, categorize any digital model (such as CAD) as a digital twin, whereas others, like S.M.E. Sepasgozar (2021), emphasize the necessity of having an associated physical object. Additionally, it is highlighted the requirement for a data flow between these two entities [37]. This paper reviews the literature on digital twins, focusing on their design and manufacturing applications. It identifies key technical criteria and establishes a systematic classification framework, based on a previous study that integrated various classification approaches.

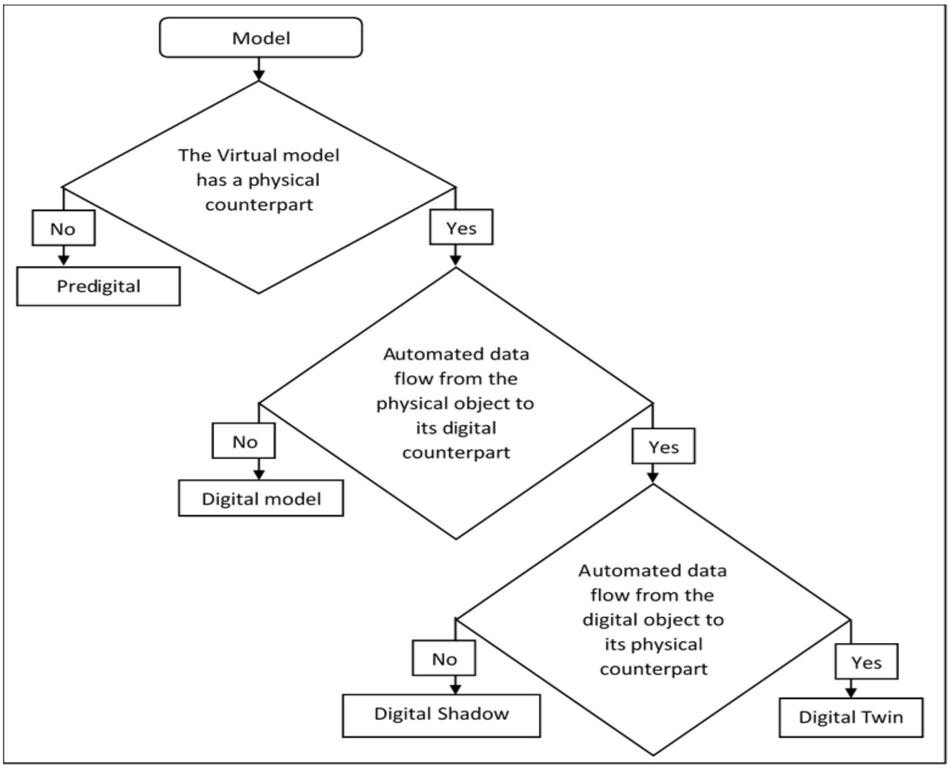

Fig.1: Flow chart of digital twins (Courtesy: Qinglin QI AND Fei Tao)

The outcome of this work is tuned to four subcategories and the same depicted in Fig.1, based on the

- The physical system's existence: The digital model under investigation might or might not match the real-world physical object it depicts.
- Model updates can occur automatically: The digital model may be easily updated with data obtained from the physical system. If not, updates based on data from the physical system will be sent to the model via user intervention.
- Control of the physical system: As a command from the physical system, data produced by the digital model's execution can be automatically sent to the physical system. If not, the digital model and its physical counterpart won't be able to automatically exchange information.
- A flow chart, shown in Fig. 1, has been developed based on these classification criteria so that readers of scientific publications pertaining to "Digital Twins" can identify the subcategory to which the digital twin in question belongs. The digital twins in this study are thus classified in 4 categories: Pre-Digital Twin (PDT), Digital Model (DM), Digital Shadow (DS) and Digital Twin (DT). These acronyms will be used in the rest of this study to describe each of these subcategories, while the term "digital twin" in all letters will be used to describe the whole thing.

o **Pre-Digital Twin (PDT)**: It is a virtual generic executable model of the envisioned system that is typically created before the physical prototype is built. It is used for decision-making and risk reduction during the design and development phase, before the physical prototype is built. Incorporates data from the design and analysis stages, but not yet real-time data from the physical object (Simulating and testing the design before physical implementation: Virtual prototypes of products, systems, or processes).

o **Digital Model (DM)**: It is primarily used for design, analysis, and simulation before physical prototypes are built. Typically, static, based on initial design data and may not include data in real time from the physical object (Visual representation and understanding of the object's form and functionality: 3D models, CAD files, simulations).

o **Digital Shadow (DS)**: Changes in the physical world are mirrored in the digital world, but not the other way around. It is a digital representation of a physical system or object with a one-way, automated data flow from the actual object to the digital model. A digital shadow's primary feature is its unidirectional data flow, which transfers information from the actual object to its digital representation.

o **Digital Twin (DT)**: A digital twin has been developed to function alongside and engage with actual physical production machinery, improving the digitalization features of computer-aided design (CAD). Cyber-physical systems utilize digital twins to depict real-time information from assets on the shop floor, creating a virtual representation of the physical system (Real-time monitoring, predictive maintenance, optimization, and performance simulation of the physical object: Digital replicas of machines, vehicles, buildings, or processes).

Digital twin's types: There are several categories of digital twins based on the degree of product enhancement. The primary distinction among these twins lies in their specific applications. It is typical for different forms of digital twins to exist concurrently within a system or process.

a) **Component/Parts twins**: As the simplest example of an operational component, component twins are the basic building block of a digital twin. Parts twins are similar in concept but refer to components that hold slightly less significance.

b) **Asset twins**: When multiple components collaborate, they create what is referred to as an asset. Asset twins make it possible to study how these elements interact, producing a substantial amount of performance data that can be examined and then turned into useful insights. To begin with, they enable the simulation of equipment components, which enhances predictive maintenance, a method that minimizes downtime and saves manufacturers significant amounts of money.

c) **System or Unit twins**: System or unit twins are the next degree of magnification, which lets you see how different assets come together to form a fully functional system. System twins provide information about how assets interact and may suggest areas for performance enhancements. Additionally, by utilizing product twinning, automotive companies can generate digital replicas of the cars they offer, track their condition, and alert vehicle owners of maintenance requirements before any failures happen, which enhances customer satisfaction and minimizes warranty costs. Thirdly, digital twins have the potential to transform a company's business model, with Kaeser, a producer of compressed air solutions, serving as a clear illustration of this trend. This organization adopted digital twin technology to monitor the data related to the air usage of their products. Rather than selling their systems outright to clients, they chose to bill customers based on the rate of air consumption. Fourth, the integration of product and asset twins is vital in shaping the industrial metaverse. Since digital twin technology makes it possible to accurately translate actual objects into the virtual world, it is inextricably tied to the metaverse. Therefore, businesses focusing on the establishment of virtual factories depend on product and asset twins to fully harness the capabilities of the metaverse.

d) **Process twins**: Process twins, at a high level of detail, illustrate the collaboration of various systems to form a complete production facility. They can help determine which precise timing tactics have the most effects on overall productivity. Digital twins for systems and processes are primarily utilized by large corporations that can invest in long-term development initiatives. Consequently, these organizations achieve higher levels of smart automation, alleviating employees from overwhelming workloads, decreasing defective batches, optimizing the use of electricity and water, improving safety, and gaining complete oversight of processes and production quality, similar to Unilever.

e) **Digital Twin Instance**: A specific digital twin linked to a particular physical product throughout its lifecycle.

f) **Digital Twin Prototype (DTP)**: A prototype of a digital twin, often used for testing and development.

g) **Digital Twin Environment (DTE)**: The environment in which digital twins are operated and managed.

Literature review:

Digital twin technologies have primarily been explored in the fields of manufacturing, aviation, and healthcare (B.R. Barricelli, E. Casiraghi, D. Fogli, 2019). The term 'digital twin' in construction research literature is confusing due to its association with BIM. Certain writers utilize the terms as if they mean the same thing, whereas other writers view them as distinct. This misunderstanding may obstruct the adoption of digital twins in the construction sector. Digital twins and BIM, which is defined as a collaborative approach for design, delivery, and maintenance, must be distinguished from one another [Y. Al-Saeed, D.J. Edwards, S. Scaysbrook. 2020; S. Kaewunruen, S. Peng, O. Phil-Ebosie. 2020; S.M.E. Sepasgozar. 2021; HM Government 2015; Valerian Vanessa Tuhaise, Joseph Handibry Mbatu Tah, Fonbeyin Henry Abanda 2023]. BIM, a 3D model developed using object-oriented software, is a crucial data repository for asset management and project communication. It contains information on geometric and functional aspects, time schedules, cost estimation, and asset management, enhancing project delivery practices when properly developed and managed (Valerian Vanessa Tuhaise et.al., 2023; T. Cerovsek. 2011; C.M. Eastman et.al., 2011; U. Çelik 2019; A. Jrade, J. Lessard.2015; M. Brunet,et.al.,2019; X. Xu, L. Ma, L. Ding. 2014). The Building Information Modeling (BIM) model has limitations in providing real-time data for construction projects and assets, which is crucial for informed decision-making. This data is often not fully utilized, leading to underutilization and ineffective decision-making. The BIM model also requires advanced technologies for storage and processing large sets of dynamic data. The digital twin system aims to address these limitations by connecting physical entities to virtual models, allowing data exchange between them, thereby addressing the limitations of BIM. A Building Information Modeling (BIM) model acts as a critical base for creating a digital twin in the construction industry. This technology establishes a link between the BIM model and the physical environment, allowing for two-way data exchange. Real-time data updates the BIM model, facilitating better asset management and informed decision-making. Digital twins utilize sophisticated data analytics methods, such as artificial intelligence, to analyze extensive datasets, which enables condition monitoring, forecasts, diagnostics, prognostics, and optimization of systems. These features have the potential to significantly increase information management and decision-making in construction procedures, which will increase construction and asset management efficiency (Valerian Vanessa Tuhaise et.al., 2023). Digital twins are increasingly being used in the construction industry, according to five systematic literature reviews. An outline of the state of digital twin research in the AECO-FM sector may be found in Ozturk's bibliometric study. The study by Boje et al. looks at how digital twins are regarded in different engineering disciplines and suggests possible areas where a digital twin might improve BIM use throughout the building phase (Valerian Vanessa Tuhaise et.al., 2023, C. Boje, A. et.al.,2020; F. Jiang, L. Ma, et.al.,2021; D.G.J. Opoku, et.al.,. 2021; M. Deng, C.C. Menassa, V.R. Kamat 2021; G.B. Ozturk 2021]. Opoku et al. (2021) explored digital twin applications in project lifecycle phases, Deng et al. (2021) examined built areas and current capabilities, and Jiang et al. (2021) investigated civil engineering applications. The reviews did not examine the current state of existing technologies for digital twin development, highlighting the significant technological challenges they present. Emerging technologies are being developed for various applications, but it's unclear which ones are key to their success. This paper explores the use of digital twins in construction, identifies research gaps, and suggests potential areas for future study. The adoption of digital technologies in the AEC industry is influenced by organizational challenges like lack of expertise, financial constraints, cultural barriers, resistance to change, and competing initiatives. A digital twin typically necessitates a data link between a physical entity and its virtual model (A. Al-Yami, M.O. Sanni-Anibire 2021; X. Zhao, et.al.,2018; U. Farooq et.al.,2020; S. Vass, T.K. Gustavsson. 2017; H. Lindblad. 2019). The structure, function, condition, location, processes, and performance of the physical environment are all reflected in the virtual representation created by modeling technology. Data connectivity is supported by the Internet of Things (IoT), enabling two-way communication between virtual and physical entities. Through application layer protocols, IoT technologies transmit vast amounts of data from many sources in the physical world to the virtual model. This data is integrated into the virtual model, providing human-understandable abstractions and inferences (M. Macchi 2018; M.J. Kaur 2020). Advanced data analytics technologies process digital twin data, providing various services to users, which are made accessible through data visualization supported by visualization technologies. The digital twin system architecture includes five development layers: data acquisition, transmission, digital modelling, data/model integration, and service, utilizing high-fidelity models, bi-directional data transfer, and processing capabilities [20,21]. The data acquisition layer involves technologies for data collection and data set creation, while the transmission layer involves networking, communication, and various protocols. The digital modeling layer evaluates physical entity parameters, creating virtual representations, while the data/model integration layer facilitates data storage, processing, analysis, visualization, and integration with AI, machine learning, and simulation engines. The study identifies four sub-categories of the data/model integration layer: data storage, data/model integration, processing, analysis, and visualization.

Framework of digital twin technology: The digital twin framework [26,35] is categorized in four stages (Fig.2)

Fig.2: Framework of Digital Twin Technology

- **Infrastructure:** Website capabilities, monitoring centers, cloud computing resources, modern hardware, and networking facilities are all examples of infrastructure. It must to be accessible for the region that uses the "digital twin" strategy.
- **Data gathering:** Along with three-dimensional information, such as 3D Geographical Information Systems (GIS), Building Information Modelling (BIM), oblique photography, geolocation data from internet usage, real-time perception data from the Internet of Things, other sensing software, and unstructured media like images, videos, and documents, data also includes traditional information, such as traditional surveying and mapping.
- **Information model construction:** The virtual environment will be modeled using data gathered from several information sources. For example, the yard, buildings, parking lots, green space, and the wharf apron loading and unloading zone are all included as features in the port operations model. Quantitative data regarding monomers will result from this. For monitoring operations in real time and visualizing data, including traffic flow, air pollution index, and real-time operating video pictures, among other things. Perception data from the Internet of Things should be imported, merged, and shown in real time on the model platform.
- **Application service platform construction:** Application platforms should incorporate planning, construction management, operation and maintenance, and public services. Testing how each design and building project will be received once it is finished is essential before putting it into action. Using the virtual and real components of this paradigm, the state of the digital twin's application during physical operations may be completely shown, and bottlenecks can be identified to improve capacity and efficiency. It is possible to forecast in advance how any modifications to plans or programs will affect the general pattern of development.

Flow of data in information management in digital twin: Following Diagram shows the flow of data (Fig.3) in Information management in Digital Twin

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Fig.3: Information flow in Digital Twin Technology

The system collects and compiles AI-detected data, performs analytical tasks, and shares information for real-time business processes, enabling efficient communication and decision-making, thereby enhancing business efficiency.

Research methodology: This paper uses a systematic literature review (SLR) to identify, evaluate, and synthesize existing knowledge on this proposed topic of subject. The SLR process involves three stages: planning, implementation, and reporting. The planning phase involves framing research questions and creating criteria for locating materials and research methods. The implementation phase involves collecting and selecting materials for the study. The reporting phase combines and analyzes the literature.

Research questions
To outline the focus of the systematic literature review, the subsequent research questions were explored:
Q1: What elements make up digital twins in applications of digital twins within the construction industry?
Q2: What technologies are currently utilized in the creation of digital twins?
Q3: What are the existing research gaps and possible directions for future investigation?

Findings: The findings of survey are as is follows:
A digital twin is made up of three main parts: a system or physical item, a virtual model (or digital copy) of that system, and the information and connection that connects them, allowing for real-time data analysis and sharing.

- **Physical Object/System**: This is the real thing that the digital twin represents, whether it be a machine, a building, a product, or a process. To gather information about its condition, performance, and surroundings, it is outfitted with sensors and additional technologies.
- **Virtual Model/Digital Replica**: CAD, PLM, and other modeling technologies are frequently used to construct this digital version of the real thing. It is a dynamic model that mimics the behavior and condition of the real item by updating in real time based on data received from it. Analysis, optimization, and simulation may all be done using the virtual model.
- **Data and Connectivity**: The infrastructure and procedures for gathering, sending, and handling data between the virtual model and the real object are included in this component. It consists of communication networks, sensors, Internet of Things devices, and middleware for data processing. The virtual model is updated using this data, which also offers insights into the functionality and behavior of the real thing. Real-time monitoring, predictive maintenance, and optimization are made possible by the data and connections that make the digital twin a dynamic and interactive representation of the physical thing.

Existing technologies used in the development of digital twins: To produce a virtual representation of physical things and systems, digital twin development uses a variety of technologies, such as cloud computing, artificial intelligence (AI), extended reality (XR), and the Internet of Things (IoT).

Core Technologies are as follows:

Internet of Things (IoT): In order to update the digital twin, real-time data from physical assets and systems is gathered via IoT devices like sensors and actuators.
Artificial Intelligence (AI) and Machine Learning (ML): The vast volumes of data gathered by IoT devices are processed using AI and ML algorithms to find trends and forecast how the digital twin will behave.
Extended Reality (XR): Users may explore and engage with the virtual representation thanks to interactive and immersive representations of the digital twin made possible by XR technologies like Virtual Reality (VR) and Augmented Reality (AR).
Cloud Computing: Cloud platforms offer the infrastructure needed to host the digital twin models and apps as well as store and analyze the massive volumes of data produced by digital twins.
Supporting Technologies are as follows:

- **Simulation Software**: Through the creation and operation of models of the actual assets and systems, simulation software enables users to evaluate various scenarios and maximize performance.
- **CAD Software**: The digital twin model is built around the geometric representation of the actual assets, which is produced using CAD software.
- **Data Analytics**: The digital twin is updated using data analytics techniques to glean insights from the data gathered by IoT devices.
- **Edge Computing**: By processing data closer to the source, edge computing lowers latency and enhances real-time performance.
- **Fog Computing**: By adding a layer of processing and storage between the edge and the cloud, fog computing expands the potential of edge computing.
- **Meta space**: Digital twins can have an engaging and participatory environment because to the metaverse.

3) The research gaps and potential areas for future research: In addition to difficulties with data quality, availability, and integration, digital twin research faces deficiencies in fundamental mathematics, statistics, and computation. Additionally, more advanced modeling and artificial intelligence techniques are required for dynamic updating and prediction. These topics, such as uncertainty quantification, data-driven and mechanistic model coupling, and interoperability among digital twin models, should be the focus of future study.

Foundational Gaps:
Mathematical, Statistical, and Computational Foundations: Further investigation into the computational, statistical, and mathematical foundations of digital twin technologies is required.
Inverse Problem Methodologies and Data Assimilation: Particularly for calibrating and updating digital twins on actionable time scales, efficient methods are required to rigorously and scalablely integrate physical observations and virtual models.
Machine Learning and AI: When it comes to problems like guiding data gathering through active and reinforcement learning and continuously updating models utilizing streaming data, AI and machine learning can be extremely helpful.

Data-Related Challenges:
Data Quality, Availability, and Affordability: To create and maintain accurate and trustworthy digital twins, it is essential to guarantee the quality, accessibility, and cost of data.
Data Integration: It is crucial to create reliable techniques for combining data from multiple sources, such as sensors, simulations, and BIM models.
Data Ownership and Privacy: It's imperative to address privacy and data ownership issues, particularly in delicate applications like security and healthcare.

Benefits of Using Digital Twins: Digital twins are utilized in various applications (Fig.4 & Fig.5) such as anomaly detection, asset management, and fleet management. They can be executed on smart assets, edge, or IT/OT layers depending on the application's response time. For instance, predictive maintenance requires real-time or time-sensitive decisions. Multiple digital twins can be deployed differently into the system topology.

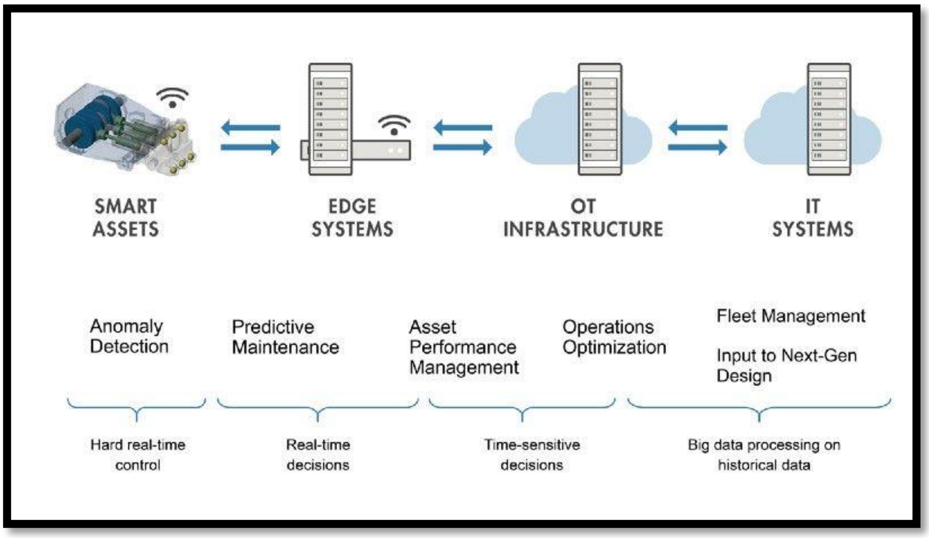


Fig.4: Application scope of Digital twin

Asset History: A digital twin captures the real asset's history, updated periodically to represent its current state. This history includes past states, which may differ based on the model's usage. Comparing operational data from one pump to others in the digital twin allows understanding of faults and fleet efficiency under similar faults.
Maintenance Strategies: Digital twins offer enhanced fleet monitoring, enabling better planning of operational events and maintenance strategies. They can assess the impact of potential pump failures on fleet efficiency and potential costs.

Simulate Future Scenarios: This strategy aids asset management and operational optimization by informing maintenance staff about anticipated failures in advance, enabling them to plan for future repairs and replacements.

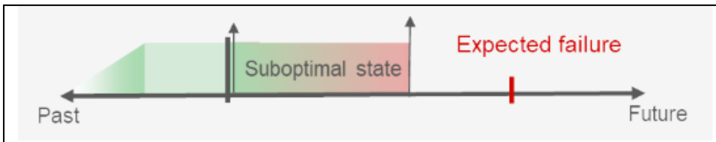
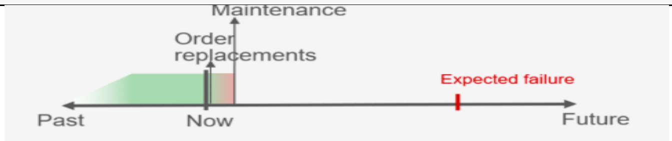
	**Scenario A: Order parts and run the pump in a suboptimal state until they arrive.**
	**Scenario B: Spend more to expedite shipping to get the parts quickly and reduce time spent running sub optimally.**

Fig.5: Maintenance Strategies

Digital Twin modeling methods: Digital twin modeling (Fig.6, Fig.7, Fig.8 & Fig.9) is a process that involves creating virtual representations of physical assets and systems that can be updated in real-time using data from sensors and other sources.

Fig.6: Digital Twin modeling methods

To optimize maintenance schedules, use a data-driven model estimating remaining useful life (RUL) based on pump data type. Similarity models can be used for complete histories of similar machines, survival models for data from failure time, and degradation models for estimating RUL without failure data but knowing a safety threshold.

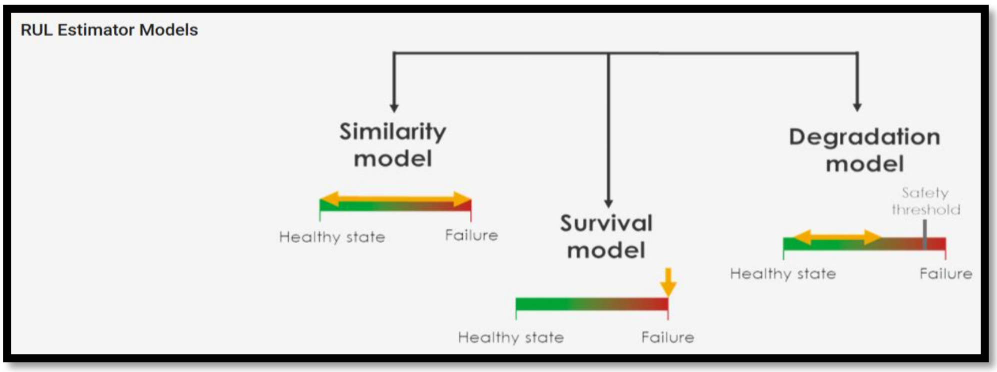


Fig.7: RUL model

To simulate future scenarios and monitor fleet behavior, a physics-based model can be used. This model connects mechanical and hydraulic components and is fed with pump data. It estimates and tunes parameters to keep the model updated. This allows for the injection of different fault types and simulation of pump behavior under different conditions.

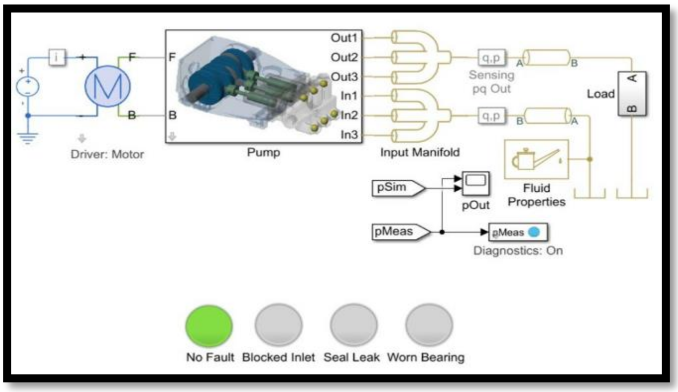


Fig.8: Physics-based model.

Data and Physics Combined - Kalman Filters: A Kalman filter can function as a digital twin, modeling pump degradation and updating it periodically to represent its current condition.

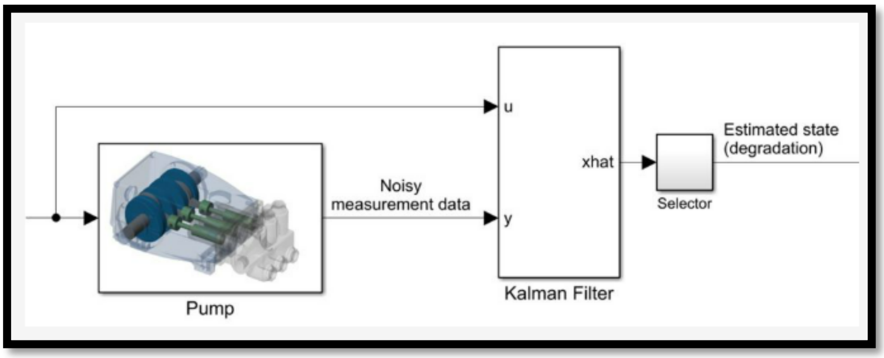


Fig.9: Data and Physics Combined - Kalman Filters

Challenges in applying digital twins: Digital twins face challenges in real-time matching complex assets, as they can exceed company culture, resources, and data governance capabilities.

The text outlines potential challenges that may arise when utilizing digital twins.

Cost: Digital twins require significant investments in technical platforms, model creation, and high-touch maintenance, despite declining expenses. It's crucial to compare their implementation with other strategies for cost-effective results.
Precise representation: Digital twins will not be exact replicas of physical counterparts in the future due to the difficulty and cost of matching complex assets' physical, chemical, electrical, and thermal states, necessitating engineers to balance their intended characteristics.
Data quality: Good data is crucial for effective models in digital twin applications, which rely on data from numerous remote sensors in challenging field settings and unreliable networks. Companies must establish procedures to manage gaps, irregularities, and identify and isolate erroneous data.
Interoperability: Despite advancements in openness and standardisation, commercial and technical obstacles persist in data interchange, particularly for digital twins relying on specific vendors' simulation or AI tools, requiring long-term partnerships with a single source.
Education: Digital twin deployment requires employees, clients, and suppliers to adapt new working practices, posing challenges in managing change and developing capabilities. Organizations must ensure users are motivated and have the necessary knowledge and resources to connect with digital twins, often requiring a significant culture shift.
Cyber security: Cybercriminals are likely to see digital twins as appealing targets. The connections between physical items and their digital counterparts provide malicious actors aiming to disrupt an organization's operations with a new vulnerability. When digital twins are employed to oversee their physical analogs, any breach could have swift and possibly catastrophic real-world consequences. Given these attributes, prioritizing the cybersecurity of digital twins is essential and will present new challenges for many organizations.
Internet: Internet access is crucial for the application of various technologies, and 5G technology is currently used. One web, a communications company, aims to build broadband satellite Internet services, but technical reformation is needed for stable connectivity.

Discussion: In this digital era, entrepreneurs are very much interested to know how the asset will behave over an operational period. To understand this concept the entrepreneurs are initially preparing digital models and understanding the operational performance of the digital model. There after entrepreneurs constructing the real time asset and data is allowed to flow either one or bi directional to addressed the challenges if arises, if any. Digital twin simplifies in addressing the issue/problem of real time asset.

Conclusion: From the study it is concluded that the digital twin is suitable for asset/s which are critical in running/operating condition under different dynamics and these dynamics, which are beyond human control as well as digital twin is suitable in attending performance failures, easily instead of attending every component through longer inspection time. But, the same/asset failure shall be studied from a digital twin and the same/asset failure performance failure and can be fixed smoothly, easily, less effort and over shorter duration/s. It may result in asset breakdown over shorter duration period.

References:

1. Al-Yami, M.O. Sanni-Anibire. (2021), BIM in the Saudi Arabian construction industry: state of the art, benefit and barriers, International Journal of Building Pathology and Adaptation 39 (1) (2021) 33–47, https://doi.org/10.1108/IJBPA-08-2018-0065.
2. Jrade, J. Lessard.(2015), An integrated BIM system to track the time and cost of construction projects: a case study, Journal of Construction Engineering 2015 (2015) 1–10, https://doi.org/10.1155/2015/579486.
3. Marefat, H. Toosi, R. Mahmoudi Hasankhanlo, A BIM approach for construction safety: applications, barriers and solutions, Engineering Construction and Architectural Management 26 (9) (2019) 1855–1877, https://doi.org/10.1108/ECAM-01-2017-0011.
4. Adrian Dima. The Four Industrial Revolutions: Transforming Manufacturing Across Centuries. https://kfactory.eu/the-industrial-revolution-short-history-of-manufacturing/
5. B.R. Barricelli, E. Casiraghi, D. Fogli. (2019), A survey on digital twin: definitions, characteristics, applications, and design implications, IEEE Access 7 (2019) 167653–167671, https://doi.org/10.1109/ACCESS.2019.2953499.
6. Boje, A. Guerriero, S. Kubicki, Y. Rezgui.(2020), Towards a semantic construction digital twin: directions for future research, Automation in Construction 114 (2020), 103179, https://doi.org/10.1016/j.autcon.2020.103179.
7. C.K. Lo, C.H. Chen, Ray Y. Zhong. (2021), A review of digital twin in product design and development, Advanced Engineering Informatics, Volume 48, 2021, 101297, ISSN 1474-0346, https://doi.org/10.1016/j.aei.2021.101297. (https://www.sciencedirect.com/science/article/pii/S1474034621000513)
8. C.M. Eastman, C. Eastman, P. Teicholz, R. Sacks, K. Liston.(2011), BIM Handbook: A Guide to Building Information Modeling for Owners, Managers, Designers, Engineers and Contractors, John Wiley & Sons, 2011, 0470541377.
9. Concetta Semeraro, Mario Lezoche, Hervé Panetto, Michele Dassisti.(2021), Digital twin paradigm: A systematic literature review, Computers in Industry, Volume 130, 2021, 103469, ISSN 0166-3615, https://doi.org/10.1016/j.compind.2021.103469.
10. D.-G.J. Opoku, S. Perera, R. Osei-Kyei. (2021), M. Rashidi, Digital twin application in the construction industry: a literature review, Journal of Building Engineering 40(2021), 102726, https://doi.org/10.1016/j.jobe.2021.102726.
11. F. Jiang, L. Ma, T. Broyd, K. Chen.(2021), Digital twin and its implementations in thecivil engineering sector, Automation in Construction 130 (2021), 103838, https://doi.org/10.1016/j.autcon.2021.103838.
12. G.B. Ozturk (2021), Digital twin research in the AECO-FM industry, Journal of Building Engineering 40 (2021), 102730, https://doi.org/10.1016/j.jobe.2021.102730.
13. H. Lindblad. (2019), Black boxing BIM: the public client's strategy in BIM implementation, Construction Management and Economics 37 (1) (2019) 1–12, https://doi.org/10.1080/01446193.2018.1472385.
14. HM Government (2015), Digital Built Britain Level 3 Building Information Modelling - Strategic Plan, Available at, https://assets.publishing.service.gov.uk/govern ment/ uploads/ system/uploads/attachment_data/file/410096/bis-15-155-digitalbuilt-britain-level-3-strategy.pdf, 2015 [Accessed 01.08.2022].

15. M. Brunet, A. Motamedi, L.M. Guenette, D. Forgues.(2019), Analysis of BIM use for asset management in three public organizations in Quebec, Canada, Built Environment Project and Asset Management 9 (1) (2019) 153–167, https://doi.org/10.1108/bepam-02-2018-0046.
16. M. Deng, C.C. Menassa, V.R. Kamat, (2021), From BIM to digital twins: a systematic review of the evolution of intelligent building representations in the AEC-FM industry, Journal of Information Technology in Construction 26 (2021) 58–83, https://doi.org/10.36680/j.itcon.2021.005.
17. M. Macchi, I. Roda, E. Negri, L. Fumagalli.(2018), Exploring the role of digital twin forasset lifecycle management, IFAC-PapersOnLine 51 (11) (2018) 790–795, https://doi.org/10.1016/j.ifacol.2018.08.415.
18. M.J. Kaur, V.P. Mishra, P. Maheshwari.(2020), The convergence of digital twin, IoT, and machine learning: Transforming data into action, in: M. Farsi, A. Daneshkhah, A. Hosseinian-Far, H. Jahankhani (Eds.), Digital Twin Technologies and Smart Cities, Springer Cham, 2020, pp. 3-17, 978-3-030-18732-3.
19. Mengnan Liu, Shuiliang Fang, Huiyue Dong, Cunzhi Xu. (2021), Review of digital twin about concepts, technologies, and industrial applications, Journal of Manufacturing Systems, Volume 58, Part B, 2021, Pages 346-361, ISSN 0278-6125, https://doi.org/10.1016/j.jmsy.2020.06.017.
20. Q. Lu, A.K. Parlikad, P. Woodall, G. Don Ranasinghe, X. Xie, Z. Liang, E. Konstantinou, J. Heaton, J. Schooling.(2020), Developing a digital twin at building and city levels: case study of West Cambridge campus, Journal of Management in Engineering 36 (3) (2020) 05020004, https://doi.org/10.1061/(asce)me.1943-5479.0000763.
21. Q. Qi and F. Tao, (2018). "Digital Twin and Big Data Towards Smart Manufacturing and Industry 4.0: 360 Degree Comparison," in IEEE Access, vol. 6, pp. 3585-3593, 2018, doi: 10.1109/ACCESS.2018.2793265.
22. Qinglin Qi, Fei Tao, Tianliang Hu, Nabil Anwer, Ang Liu, Yongli Wei, Lihui Wang, A.Y.C. Nee. (2021), Enabling technologies and tools for digital twin, Journal of Manufacturing Systems, Volume 58, Part B, 2021, Pages 3-21, ISSN 0278-6125, https://doi.org/10.1016/j.jmsy.2019.10.001.
23. S. Kaewunruen, S. Peng, O. Phil-Ebosie.(2020), Digital twin aided sustainability and vulnerability audit for subway stations, Sustainability 12 (19) (2020) 7873, https://doi.org/10.3390/su12197873.
24. S. Vass, T.K. Gustavsson. (2017), Challenges when implementing BIM for industry change, Construction Management and Economics 35 (10) (2017) 597–610, https://doi.org/10.1080/01446193.2017.1314519.
25. S.M.E. Sepasgozar.(2021), Differentiating digital twin from digital shadow: elucidating a paradigm shift to expedite a smart, sustainable built environment, Buildings 11(4) (2021) 151, https://doi.org/10.3390/buildings11040151.
26. Shailendra Pawaskar, Ravindra Dhonde (2022), Digital Twin Technology: A Review Of Applications And Challenges, Futuristic Trends in Management e-ISBN: 978-93-5747-733-8, IIP Proceedings, Volume 2, Book 6, Part 4, Chapter 4.
27. T. Cerovsek. (2011), A review and outlook for a 'building information model'(BIM): a multi-standpoint framework for technological development, Advanced Engineering Informatics 25 (2) (2011) 224–244, https://doi.org/10.1016/j.aei.2010.06.003.
28. T.O. Olawumi, D.W.M. Chan, J.K.W. Wong, A.P.C. Chan, Barriers to the integration of BIM and sustainability practices in construction projects: a Delphi survey of international experts, Journal of Building Engineering 20 (2018) 60–71, https://doi.org/10.1016/j.jobe.2018.06.017.
29. U. Çelik (2019), 4D and 5D BIM: A System for Automation of Planning and Integrated Cost Management, Eurasian BIM Forum, Springer, 2019, pp. 57–69, https://doi.org/10.1007/978-3-030-42852-5_5.

30. U. Farooq, S.K.U. Rehman, M.F. Javed, M. Jameel, F. Aslam, R. Alyousef.(2020),, Investigating BIM implementation barriers and issues in Pakistan using ISM approach, Applied Sciences 10 (20) (2020) 7250, https://doi.org/10.3390/app10207250.
31. Valerian Vanessa Tuhaise, Joseph Handibry Mbatu Tah, Fonbeyin Henry Abanda. (2023), Technologies for digital twin applications in construction, Automation in Construction 152 (2023) 10493., https://doi.org/10.1016/j.autcon.2023.104931
32. X. Xu, L. Ma, L. Ding. (2014), A framework for BIM-enabled life-cycle information management of construction project, International Journal of Advanced Robotic Systems 11 (8) (2014) 126, https://doi.org/10.5772/58445.
33. X. Zhao, P. Wu, X. Wang. (2018), Risk paths in BIM adoption: empirical study of China, Engineering Construction and Architectural Management 25 (9) (2018) 1170–1187, https://doi.org/10.1108/ECAM-08-2017-0169.
34. Y. Al-Saeed, D.J. Edwards, S. Scaysbrook. (2020), Automating construction manufacturing procedures using BIM digital objects (BDOs), Construction Innovation (2020), https://doi.org/10.1108/CI-12-2019-0141.
35. Yao, H., Wang, D., Su, M., & Qi, Y. (2021, March). Application of Digital Twins in Port System. In Journal of Physics: Conference Series (Vol. 1846, No. 1, p. 012008). IOP Publishing.
36. B. Ravinder, Fire Door Awareness Among the Stake Holders of Construction Industry (2020). International Journal of Application or Innovation in Engineering & Management (IJAIEM), 9(6), 63-68, June 2020, https://ssrn.com/abstract=3648824
37. Jrade, A., & Lessard, J. (2015). An Integrated BIM System to Track the Time and Cost of Construction Projects: A Case Study. Journal of Construction Engineering, 2015, 1–10. https://doi.org/10.1155/2015/579486