Chapter 8
COGNIBUILD: Cognitive Digital Twin Framework for Advanced Building Management and Predictive Maintenance

Sofia Agostinelli

Abstract According to contemporary challenges of digital evolution in management and maintenance of construction processes, the present study aims at defining valuable strategies for building management optimization. As buildings' and infrastructures' Digital Twins (DT) are directly connected to physical environment through the Internet of Things (IoT), asset management and control processes can be radically transformed. The proposed DT framework connects building information model (BIM) three-dimensional objects to information about the planned maintenance of components, supplying system's self-learning capabilities through input data coming from Building Management Systems (BMSs), ticketing, as well as maintenance activities' data flow both as-needed or unexpected. The concept of real-time acquisition and data processing set the basis for the proposed system architecture, allowing to perform analysis and evaluate alternative scenarios promptly responding to unexpected events with a higher accuracy over time. Moreover, the integration of artificial intelligence (AI) allows the development of maintenance predictive capabilities, optimizing decision-making processes and implementing strategies based on the performed analysis, configuring a scalable approach useful for different scenarios. The proposed approach is related to the evolution from reactive to proactive strategies based on Cognitive Digital Twins (CDTs) for Building and Facility Management, providing actionable solutions through operational, monitoring and maintenance data. Through the integration of BIM data with information systems, BMS, IoT and machine learning, the optimization and real-time automation of maintenance activities are performed, radically reducing failures and systems' breakdowns. Therefore, integrating different technologies in a virtual environment allows to define data-driven predictive models supporting Building Managers in decision-making processes improving efficiency over time and moving from reactive to proactive approaches.

Keyword Cognitive building · Artificial intelligence · Digital Twin · Predictive maintenance · Facility management · Building information modeling

S. Agostinelli (✉)
Sapienza University of Rome, Rome, Italy
e-mail: sofia.agostinelli@uniroma1.it

E. Arbizzani et al. (eds.), *Technological Imagination in the Green and Digital Transition*, The Urban Book Series, https://doi.org/10.1007/978-3-031-29515-7_8

8.1 Introduction

The new Industrial Revolution (Oliveira and Afonso 2019) is related to digital automation enhancing quality and effectiveness of processes.

The construction sector is facing such a slow digital growth named Construction 4.0 involving new digital strategies based on technologies, connectivity, devices and cloud platforms. Interoperability of data and automation of processes are some of the main goals toward decision-making systems' decentralization, even though the construction industry is still appearing resistant.

Internet of Things (IoT), smart sensors, cloud computing, 5G networks, Extended Reality (XR) and Digital Twins (DT) are new paradigms of Construction 4.0 in the operation and maintenance (O&M) phase, which actually represents one of the higher costs of a building's life cycle (30%), as observed by Mourtzis et al. (2017).

New building maintenance strategies based on digital systems and data-driven technologies introduce proactive approaches to Facility Management (FM) of building systems such as failure prediction, effort estimation, or energy consumption optimization (Jasiulewicz-Kaczmarek et al. 2020).

Predictive maintenance is the main objective of such data-driven strategies, which can provide up to 630 billion in maintenance savings in 2025, as observed by McKinsey (2022).

In O&M 4.0, fault prediction and production efficiency are enabled by two main components: (a) sensor data and (b) data analysis across the entire life cycle of assets from design to the operation and maintenance phase.

In this regard, the present study aims at investigating different O&M strategies introducing the use of Digital Twins (DTs). In fact, the Building Management phase could be redefined using DT-based solutions for virtual and physical integration (Qi and Tao 2018) providing new DT-enabled strategies for operation and maintenance optimization.

8.2 Digital Twin Paradigm in Operation and Maintenance

8.2.1 Digital Twin Definitions

The concept of DT first appeared in 2002, and since then, many definitions evolved over time. In 2012, Dr. Michael Grieves introduced a first clear definition of the DT concept as the connection of data between physical and virtual products (Grieves and Vickers 2017). This enabling information set consists of data related to the assets such as geometry, operational and technical information up to their functional behavior. In this regard, Rosen defined the DT as a mirror between physical and virtual objects allowing data analysis across the entire asset life cycle (Rosen et al. 2015). Moreover, the concept of DT is enabled by algorithms for data-driven actions and decision-making systems. In fact, the effective relation between physical and

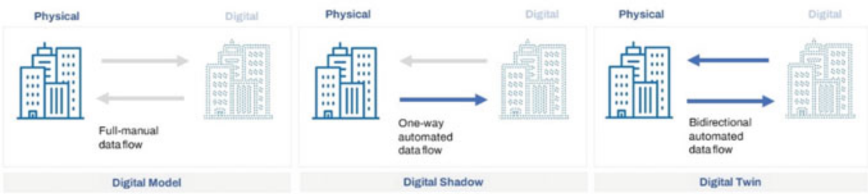

Fig. 8.1 Digital model, digital shadow, and digital twin (Kritzinger et al. 2018)

digital is enabled by data acquisition systems and processing technologies, with the aim of providing predictive capabilities (Liu et al. 2019) in order to promptly respond to the unexpected.

Specifically, DTs are composed of three main parts: physical, virtual and the connection between them. As mentioned, the DT is considered as a virtual mirror describing the physical properties of the system, delivering and receiving information (Tharma et al. 2018) for control, monitoring and decision-making processes.

An effective DT needs to be always connected and synchronized while running simulations of the physical counterpart over time. Depending on data flow and interaction levels between physical and digital, DT is defined in different key levels (Fig. 8.1) (Kritzinger et al. 2018):

- Digital Model—data flow between physical and digital is full-manual.
- Digital Shadow—only data flow from physical to digital is automatic.
- Digital Twin—data flow between physical and digital is bidirectionally automatic.

In the third level, the DT acquires data from sensors or on-site inspections, and it is also able to provide insights in terms of actions to be performed on the physical asset, such as the maintenance tasks as resulted from the status information acquired from sensors.

8.3 Maintenance Strategies and DT Application

In this paragraph, different maintenance strategies are analyzed and related to potential outcomes from DT implementation as defined in Table 8.1.

Reactive maintenance—it consists of maintenance activities not previously planned and caused by breakdowns (Swanson 2001) resulting in renewal of the damaged asset and causing big impacts on costs due to service interruption and production delays, etc.

As this type of maintenance approach is based on asset repairing, DTs can be applied to promptly detect failure's causes through models and simulations. However, the application of DTs determines improvements in the use of proactive maintenance approaches.

Table 8.1 Maintenance strategy and potential outcomes from DT implementation

Maintenance strategy	Definition	Implementation of DTs
Reactive maintenance	Unplanned maintenance resulted from breakdowns and damaged assets	DTs allows failure detections through models and simulations
Preventive maintenance	Proactive strategy defined by asset managers aimed at preventing or reducing failures	DTs can improve maintenance planning through data-driven strategies
Condition-based maintenance	Deviation monitoring from asset's optimal behavior through IoT, connectivity and cloud computing technologies, anticipating a planned maintenance activity	Data acquisition from sensors supplies analytical models creating a real-time knowledge base for cognitive systems
Predictive maintenance	Predicting a system's remaining life by merging data from different sources through data-driven or model-driven approaches	DTs analyze the asset's current state and behavior resulting in valuable predictions of component breakdowns
Prescriptive maintenance	Optimization of maintenance predictions using historical and real-time data and resulting in proactive activity plans	CDTs provide actionable information on maintenance activities enabled by artificial intelligence based on historical and real-time data

Preventive maintenance—it is a proactive maintenance strategy aimed at preventing or reducing breakdowns (Shafiee 2015) in order to minimize/avoid service interruptions. This approach is based on the asset manager's experience who defines time and frequency and planning service interruption (Bashiri et al. 2011). This strategy is based on over-maintaining strategies ensuring safety and productivity but still resulting in higher costs.

In this scenario, DTs can provide great improvements through data-driven planning systems for maintenance activities as it is traditionally developed by asset managers.

Condition-based (CBM) maintenance—it is based on monitoring the deviation from asset's optimal behavior through the use of IoT, connectivity and Cloud computing technologies, usually resulting in anticipating a planned maintenance activity (Nikolaev et al. 2019). This kind of approach can be improved by artificial intelligence systems acquiring and processing maintenance actual data over time (Mabkhot et al. 2018).

Following CBM strategies, sensors and real-time communication provided by the configuration of DTs help improving and supporting decision-making.

Data acquisition from sensors supplies the analytical models creating a knowledge base for cognitive systems resulting in asset condition representation for real-time monitoring.

Predictive maintenance—it is based on simulating and predicting a system's remaining lifetime combining and analyzing data from different sources (Fang et al. 2017; Werner et al. 2019) through data-driven approaches based on the availability of a large amount of sensors' data providing information on the asset state. Data analysis algorithms are performed and provide results based on data processing (Liu et al. 2018). This data-driven strategy is based on mathematical analytical models describing the component degradation (Sivalingam et al. 2018).

As abovementioned, Digital Shadows are introduced in CBM and predictive maintenance, as the Digital Model is automatically provided with state information.

DTs are based on predictive models evaluating and analyzing the asset's current state and behavior resulting in valuable predictions of possible component breakdowns.

Prescriptive maintenance—it is based on the optimization of maintenance merging historical and real-time data and resulting in proactive activity plans based on prediction (Consilvio et al. 2019; Matyas et al. 2017) in order to optimize cost, productivity, service and safety.

In prescriptive maintenance strategies, the integration of DTs is essential, as they provide actionable information on maintenance activities based on historical and real-time data. This integration involves the DT in a sort of activities' recommendation systems for operators through data analytics and artificial intelligence-enabled Cognitive Digital Twins (CDT). Despite progresses in this research field, applications of such CDT-based prescriptive maintenance are still only found in energy and manufacturing industry.

Adopting proactive strategies in maintenance is necessary to avoid breakdowns and detect inefficiencies by constantly monitoring the asset. In this way, real-time information is obtained, and behavior analysis is constantly performed allowing prompt diagnosis when failures occur.

Such proactive approach can be evolved combining historical and real-time data analysis through predictive models, resulting in failure prediction. This strategy can be applicable to several contexts and sectors where maintenance costs are high (Tao et al. 2019), allowing advantages such as limited downtimes and breakdowns, cost savings, enhanced productivity, clearly defined maintenance activities, reduced energy consumption, enhanced asset security.

In the diagram below (Fig. 8.2), information needed and monitoring approaches in proactive and reactive maintenance strategies are compared, and the CDT scenario is introduced.

The creation of accessible cloud-based CDTs providing real-time status information is a good chance to improve advanced predictive strategies, optimizing and reducing unnecessary activities (Tang et al. 2018; Pivano et al. 2019; Liew et al. 2019). In this regard, Immersive Extended Reality (XR) is also a valuable technology to visualize data and show component failures.

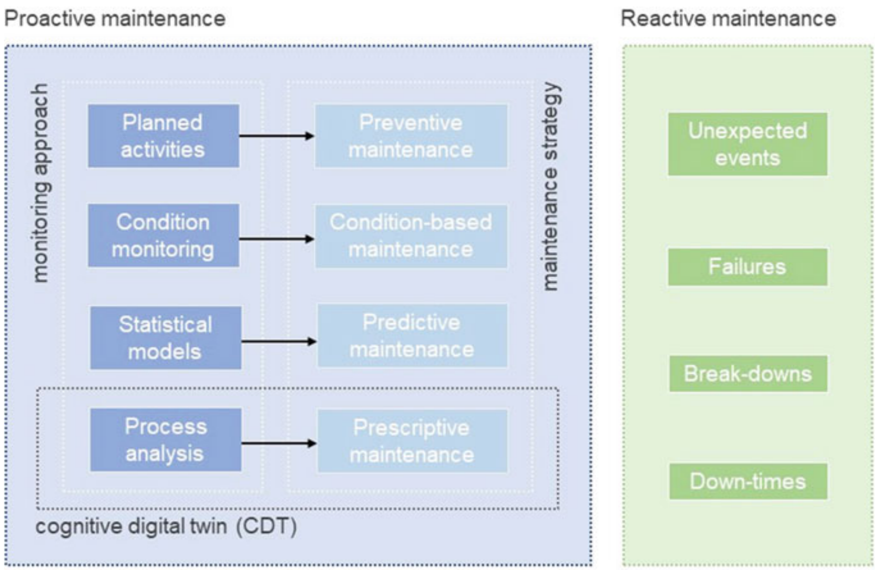

Fig. 8.2 CDT proactive strategies versus reactive maintenance

8.4 COGNIBUILD—A Cognitive Digital Twin Framework for Building Maintenance

When integrating asset, operational and historical data from a variety of sources, data availability becomes a prominent issue.

Big Data Management platforms enabling scalability, replicability and ubiquity are needed, optimizing data fusion and improving data models. Also, cybersecurity and blockchain are elements to be considered for ensuring data security (Longo et al. 2019).

As mentioned, the use of DTs is scalable and applicable in different maintenance approaches; for example, in preventive strategies, DTs can be used in the planning scheduling phase. In CBM, DTs provide real-time asset and health monitoring obtaining predictive solutions.

In this regard, DT systems need data from different sources in order to predict the evolution of asset's degradation based on the acquired operational data.

To this end, improvements in collecting and integrating information in data warehouses are still necessary.

Implementing asset monitoring in building management based on IoT technologies may overcome the lack of data (Kraft and Kuntzagk 2017), as well as the use of building information models (BIMs) as a data source. Also, synthetic simulated data could be a solution as long as a methodology for simulation scenarios is well-defined.

Even, data quality is a challenge to be overcome through specific algorithms for data preprocessing to improve the integrity of monitored data.

In the proposed scenario, building management and maintenance operations can be based on predictive systems, reducing operating costs, malfunctions and breakdowns through DT-enabled intelligent systems, developing cognitive capabilities and analyzing data from different sources (Raza et al. 2020).

The COGNIBUILD approach is based on the development of DTs from information modeling (BIM) connecting three-dimensional objects to operation and maintenance data. The model acquires self-learning capabilities analyzing input data coming from BMS systems, ticketing and through AI algorithms processing expected/unexpected events.

Therefore, AI systems enable cognitive and predictive capabilities on maintenance activities, optimizing decision-making processes and implementing prescriptive strategies based on data analysis. In this regard, the proposed framework is characterized by scalability and replicability on different contexts.

Then, BIM data represent a fundamental part of the DT, as it reproduces geometric and informative characteristics in a three-dimensional database, where the objects/components of the model are filled with specific attributes describing their functional/performances/operational data.

Receiving input and signals from sources like sensors, Building Management System (BMS) and Building Energy Management Systems (BEMS) or ticketing systems for maintenance operations, etc., the DT enriches its knowledge base developing self-learning and predictive capabilities enhanced by AI algorithms.

Digital Management Systems can be valuable sources for real-time data management of information related to the life cycle of buildings, enabling what-if analysis and simulations of scenarios for decision-making.

The proposed CDT framework (Fig. 8.3) is based on (a) BIM maintenance data directly connected and updated by (b) BMS systems, (c) ticketing systems and (d) computer vision-based sensors. In this context, (a) provides checklists and maintenance scheduling as planned, as well as (b), (c) and (d) allow the generation of maintenance intervention sheets.

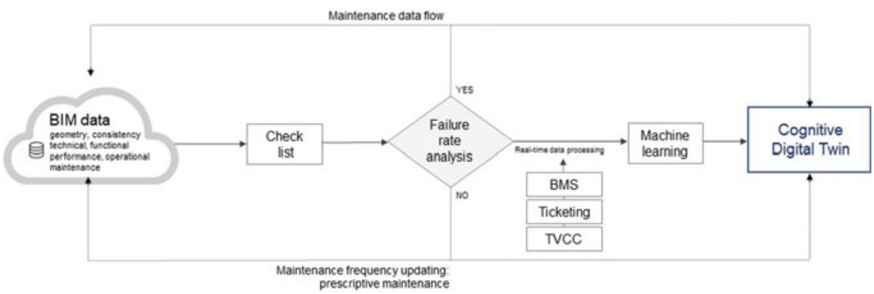

Fig. 8.3 Cognitive digital twin-based maintenance strategy

Therefore, planned checklists and data coming from sensors and maintenance systems are analyzed by machine learning algorithms, comparing expected and unexpected events and resulting in a new prescriptive maintenance frequency according to the following algorithm:

$$\mathrm{Mp} = \mathrm{Mppl} - \left[\mathrm{Mppl} * (\mathrm{fr} - \mathrm{frth})\right]$$

- fr is the real failure rate.
- frth is the threshold limit of the failure rate.
- Mppl is the planned maintenance frequency.
- Mp is the new CDT-based maintenance frequency.

According to the abovementioned, the CDT analyzes the scheduled maintenance cycle of components through statistical model-based evaluations resulting in updated frequency for the component maintenance.

If the failure rate is minor than 5%, then the planned maintenance frequency is considered as adequate and does not need to be shortened or updated.

8.5 Conclusions

Evolving from corrective to prescriptive maintenance strategies is a gradual process involving the application of DTs (Mihai et al. 2021).

Regulatory issues may exist for operation and maintenance approaches in critical assets as well as in potentially impactful contexts. According to the abovementioned, many operators still follow preventive and over-maintaining management strategies.

Moving forward to DT-based prescriptive approaches needs a correct classification of activities and a complete integration of advanced technologies such as cloud computing, data processing, IoT, data warehouses, data models, communication networks, cybersecurity and blockchain.

In this scenario, the proposed concept of CDT is based on automated interactions between physical and digital allowing advances in maintenance strategies and building management.

Barriers in data quality and availability can be overcome by the integration of IoT systems. The COGNIBUILD system introduces maintenance procedures based on the optimization of performed activities (Agostinelli et al. 2021), combining real-time and historical data and providing solutions in terms of valuable recommendation strategies using machine learning.

In this research scenario, progresses in cognitive technologies, artificial intelligence and calculation will provide enhanced capabilities to achieve a full-digital self-learned operation and maintenance approach.

References

Agostinelli S, Majidi Nezhad M, Cumo F, Heydari A, Muzi F (2021) Predictive maintenance strategy based on big data analysis and machine learning approach for advanced building management system. In: Proceedings of SEEP 2021 international conference, Vienna, Austria

Bashiri M, Badri H, Hejazi TH (2011) Selecting optimum maintenance strategy by fuzzy interactive linear assignment method. Appl Math Model 35:152–164

Consilvio A et al. (2019) Prescriptive maintenance of railway infrastructure: from data analytics to decision support. In: MT-ITS 2019 - 6th international conference on models and technologies for intelligent transportation systems

Fang X, Gebraeel NZ, Paynabar K (2017) Scalable prognostic models for large-scale condition monitoring applications. IISE Trans 49:698–710

Grieves M, Vickers J (2017) Digital twin: mitigating unpredictable, undesirable emergent behavior in complex systems. Transdisciplinary Perspectives on Complex Systems. Springer International Publishing, Cham, pp 85–113

Jasiulewicz-Kaczmarek M, Legutko S, Kluk P (2020) Maintenance 4.0 technologies—new opportunities for sustainability driven maintenance. Manag Prod Eng Rev 11:74–87

Kraft J, Kuntzagk S (2017) Engine fleet-management—the use of digital twins from a mro perspective. In: Proceedings of the ASME Turbo Expo 1

Kritzinger W, Karner M, Traar G, Henjes J, Sihn W (2018) Digital Twin in manufacturing: a categorical literature review and classification. IFAC- PaperslOnLine 51(11):1016–1022

Liew JX, Bin J, Liu Z (2019) Software as a service: the future of NDI data analysis in the cloud. Insight Non-Destruc Test Cond Monit

Liu Z, Meyendorf N, Mrad N (2018) The role of data fusion in predictive maintenance using digital twin. AIP Conf Proc 1949(1):020023

Liu J et al (2019) Dynamic evaluation method of machining process planning based on digital twin. IEEE Access 7:19312–19323

Longo F, Nicoletti L, Padovano A (2019) Ubiquitous knowledge empowers the smart factory: the impacts of a service-oriented digital twin on enterprises' performance. Annu Rev Control

Mabkhot MM, Al-Ahmari AM, Salah B, Alkhalefah H (2018) Requirements of the smart factory system: a survey and perspective

Matyas K, Nemeth T, Kovacs K, Glawar R (2017) A procedural approach for realizing prescriptive maintenance planning in manufacturing industries. CIRP Ann Manuf Technol 66:461–464

McKinsey (2022) Unlocking the potential of the internet of things. McKinsey. Available online: https://www.mckinsey.com/business-functions/mckinsey-digital/our-insights/the-internet-of-things-the-value-of-digitizing-the-physical-world. Accessed 9 Jan 2022

Mihai S, Davis W, Hung DV, Trestian R, Karamanoğlu M, Barn BS, Prasad R, Venkataraman H, Nguyen H (2021) A digital twin framework for predictive maintenance in industry 4.0. In: International conference on high performance computing & simulation, Barcelona, Spain

Mourtzis D, Zogopoulos V, Vlachou E (2017) Augmented reality application to support remote maintenance as a service in the robotics industry. Proc CIRP 2017(63):46–51

Nikolaev S, Belov S, Gusev M, Uzhinsky I (2019) Hybrid data-driven and physics-based modelling for prescriptive maintenance of gas-turbine power plant. In: IFIP Advances in information and communication technology, vol 565, pp 379–388

Oliveira M, Afonso D (2019) Industry focused in data collection: How industry 4.0 is handled by big data. ACM Int Conf Proc Ser 2019:12–18

Pivano L, Nguyen DT, Ludvigsen KB (2019) Digital twin for drilling operations -towards cloud-based operational planning. In: Proceedings of the annual offshore technology conference

Qi Q, Tao F (2018) Digital twin and big data towards smart manufacturing and industry 4.0: 360 degree comparison. IEEE Access 6:3585–3593

Raza M, Kumar PM, Hung DV, Davis W, Nguyen H, Trestian R (2020) A digital twin framework for industry 4.0 enabling next-gen manufacturing. In: 2020 9th international conference on industrial technology and management (ICITM), pp 73–77

Rosen R, Von Wichert G, Lo G, Bettenhausen KD (2015) About the importance of autonomy and digital twins for the future of manufacturing. IFAC-Papers Online 28(3), 567–572

Shafiee M (2015) Maintenance strategy selection problem: an MCDM overview. J Qual Maint Eng 21:378–402

Sivalingam K, Sepulveda M, Spring M, Davies P (2018) A review and methodology development for remaining useful life prediction of offshore fixed and floating wind turbine power converter with digital twin technology perspective. In: Proceedings 2018 2nd international conference green energy applied ICGE, pp 197–204

Swanson L (2001) Linking maintenance strategies to performance. Int J Prod Econ 70:237–244

Tang S, Wang R, Zhao X, Nie X (2018) Building cloud services for monitoring off-shore equipment and operators. Proceedings of the Annual Offshore Technology Conference 2:852–864

Tao F, Zhang H, Liu A, Nee AYC (2019) Digital twin in industry: state-of-the-Art. IEEE Trans Ind Inf 15:2405–2415

Tharma R, Winter R, Eigner M (2018) An approach for the implementation of thedigital twin in the automotive wiring harness field. Proc Int Design Conf DESIGN 6:3023–3032

Werner A, Zimmermann N, Lentes J (2019) Approach for a holistic predictive maintenance strategy by incorporating a digital twin. Proc Manuf 39:1743–1751

Zakiyudin MZ, Fathi MS, Rambat S, Tobi M, Uzairiah S, Kasim N, Latiffi AA (2013) The potential of context-aware computing for building maintenance management systems. Appl Mech Mater 405:3505–3508