UDC 004. 942: 519.876.5 **doi:** https://doi.org/10.20998/2522-9052.2023.2.11

Anastasiya Zakharchenko, Oleksandr Stepanets

National Technical University "Igor Sikorsky Kyiv Polytechnic Institute", Kyiv, Ukraine

DIGITAL TWIN VALUE IN INTELLIGENT BUILDING DEVELOPMENT

Abstract. The aim of the research. This article discusses the use of the Digital Twin in automation and its impact on the resulting solution. The research aims to illuminate the Digital Twin concept explanation and systematise the knowledge base and fulfill information gaps. **Research results.** The paper overviews the history of the concept and determines the main phases of Digital Twin development. The significant attention was paid to the classification issue to show the huge variation depending on Digital Twin's purpose, lifecycle phase, the scale of the physical twins and data amount in order to explain the twin's relation and the hierarchy of complex system. The defined capabilities and values of the concept identify the possible use cases and explain the potential benefits of Digital Twin implementation. Also, this paper takes a look at the use of Digital Twin in the area of building automation. This concept potentially may act as the integration platform for building management systems (BMS) and building information modelling (BIM) technologies with IoT solutions. The discussion of Digital Twin implementation for the building automation complex is presented. We conclude that the Digital Twin can integrate human factor to the control system by using the indexes of climate satisfaction, the feedback functionality and human-machine interfaces. As a result, the improvement of system efficiency depends on the coordination and orchestration of equipment operating mode. **Conclusion**. The Digital Twin has a high potential for energy efficiency improvements, as it considers many factors, integrates a huge amount of data and continuously improves themselves with real-world data.

Keywords: Simulation; Data-based control; Real-time control; Internet of Things; Digital Twin; Knowledge-based control; Building Automation.

Introduction

An important topic in control technology today is the collection, management and analysis of data, which has received a significant amount of attention from academics and industry. The trend to digitalisation and intellectualisation of various sectors of production and technology, including building maintenance, is generating enormous interest in the IIoT (Industrial Internet of Things) concept. In this way, data can be directly collected by smart devices and transmitted to the cloud for further processing and storage. However, with the rapid growth of data volume, they will create challenges in data organisation, management and usage.

Improving the energy efficiency of the system operation can be achieved by improving the control algorithms. It is associated with the advanced analytic, additional parameters, predicting the object behavior, equipment diagnostics, etc. All these cases, combined with digitalisation, the need for online monitoring, operational flexibility, lead to the necessity of using a specific integration platform, like the Digital Twin [1]. The technological push for the development of the twin concept includes the availability of low-cost sensors, the development of cloud and edge computing, computing hardware, machine learning and artificial intelligence technologies [2]. From this point of view, Digital Twins become an extension of technological development and an example of data science application that filters, processes and integrates the massive amount of data with different data types [1].

While Digital Twins vary greatly depending on the purposes and data amount, it is a technology for virtualising the physical world. Digital Twins become the proxy for a physical entity, so it can interact with any application to exchange the data [3].

An overview of operating costs indicates the potential for savings by optimising and coordinating the systems' operation to promote energy efficiency [4]. A building is a complex object in terms of maintenance, as it has many connected engineering systems, external and internal disturbances that are difficult to predict. So, the system integration of the building is a priority task for today. Therefore, the use of Digital Twin in building automation has a great potential for energy-efficient system design. This research is aimed to provide analysis in three main blocks:

1) the current knowledge base on the Digital Twin topic with an enabling technology overview;

2) the information systematisation and filling the knowledge gaps;

3) applying the described technologies and use cases in building automation.

This paper is organized as follows. Section 2 presents the methodology of the literature review and shows the summaries of considered papers. Section 3 introduces the historical aspects of Digital Twin concept. Section 4 describes the capabilities and values of Digital Twin implementation and provide the general classification and overview of certain enabling technologies. Section 5 discusses possible Digital Twin implementation issue in order of the building automation environment. Finally, Section 6 presents our conclusions.

1 Methodology

The article research approach is divided into several steps. The first step of the study was to identify the purpose of the paper and to frame the research questions. It gives the vector of the following work and helps to define desirable results and its criteria. The search took place in the databases of Science Direct, Google Scholar and among the technical documentation and white papers of the world's leading companies, scientific and market leaders, including Siemens, Emerson, XMPro, ABB, Seebo, AnyLogic, ARUP, Oracle, Johnson Controls, Fraunhofer and others. The review of the technical documentation was carried out to study the proposals for practical implementation or specific examples of application and to consider a more commercial point of view.

The search process was iterative. At first, we considered 60 sources and sifted out those that did not fit the general topic. As their analysis did not answer all the questions, it was decided to expand the list of literature. The next search was more specialized and related to topics in which we did not get information, including Digital Twin values, building Digital Twin application, and papers in the field of building energy consumption. The main inclusion criteria based on suitability for the purposes of the study, its research question and direct relation to the Digital Twin. Also, the authority and availability of full text had significant value of the selection. The final paper allocation, except standards, is shown in Table 1 by the publication type.

Table 1 – **Ranking the papers collection by publication type**

Publication type	Number of papers
Journal	37
Conference	11
Book (section)	4
White paper and reports	16

2 A brief overview of Digital Twin

The first approach of Digital Twin realization belonged to NASA [5], which was a "pioneer" of this technology during the Apollo program in the 1970s [6]. However, the term Digital twin appeared far more later at the Grieves's presentation about Product Lifecycle Management (PLM) in 2003 [1, 6–8]. Currently, there is no standardized definition of Digital Twin [5]. It is possible to highlight three different interpretations of the Digital Twin term, which emphasize its continuous evolution (Fig. 1) [9–11].

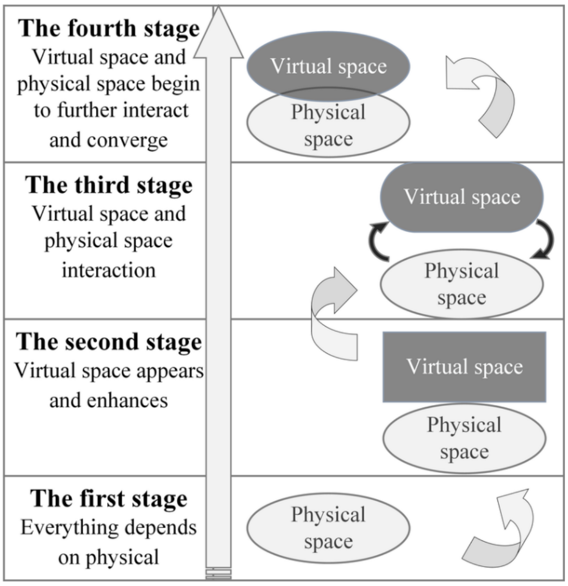

Fig. 1. The four stages of the Digital Twin evolution

The first one was introduced by NASA in 2010 as "an integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its flying twin. It is ultra-realistic and may consider one or more important and interdependent vehicle systems" [5, 12–14].

The second interpretation was provided by Siemens in 2016 and focuses on the simulated and visible 3D model and it was the appropriate vision of a broad industrial audience [9]. Thus, the Digital Twin topic turned numerous researchers' attention and give rise to an exponential increase in the number of relevant publications [7].

The state-of-the-art concept of Digital Twin appeared in 2018 by extending the existing 3-dimension Digital Twin model and adding Data and Services dimensions [7, 10]. This change was intended to facilitate the further application of Digital Twins in various fields. The 5-dimensional model consists of a physical entity (PE), virtual entity (VE), digital twin data (DD), service system (SS), connection (CN) (Fig. 2).

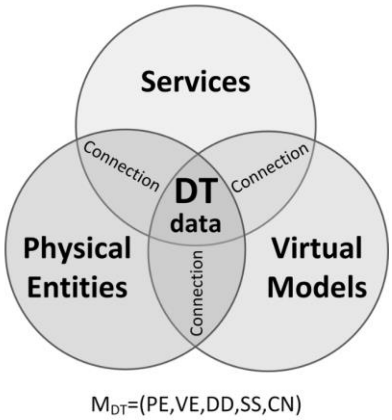

Fig. 2. Five-dimension digital twin model

3 Understanding of Digital Twin

3.1 Classification

3.1.1 General classification

Based on the reviewed literature, it can be concluded that the classification theme is very complex and does not have a clear common position of the authors. If we consider the classification of Digital Twins in general, there are divisions by *the level of integration, focused area or product lifecycle phase, and the scale of the physical twins*. The division by level of integration separates 3 following groups: digital model, digital shadow and Digital Twin. In this case, the data flow between the physical and digital counterparts are characterized and the differences in understanding of the concept are explained below (Fig. 3) [8, 15–19].

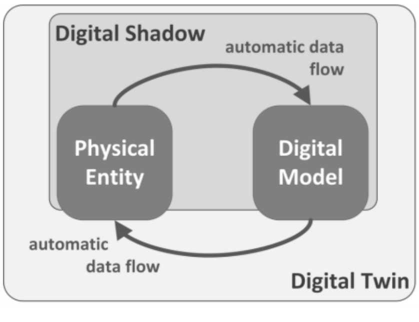

Fig. 3. The data flow in Digital Model, Digital Shadow and Digital Twin

The first group includes digital representations that are manually modelled and have no direct mechanisms for automatic data exchange in any direction. The Digital Shadow is provided by a one-way data stream and changes in the state of the physical object led to updates in its shadow. But there is no feedback from the analytical data. The Digital Twin is characterised by a bidirectional data flow and an integration between the digital and physical objects. In the context of the Digital Twin development path under consideration (section 3), in our opinion, this classification is not indicative, as current trends in technology lead to the view that only the last group meets the true criteria and requirements of this concept.

Classification by industry focus or by product lifecycle phase involves the division into Design, Manufacturing, Service, and Retire phases [17]. However, their usage is more relevant to industrial applications [19]. In the context of the considered industries, the Digital Twin can and should be functional in all phases of the life cycle, which can be realised by having a single Digital Twin with several models of the object that characterise a physical entity from different sides.

It is also possible to classify the Digital Twin by the scale of their physical objects into the following groups: critical component, piece of equipment, single machine, production line, processes and systems [16], [20]. Moreover, the twins of complex objects can integrate Digital Twins of their component elements, which is in line with the ideology and the trends of this concept. Thus, the relation between the Digital Twins is more complex and is divided into the following groups [21]:

- Hierarchical relation: the twins of complex objects consist of Digital Twins of their component elements. In this manner, the Digital Twin replicates the architecture of a real object.
- Associational relation: the relationship between Digital Twins with technologically associated processes or facilities.
- Peer-to-peer relation: the relationship between Digital Twins of the same or similar type of equipment that perform the same or similar functions.

Despite the spread of such a general classification, in our opinion, its relevance will decrease with the development of Digital Twins, as predicted in section 3. Thus, there is much more interest in classifying the technologies that can be used to create the Digital Twin.

3.1.2 Enabling technologies classification

In accordance with the definitions of the Digital Twin, described in the previous sections, the following four categories of enabling technologies can be identified: modelling, data management, services and connection technologies [7, 19]. Fig. 4 summarises this information and presents the technological architecture of the Digital Twin.

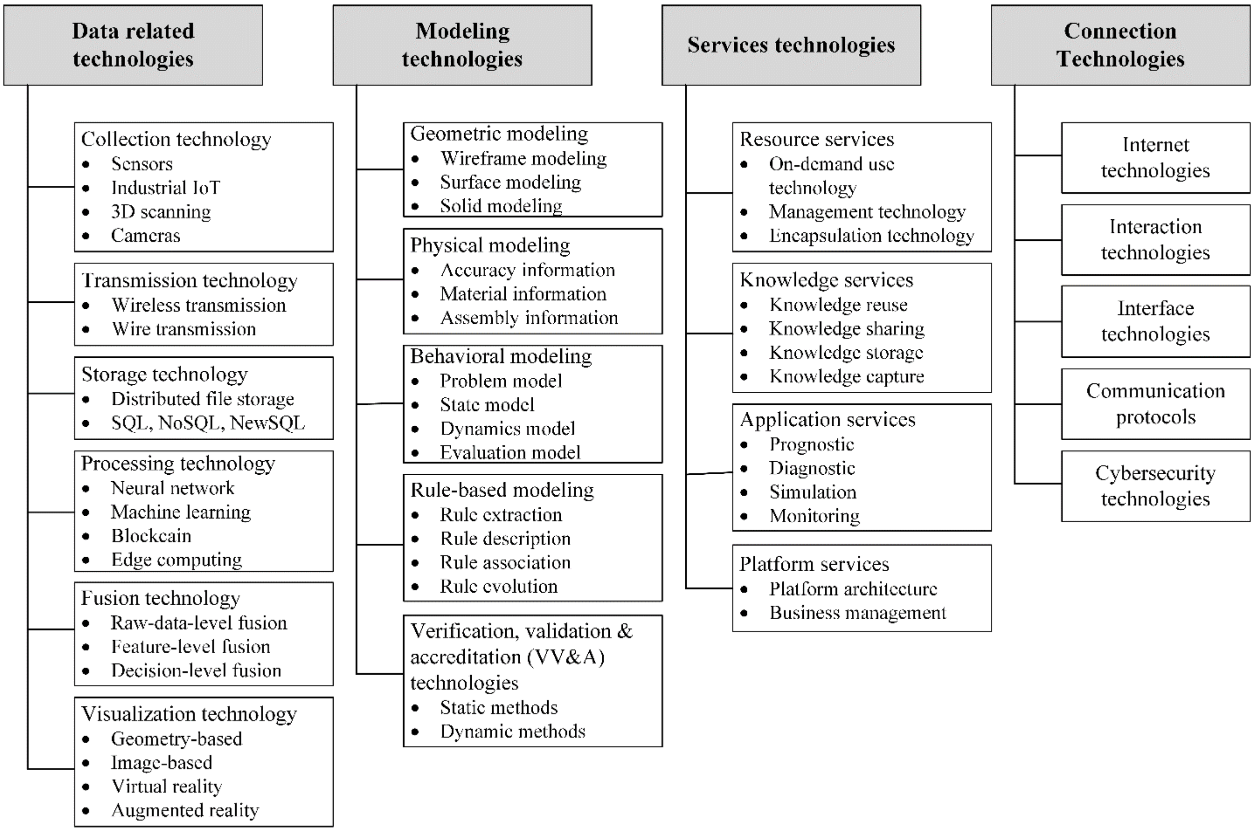

Fig. 4. The technological architecture of the Digital Twin

Data related technologies summarise data lifecycle and their transfer into information and further into knowledge. The Digital Twin should contain data about the physical environment that are required to represent and analyze the behavior and states of the real-world object [22]. It is characterised by the following phases: collection, transmission, storage, processing, fusion and visualization [7, 19]. The beginning of the data path starts with the operation of sensors, cameras, RFID tags, IT gadgets, 3D scanning, etc. to collect complete information about a particular physical environment.

The next step is *data transmission* using wired and wireless technologies that need to be performed in real or near real-time to provide data processing and analytics. Due to the volume of information collected and the high demands on processing time, it may be necessary to pre-process the data. For this purpose, the concept of edge computing is ideally suited and reduces the complexity and cost of transmission [19].

Obtaining multisource data requires *data fusion* through their synthesis, filtering, correlation, and integration. Data fusion includes raw-data-level fusion, feature-level fusion, and decision-level fusion [7].

An important stage of the data life cycle is *visualization*, which includes various graphical methods of presentation: histogram, pie chart, line chart, map, bubble chart, tree chart, dashboards, etc. Virtual and augmented reality technologies can also bring development in this direction [23].

Modelling technologies could be classified in a couple of ways. First of all, the modelling approaches can be divided according to the amount of physical knowledge used [5]:

- black-box is a mathematical data-driven model;
- white-box is a physical-based model;
- gray-box is a combination of previous types.

On the other hand, Digital Twin involves geometric, physical, behavioral, and rule-based modelling. As mentioned earlier, single Digital Twin can obtain several models, that bring different information about the physical object [7]:

- the geometric model describes geometric and tolerance information;
- the physical model includes accuracy material and assembly information;
- the behavioral model provides information about the way in which the physical entity performs functions, reacts to changes, interacts with others and maintains health;
- the rule-based model defines rules derived from historical data, expert knowledge and predefined logic.

To ensure the model accuracy and simulation confidence, *Verification Validation and Accreditation* (VV&A) analyses the relevance of the running result to the requirements, evaluates the models' sensitivity and tests the transformation from models to program codes [6, 7, 10, 24]. *Service technologies* could be divided into four groups: resource services, knowledge services, application services, platform services [7] (Fig. 4). A number of services operate at the upper most level and use integrated knowledge to generate added value through advanced analysis and validation [25]. The main benefit of services using is an on-demand operating organization. This means that the services will be provided at the right time and to the right extent. Otherwise, it was necessary to provide all resources, software mechanisms and organise their maintenance, updates and management locally, which makes the owner of the system responsible for its operation. Also, the computing capacity is selected with a reserve to cover peak loads and ensure the appropriate level of reliability. In case of service, we delegate this responsibility, which could save time and money.

Connection technologies achieve bidirectional data interaction based on intelligent data interaction devices and communication interfaces [25–27]. The definition and understanding of the required technology are closely linked to the 5-D Digital Twin model that was described earlier. Each of its elements is interconnected with the others and forms six different connection options [7]:

- Physics-Services;
- Physics-Model;
- Physics-Data;
- Service-Model;
- Service-Data;
- Model-Data.

It also includes the links between the components of each element, the environment, among the various Digital Twins and even human-machine relations. As an example, Digital Twins can store their data in different databases [14]. There are vast differences in the technology's usage depending on the architecture of the Digital Twins, the environment and the availability of edge computing. The connections are enabled using several technologies, such as Internet technologies, human-computer interaction technologies, security technologies, interface technologies, communication protocols, etc [7].

3.2 The Digital Twin capabilities

The Digital Twin concept includes a wide range of capabilities. However, the list of its functions were changed with Digital Twin evolution [9], so the range of possible capabilities is generalized in Table 2 [28]. It is describing the Digital Twin value and use cases throughout the lifecycle of a real object with the classification of selected papers by their focus area and described technology.

The brief review of the mentioned capabilities is given below.

The PLM theory became the source of Digital Twin creation and it originally was an idea of the digitalization process and mostly means the approach for the holistic control and administration of product-related information [5]. PLM integrates all data and information collected along the item lifecycle in order to increase productivity and efficiency level by the interconnection of different isolated and fragmented processes and characteristics [29]. It supports five lifecycle phases: planning phase, create-phase, build phase, sustain phase and disposal phase [5].

The mount of the Digital Twin documentation includes operational instructions and service records that are used in further analysis. For example, maintenance records may be used to inform the manufacturer about detecting issues that would be noted and used to increase the quality of its product [22].

Table 2 – **The Digital Twin capabilities**

FUNCTIONALITY	FEATURE	PLAN	BUILD	OPERATE	MAINTAIN
All documents associated to equipment throughout its lifecycle	Document management	PLM	PLM	Operation instructions	Service record
		[5, 11, 14, 17, 29, 54, 62–64]		[25, 54]	[15, 54]
Digital representation of the equipment that can mimic properties and behaviours of a physical device	Model	Physical properties predict		Optimization	Diagnostics
		[2, 5, 7, 44, 55, 65]		[3, 5, 30, 31, 44, 65, 66]	
Representation of a physical device in a simulation environment to study its behaviour	Simulation	Design simulation	Virtual commissioning		
		[5, 35, 55]	[5, 22, 25, 45, 67]		
Properties of a physical device mapped to a 3D digital representation	3D representation	Design drawings	Manufacturing instructions		Service instructions
		[7, 37]			[27]
Standardized data model for connectivity, analytics, and/or visualization	Data model	Engineering data	Production data	Operational data	Service data
		[1, 14, 37, 49, 68]		[1, 49, 68–70]	[36]
Graphical representation of the object either on a supervisory screen or personal device	Visualization			Operational state display	Health status display
				[2, 7, 11, 21, 44, 65]	
Alignment of a model with real-world parameters	Model synchronization			Real-time movement	Model inversion
				[23, 30, 55, 66, 68]	
Algorithms and computational results based on measured properties of a physical device	Connected analytics			Operational KPIs	Asset health KPIs
				[37]	

The modelling function usually is mentioned by a different author as a central component of Digital Twins. Generally, Digital Twin is a simulation of the real world and the capable modelling environment is crucial [30], [31]. It obtains the wide research area directed at the development of more accurate digital models. The virtual model can adapt in real-time to the physical object changes to generate up-to-date data, predict properties, optimization and even diagnostic for maintaining equipment [27, 32]. It could represent a system, part or a family of parts while the Digital Twin represents an instance. Simulation has been underlined as the most appropriate method to model dynamic material and energy flows in the conditions of the complexity of process interactions and a large volume of variables [33, 34]. The purpose of a simulation is to study behaviour and performance of a physical device [14] and to determine the characteristics or make predictions about the real system using the data that cannot be measured during the operation process. In this context, the Digital Twin gets a wide analytical possibility and has a lot of data that is supported by 3D representation of the system or object and contains the geometrical information about the entity starting with design drawings. The advantage of this feature is not only the provision of 3D content and real-time analysis to workers [20], but its use for training sessions with remote, hazardous or sensitive equipment of users, technicians or operators [7, 35]. Virtual representation might be so accurate that a human could operate the system or object exactly the same as in the physical world [20]. So it reduces the waste of time and money to gain users or workers experience.

3D simulation not only provides insight into the physical and geometric organisation of objects, but is also important for fault diagnostics, helping to identify the cause of a malfunction or to find a solution [36]. The Digital Twin is data-driven technology. The data model is designed to achieve different tasks: control, processing, diagnostics and condition monitoring, and analytics [37]. As a result, it integrates a vast amount of data that are generated during the object life cycle, including the planning, operating, maintaining and end-of-life phase. The data cycle consists of collection, transmission, storage, processing, fusion and visualization stages [7] and it mainly means that all Digital Twin function is dependent on the data flow and its transformation to information. The accumulated knowledge needs to be properly presented to the user or operator in an intuitive and interactive way for the purpose of his prompt and correct reaction. The generation of data begins even before the physical object appears, by preserving the planning phase documentation, developing digital models, etc. and inheriting data and knowledge from previous generations of similar physical objects.

The digitisation process leads to a perception complication of information through its complexity and volume, which caused a growth in tools, technologies and services for processing and visualization of information for its analysis, support for operator, user and manager decision-making [27]. The Digital Twin's ability to visualise data should be a key parameter to use, evaluate and understand the amount of information it generates.

The range of mathematical models, calculation methods, software and service solutions allow the model to be synchronised with a real object in real-time [37]–[39]. It enables obtaining additional data during operation and use it to optimise control, diagnostics and monitoring [17]. Comparison and processing of the Digital Twin data with real measurements keep the modelling accurate and relevant by ensuring a bidirectional connection between the physical process and the virtual system.

The operation state display comes from a real-time data stream and is presented as plots, characteristics and time-series data generated by the simulations. The health status is displayed on the local application, gateway or cloud as an alarm and notification [37]. Information dashboards based on Digital Twins could be improved with included information (historical data, real-time data, and predicted data) and models that enable the use of 3D visual monitoring technologies, Augmented Reality (AR) or Virtual Reality (VR) as well as displaying near real-time analytics [19], [20].

A set of *Key Performance Indicators (KPIs)* is generated to assess the performance of the system, which can be linked to various targets to help evaluate the relevance of performance to specific business objectives by measuring assets' health, wear and performance [2], [40]. The set of KPIs includes [37]:

- operational KPIs - are based on process, electrical, mechanical and control data;
- asset health KPIs - use specific services and diagnostic KPIs - process, electrical, mechanical and control data.

The measurable performance indicators for a smart building context may include energy efficiency, equipment service and operating costs, number of failures, specific emissions of pollutants, room efficiency etc. The KPIs are based on the process data. The evaluation of the asset health often uses algorithms that determine the risk of failure and its remaining useful life. Although, as a rule, only these health KPIs do not reflect a performance degradation, which can impair performance long before the actual failure or end of life. An analyst based on digital twins can detect performance degradation using access to large amounts of data [41].

3.3 Value of Digital Twin

In addition to the technical features presented above, it is equally significant to describe the strategic advantages of using digital twin solutions. These values were partly mentioned in the capabilities of the Digital Twin itself (Table 2). All advantages were generalised in Fig. 5 and are described below. Generally, we divided the advantages into 5 groups.

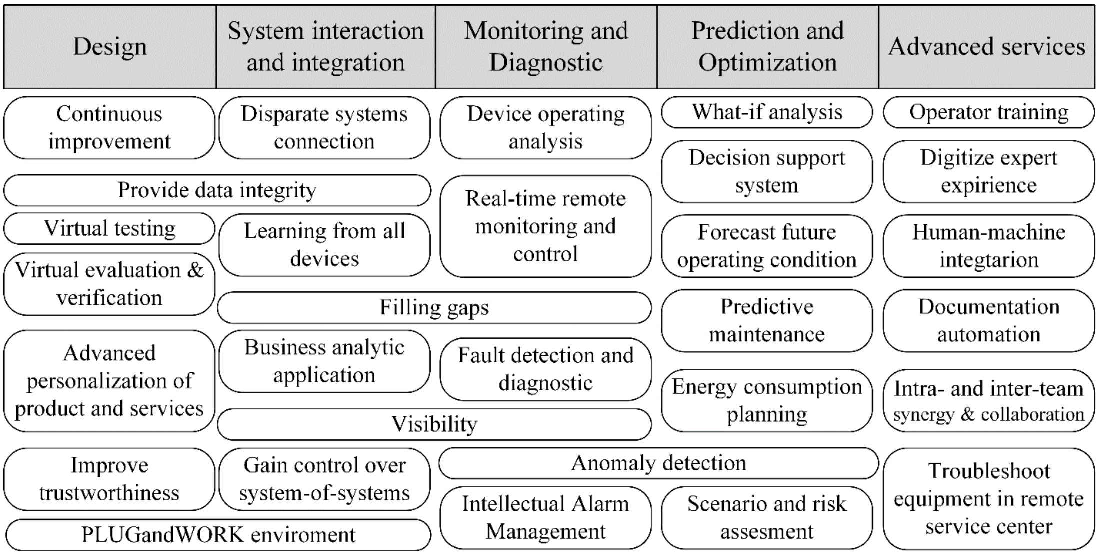

Fig. 5. Value of Digital Twin

3.3.1 Design

The digital twin has extensive facilities at the system design stage. It includes virtual testing of the digital twin or system before its actual operation by applying 3D models, behavioural and other models and their subsequent virtual validation and verification with data integrity analysis [19, 25, 27, 42]. It ensures, above all, an increase in system reliability through automatic verification of system requirements, element compatibility analysis, etc. [3, 25]. The Digital Twin makes it possible to personalise the system and services to meet the requirements and preferences of users, market trends and legislative requirements at the design stage [2], while the coverage of a large number of digital technologies and innovations becomes the basis for continuous improvement of the system [43].

3.3.2 System interaction and integration

The Digital Twin provides mechanisms for interconnecting a system of heterogeneous objects [11], their communication, organisation and analytics. It enables data from all devices to be received, compared and analysed [44]. The Digital Twin allows to provide complete, detailed information and increase the level of control over an object or a system of objects, on the one hand, and facilitate the integration of the object into the system, on the other. The creation of complex systems can lead to the fragmentation of knowledge about its elements and processes, which complicates access to useful information. The use of the Digital Twins concept helps to solve this problem by making it easier to obtain data for the next generations of objects [19] and transfer information when there is a change of ownership, audit, etc. [3]. The continuous accumulation of data throughout the life cycle and its analysis supports decision-making during the design and operation phase without the need for additional requests and information collection [19]. The intelligence and self-description capability of the Digital Twin makes it possible to create a Plug-and-Work environment where new components can be linked at runtime and automatically integrated at the functional level, business analytics and other IIoT solutions [45].

3.3.3 Monitoring and diagnostic

A Digital Twin can be described as a near-real-time digital image of a physical system providing monitoring, diagnostics, optimisation functions, etc. [7], [43]. An important advantage of Digital Twins is the visibility through the transparency of the processes and operations that take place in the system, the mapping of the links between structural elements, which are necessary to improve productivity and a deeper understanding of the object by the user or operator [20]. It enables real-time visualisation of equipment that is used by real people and operating in a particular environment [11]. The integration of heterogeneous systems and real-time work simulations makes it possible to fill in data that cannot be obtained at a physical object or is not rational, for example [44]:

- It is too expensive to install sensors on all equipment in all locations;
- The sensor can make the equipment run worse or interfere with it;
- It is not possible to provide reliable, economically justified communication with the sensor;
- Data is collected at different time intervals.

The Digital Twin makes it possible to monitor the status of equipment in real-time and to detect when devices are not working efficiently or are not interacting properly and provide extended information about them. The ability to detect anomalies is one of the pressing themes of IIoT [44]. It detects when the system is not working properly and helps to determine what may be the cause or how long it will last before it breaks down [39]. The anomaly does not always indicate an error, but may only show a state that has not been seen before [44].

3.3.4 Intellectual Alarm Management

Intellectual Alarm Management is another important application of the Digital Twin. Its purpose is to alert and support operator or user solutions when they arise. Alarm flooding means that one emergency causes many other errors and prevents the quick identification of the root cause of the fault [46]. Digital Twin helps to avoid such flooding.

3.3.5 Prediction and optimization

The use of physics models makes it possible to predict the behaviour and state of equipment, which includes forecasting future operating conditions [2, 43]. It is important for the implementation of the decision support system, making it possible to obtain more informed or effective solutions and to deepen knowledge about the physical object. Scenarios and risk assessments are performed to detect unexpected behaviour situations, study them and find ways to mitigate or solve them [2]. Data from the different states of the object that are generated by the what-if analysis can be used [27]:

- to improve future system designs;
- to optimise service cycles;
- to outline ideas for new system applications;
- to approve preliminary design solutions;
- to predict the response of the system to various types of field disruptions.

The analysis of the system's operation enables predictive maintenance, based on the anomaly detection, what-if analysis, fault detection and planning capabilities described earlier [5, 27, 42, 47, 48]. It helps to reduce maintenance costs and prevent serious equipment breakdowns. The set of prediction functions described above makes it possible to carry out energy consumption, maintenance and cost planning, which is positive for commercial institutions and private use.

It provides an opportunity to improve operating conditions, to understand the relationship between indoor climate and the amount of energy used or its cost. The values of the Digital Twin involve a positive impact on the environmental and energy consciousness for users and teach them to understand their responsibility.

4 Digital Twin in building automation

4.1 General overview

The application of Digital Twin technology in the area of intelligent buildings has its specifics. In particular, some technologies, principles and standards already exist to support the building's life cycle. It is necessary to determine the place of the Digital Twin concerning them and answer the questions:

- What benefits does it offer for building automation?
- What practical sense do the mentioned features have?

First of all, it is necessary to get acquainted with the terminology used in the field of building automation.

The terms building automation and control system (BACS), building management system (BMS) are synonymous according to EN 15232. They incorporate all systems, equipment and services designed to manage, monitor, and optimise the performance of building engineering systems to improve their energy efficiency, cost savings and safety [4]. The term building automation system (BAS), which is widely used in literature, is also equivalent in meaning [49]. This system integrates the control functions of multiple electrical devices, heating, ventilating, cooling, air conditioning, hot water and lighting appliances and has the task of providing user comfort with energy performance improving [50].

A similar meaning is expressed in the energy management system (BEMS), which is part of the BMS and focuses on optimising energy consumption. BEMS is a computerised system for monitoring and controlling, which includes data collection, logging, reporting, and analysis of energy consumption. There are many realisations of BEMS from numerous manufacturers, generally performing seven functions [50]:

- installation management and control (sequencing control and process control);
- energy-management functions;
- risk-management functions (fire alarm systems and security systems);
- information-processing functions;
- performance monitoring and diagnosis (fault detection and diagnosis technology, automatic commissioning technology, and smart maintenance technology);
- facility management.

BMS needs to use models of building and its engineering systems behaviour to achieve its potential in the field of energy efficiency.

Often the building's structural elements are planned separately by different consultants, contractors, and other stakeholders. The lack of coordination can lead to serious problems and collisions during the construction phase [51, 52]. The term building information modelling (BIM) refers to the process of developing an intellectual model that brings together the work of specialists in the architecture, engineering, and construction industry [53,[54]. Initially, the BIM concept was considered to improve collaboration between the various participants in design and construction processes, but it quickly became incorporated into related areas, gaining applications throughout the building's life cycle and providing strong interdisciplinary cooperation [8, 52, 53]. BIM is applicable at various stages of the life cycle for both new and existing buildings [24, 53]. BIM provides for the collection and comprehensive processing of all architectural, technological, economic and other information about the object [49] from conception to dismantling of the building and enables the integration of knowledge from different disciplines into one model [53]. On the other hand, in combination with the digitalization trend in the real estate sector, the volume of information obtained by BIM, their complexity and abundant have increased exponentially, causing a ”drowning in data” [27, 52], which must be processed and stored to obtain valuable knowledge.

The difference between BIM and the Digital Twin is that BIM represents a process, while the Digital Twin is a virtual representation of an object in real-time [55]. Due to outdated formats and standards, the current state of BIM does not allow for integration with IIoT solutions [52] or BMS platforms [53], which limits the application of data. The unique aspect of the building as a control object is that it is a complex socio-technological system. This feature cannot be involved with BIM. Moreover, it requires a large amount of memory and computation power and includes advanced end-user interaction by BMS [50].

The result of BIM is a static informational model, which does not support dynamic modelling, but contains most of the information required by the Digital Twin. Siemens defines the Digital Twin of a building as ”a digital copy of a physical building, which includes a 3D model of a facility combined with dynamic data to allow easy-to-understand visualization and analysis” and consists of [51]:

- Digital Twin of the devices in a building;
- Digital Twin of the structural components of a building;
- Digital Twin of the dynamic data (performance data, time-series data).

Thus, the Digital Twin capabilities mentioned in the previous chapters have been partly explored in BIM, BMS and BEMS. The Digital Twin should provide them with enhanced analytics and interact to form a complex for efficient building management or take over their functions (Fig. 6).

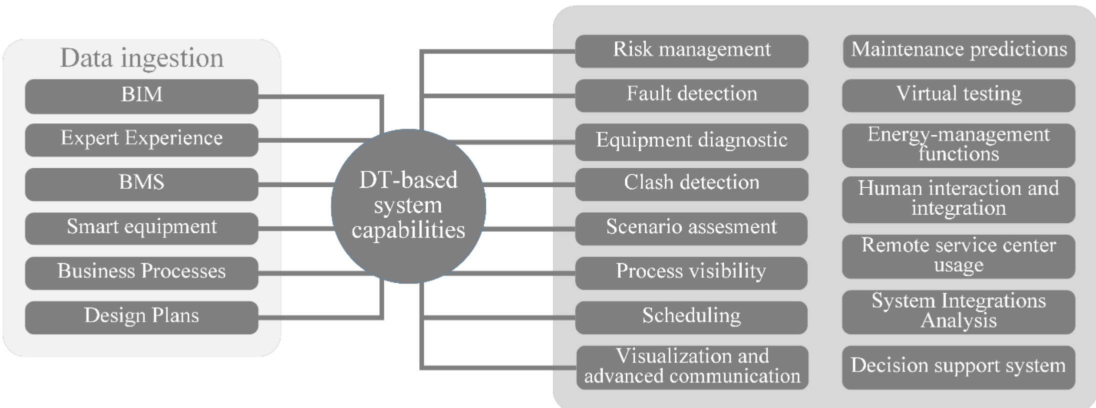

Fig. 6. Building Digital Twin implementation

The application of the Digital Twin solution comes through the potential of using dynamic realtime modelling and the ability to connect services to implement or improve certain BMS functions. Building energy systems are characterised by non-linear behaviour, stochastic environmental interactions [5] and the uniqueness of each object and operating mode. The accuracy of energy analysis and building performance forecasts is closely linked to the accuracy of modelling, which is influenced by several factors. Firstly, the use of real object data makes it possible to refine the model and maintain its relevance in the process of equipment operation [49, 51]; secondly, the use of real-time data for calculations makes it possible to improve the accuracy of forecasts [53].

The Digital Twin makes it possible to create a digital version of the building infrastructure, including its engineering systems. Such a system can investigate building usage modes and user preferences using AI technology. The obtained information is used to optimise the performance of the physical twin using analysis of different system scenarios, which gives different modelling results parallel with the actual operation [5]. Based on the results, it is possible to select the workflow scenario automatically according to predetermined criteria, or with the user's participation when the Digital Twin acts as an advisor.

4.2 Control strategy

Considering the heating and cooling sector as an example, which is one of the most energy-intensive building systems, the realisation of control algorithms will be highly dependent on the type of building and its operating mode. The control of non-residential and residential buildings is a little different in principle. The first category includes industrial and commercial (showrooms, offices, shopping malls, etc.) buildings, theatres, and museums. They are characterised by the presence of defined working hours or production plan, the ability to predict the occupancy of a building and the type of human activities. Also, they could have some technological constraints associated with indoor climate parameters. Moreover, non-residential buildings sometimes have a facility manager, who is responsible for maintaining a comfortable and safe environment and making operational decisions. These parameters allow us to improve the building model, which increases the accuracy of the technological parameter prediction.

The occupants' presence and behaviour can significantly affect the correctness of predictions and represents one of the essential factors that determine energy consumption in buildings [56]. Therefore, this factor needs to be considered in both building types. The easiest option for incorporating occupancy into a building behaviour model is the use of schedules. However, it may not be flexible enough for residential building management, as the daily routines may vary due to certain events in the lives of the residents.

In this case, users manage and adapt the building performance to their own needs during operation, without having as much competence as, for example, a facility manager. Thus, the management of a residential building requires an interaction between the occupants and the building. The occupant actively participates in supervision using flexible, user-friendly decision-supported interfaces. The collected operational and historical data are used to examine the correlations in human behaviour and to integrate them into the Digital Twin.

There are different objectives for building management, which will determine the used analytics and datasets. It is usual to consider criteria such as comfort, cost of maintenance and energy efficiency. The last two are often wrongly equated with one another.

The calculation of an optimal operating plan for heating, cooling and other energy-consuming equipment aims to minimise the total energy usage, its cost or the prioritisation of energy sources and is based on weather forecasts, operating conditions, etc [57]. Energy consumption minimisation does not necessarily lead to maintenance cost minimisation.

This result requires the introduction of algorithms that take into account the availability of different energy sources, their efficiency and tariff variability. Thus, the accumulation of thermal energy in ”lowcost” periods may reduce the overall energy cost, but may not be optimal in terms of the energy consumed. Other options for control objectives are shifting energy use away from peak periods of the power grid, prioritising the use of renewable energy sources, minimising greenhouse gas emissions, etc. [58].

One of the main functions of building automation systems is to provide quality of the indoor environment, including acoustic comfort, visual comfort, indoor air quality and thermal comfort for occupants or users. Some standards and methods represent the requirements and allow the assessment of the human satisfaction level in the numerical form [59, 60].

Optimal climate control can improve productivity and reduce the risk of human illness. The simplest and most common control option is to keep the temperature in the building within a defined range, although this option does not always give the most comfortable result. Consequently, the Predicted Mean Vote (PMV), and Predicted Percentage Dissatisfied (PPD) indexes have been developed for this purpose. PMV indicates the heat sense for the human body and PPD assesses the percentage of people who feel heat discomfort. PPD can be derived from PMV [61].

The PVM index is a complex non-linear equation that considers a large number of parameters, such as metabolic rate, clothes heat transfer resistance, airspeed and temperature, air velocity and others. The index value is dimensionless and represents a scale from -3 to +3, where zero value will correspond to the most comfortable conditions [61].

The use of non-linear indicators in the optimisation process makes the assessment of the environment more realistic, but it complicates the calculation and requires more computing power. Thus, the inclusion of the human factor in the building's Digital Twin provides additional subjective information about the object, which enables a more comprehensive data analysis for making management decisions. Moreover, the Digital Twin can include far more virtual sensors than are actually installed, thereby filling information gaps that could not be obtained from the sensor data.

Conclusion

Although the idea of a Digital Twin is not a new one, the development of modern data collection, transmission, processing, modelling and service technologies together with the development of hardware finally gives the possibility to consider its wide usage. This complex of technologies offers a wide range of capabilities during all lifecycle of physical twins. No matter the focus area, product lifecycle phase, the scale of the physical twins or used enabling technologies, Digital Twin save its concept of being the virtual representation of the physical world and act as a proxy to organise the complex analytical, controlling, diagnostic and interaction processes.

The main Digital Twin ideology is visibility, which is open to interpretation in several ways. Basically, this means the possible presence of 3D models that helps to inspect and explore the equipment even if it is hidden from human eyes. Also, it includes visibility throughout the timeline. It means the representation of physical twins' past historical, real-time and predicted future operating states. Digital Twin promotes the accuracy of prediction by updating the object model with new data during its work. The prediction function directly impacts on the anomaly detection, what-if analysis, fault detection and planning capabilities. Finally, visibility means filling the gap by using virtual sensors if it is not able to get real-world measurements and provide the user interface that represents the information in an intuitive form.

All these features are applicable in predictive control concepts, predictive maintenance, system improvement testing, staff training and business analytics, etc. And these conclusions are fully suitable for the building automation area.

Concerning the building automation environment, the Digital Twin solutions should provide BIM and BMS with advanced functionality, solve the problem of system integration with IIoT solutions, or take over their function. The Digital Twin for the building has to consider the human component as a significant source of disturbance and as the main purpose of facility controlling. The realisation of human satisfaction assessment may include the complex indexes, feedback functionality and intuitive interfaces for human-machine interaction. Whether it is a residential or commercial building, the Digital Twin has a high potential for energy efficiency improvements, as it considers many factors, integrates a huge amount of data and continuously improves themselves with real-world data.

REFERENCES

1. F. Tao, F. Sui, A. Liu, *et al.*, "Digital twin-driven product design framework," *International Journal of Production Research*, vol. 57, pp. 3935–3953, 12 2019. doi: 10.1080/00207543.2018.1443229.
2. A. Rasheed, O. San, and T. Kvamsdal, "Digital twin: Values, challenges and enablers," *IEEE Access*, vol. 8, pp. 21980–22012, 2019. doi: 10.1109/ACCESS.2020.2970143.
3. P. van Schalkwyk, "XMPro. The Ultimate Guide to Digital Twins," Tech. Rep., 2019. [Online]. Available: https://xmpro.com/digital-twins-the-ultimate-guide/.
4. "En 15232:2012 - Energy performance of buildings—impact of building automation, controls and building management," European Committee for Standardization, Standart, 2012. Available at: https://standards.iteh.ai/catalog/standards.
5. C. Vering, M. Nu¨renberg, P. Mehrfeld, D. Coakley, M. Lauster, and D. Mueller, "Unlocking potentials of building energy systems' operational efficiency: Application of digital twin design for HVAC systems," in *Building Simulation 2019*, 2019, pp. 1304–1310. doi: 10.26868/25222708. 2019.210257.
6. D. J. Wagg, K. Worden, R. J. Barthorpe, and P. Gardner, "Digital Twins: State-of-The-Art and Future Directions for Modeling and Simulation in Engineering Dynamics Applications," *ASCEASME Journal of Risk and Uncertainty in Engineering Systems, Part B: Mechanical Engineering*, vol. 6, p. 030901, 3 2020. doi: 10.1115/1.4046739.
7. Q. Qi, F. Tao, T. Hu, *et al.*, "Enabling technologies and tools for digital twin," *Journal of Manufacturing Systems*, pp. 3–21, 2019. doi: 10.1016/j.jmsy.2019.10.001.
8. D. Jones, C. Snider, A. Nassehi, J. Yon, and B. Hicks, "Characterising the Digital Twin: A systematic literature review," *CIRP Journal of Manufacturing Science and Technology*, vol. 29, pp. 36–52, 2020. doi: 10.1016/j.cirpj.2020.02.002.
9. R. Drath, "The Digital Twin: The evolution of a key concept of Industry 4.0," *visIT Industrial IoT - Digital Twin*, pp. 6–7, 2018. [Online]. Available: www.iosb.fraunhofer.de.
10. F. Tao and M. Zhang, "Digital twin shop-floor: A new shop-floor paradigm towards smart manufacturing," *IEEE Access*, vol. 5, pp. 20418–20427, 2017. doi: 10.1109/ACCESS.2017.2756069.
11. L. Kitain, "The new age of manufacturing: Digital Twin technology & IIoT," Tech. Rep., 2018. [Online]. Available: https://www.seebo.com/digital-twin-technology/.
12. M. Macchi, I. Roda, E. Negri, and L. Fumagalli, "Exploring the role of digital twin for Asset Lifecycle Management," *IFAC-PapersOnLine*, vol. 51, pp. 790–795, 11 2018. doi: 10.1016/j. ifacol.2018.08.415.
13. J. Ovtcharova and M. Grethler, "Beyond the Digital Twin – making analytics come alive," *visIT Industrial IoT - Digital Twin*, pp. 4–5, 2018. [Online]. Available: www.iosb.fraunhofer.de.
14. G. N. Schroeder, C. Steinmetz, C. E. Pereira, and D. B. Espindola, "Digital twin data modeling with AutomationML and a communication methodology for data exchange," *IFAC-PapersOnLine*, vol. 49, pp. 12–17, 2016. doi: 10.1016/j.ifacol.2016.11.115.
15. H. Zhang, L. Ma, J. Sun, H. Lin, and M. Thu¨rer, "Digital twin in services and industrial product service systems: Review and analysis," in *Procedia CIRP*, vol. 83, Elsevier B.V., 2019, pp. 57–60. doi: 10.1016/j.procir.2019.02.131.
16. C. Cimino, E. Negri, and L. Fumagalli, "Review of digital twin applications in manufacturing," *Computers in Industry*, vol. 113, p. 103130, 2019. doi: 10.1016/j.compind.2019.103130.
17. W. Kritzinger, M. Karner, G. Traar, J. Henjes, and W. Sihn, "Digital twin in manufacturing: A categorical literature review and classification," *IFAC-PapersOnLine*, vol. 51, pp. 1016–1022, 11 2018. doi: 10.1016/j.ifacol.2018.08.474.
18. A. Fuller, Z. Fan, C. Day, and C. Barlow, "Digital twin: Enabling technologies, challenges and open research," *IEEE Access*, vol. 8, pp. 108952–108971, 2020. doi: 10.1109/ACCESS.2020.2998358.
19. M. Liu, S. Fang, H. Dong, and C. Xu, "Review of digital twin about concepts, technologies, and industrial applications," *Journal of Manufacturing Systems*, vol. 58, pp. 346–361, 2020. doi: 10. 1016/j.jmsy.2020.06.017.
20. P. Raj and C. Surianarayanan, "Chapter Twelve - Digital twin: The industry use cases," in *The Digital Twin Paradigm for Smarter Systems and Environments: The Industry Use Cases*, ser. Advances in Computers, vol. 117, Academic Press Inc., 2020, pp. 285–320. doi: 10.1016/bs.adcom.2019.09.006.
21. P. van Schalkwyk, S. Malakuti, and S.-W. Lin, "A Short Introduction to Digital Twins," The Industrial Internet Consortium, Tech. Rep., 2019. Available: https://www.iiconsortium.org/ news/joi-articles/2019-November-JoI-A-Short-Introduction-to-Digital-Twins.pdf.
22. S. Malakuti, P. Schalkwyk, B. Boss, *et al.*, "Digital Twins for Industrial Applications. Definition, Business Values, Design Aspects, Standards and Use Cases," Tech. Rep., 2020. Available: https://www.iiconsortium.org/digital-twins-for-industrial-applications.
23. Y. Lu and X. Xu, "Resource virtualization: A core technology for developing cyber-physical production systems," *Journal of Manufacturing Systems*, vol. 47, pp. 128–140, 2018. doi: 10.1016/ j.jmsy.2018.05.003.

24. G. Angjeliu, D. Coronelli, and G. Cardani, "Development of the simulation model for digital twin applications in historical masonry buildings: The integration between numerical and experimental reality," *Computers and Structures*, vol. 238, p. 106282, 2020. doi: 10.1016/j.compstruc.2020. 106282.
25. G. F. Schneider, H. Wicaksono, and J. Ovtcharova, "Virtual engineering of cyber-physical automation systems: The case of control logic," *Advanced Engineering Informatics*, vol. 39, pp. 127–143, 2019. doi: 10.1016/j.aei.2018.11.009.
26. F. Xiang, Y. Huang, Z. Zhang, and Y. Zuo, "Digital twin driven energy-aware green design," in *Digital Twin Driven Smart Design*. 2020, pp. 165–184, isbn: 9780128189184. doi: 10.1016/B9780-12-818918-4.00006-3.
27. A. Madni, C. Madni, and S. Lucero, "Leveraging digital twin technology in model-based systems engineering," *Systems*, vol. 7, p. 7, 1 2019. doi: 10.3390/systems7010007.
28. K. E. Harper, C. Ganz, S. Malakuti, and S. Scientist, "Digital twin architecture and standards," Tech. Rep., 2019.
29. F. Tao, M. Zhang, and A. Nee, "Chapter 2 applications of digital twin," in *Digital Twin Driven Smart Manufacturing*. Elsevier, 2019, pp. 29–62. doi: 10.1016/b978-0-12-817630-6.00002-3.
30. Anylogic, "An introduction to digital twin development," Tech. Rep., 2018. [Online]. Available: https://www.anylogic.com/resources/white-papers/an-introduction-to-digital-twindevelopment/.
31. A. Papacharalampopoulos and P. Stavropoulos, "Towards a digital twin for thermal processes: Control-centric approach," in *Procedia CIRP*, vol. 86, Elsevier B.V., 2020, pp. 110–115. doi: 10.1016/j.procir.2020.01.015.
32. P. Verboven, T. Defraeye, A. K. Datta, and B. Nicolai, "Digital twins of food process operations: The next step for food process models?" *Current Opinion in Food Science*, vol. 35, pp. 79–87, 2020. doi: 10.1016/j.cofs.2020.03.002.
33. V. J. Mawson and B. R. Hughes, "Thermal modelling of manufacturing processes and HVAC systems," *Energy*, vol. 204, p. 117984, 2020. doi: 10.1016/j.energy.2020.117984.
34. G. P. Lydon, S. Caranovic, I. Hischier, and A. Schlueter, "Coupled simulation of thermally active building systems to support a digital twin," *Energy and Buildings*, vol. 202, p. 109298, 2019. doi: 10.1016/j.enbuild.2019.07.015.
35. Emerson, "Emerson Digital Twin: A key technology for digital transformation," Tech. Rep., 2019. [Online]. Available: https://www.emerson.com/documents/automation/emerson-digitaltwin-a-key-technology-for-digital-transformation-en-5262472.pdf.
36. V. Gopinath, A. Srija, and C. N. Sravanthi, "Re-design of smart homes with digital twins," *Journal of Physics: Conference Series*, vol. 1228, p. 012031, 1 2019. doi: 10.1088/1742-6596/1228/1/ 012031.
37. P. Lipnicki, D. Lewandowski, D. Pareschi, E. Ragaini, and G. Perrone, "Digital avatars for powertrains expand digital twin concept," *ABB Review. Digital twins and simulations*, pp. 52–57, 2019. Available: https://global.abb/group/en/technology/abb-review.
38. M. P. Acharya and M. J. Mousavi, "Real-time AI powered by edge-deployed digital twins," *ABB Review. Digital twins and simulations*, pp. 14–19, 2019. [Online]. Available: https://global.abb/ group/en/technology/abb-review.
39. M. Bevilacqua, E. Bottani, F. E. Ciarapica, *et al.*, "Digital twin reference model development to prevent operators' risk in process plants," *Sustainability (Switzerland)*, vol. 12, p. 1088, 3 2020. doi: 10.3390/su12031088.
40. C. Ganz, "Cloud, edge and fog computing," *ABB Review. Digital twins and simulations*, pp. 78–79, 2019. [Online]. Available: https://global.abb/group/en/technology/abb-review.
41. K. Smiley, X. Qu, T. Galoppo, *et al.*, "Managing solar asset performance with connected analytics," *ABB Review. Digital twins and simulations*, pp. 34–41, 2019. [Online]. Available: https://global. abb/group/en/technology/abb-review.
42. T. Y. Melesse, V. D. Pasquale, and S. Riemma, "Digital twin models in industrial operations: A systematic literature review," in *Procedia Manufacturing*, vol. 42, Elsevier B.V., 2020, pp. 267–272. doi: 10.1016/j.promfg.2020.02.084.
43. L. Manca, R. Grugni, and R. Mirzazadeh, "Digital twin. a digital copy of reality that enables you to simulate and find answers in a risk free and secure environment.," Tech. Rep., 2019. Available: https://www.eng.it/en/white-papers/digital-twin.
44. B. Klenz, "How to use streaming analytics to create a real-time Digital Twin," in *Proceedings of the SAS Global Forum 2018 Conference. Cary, NC: SAS Institute Inc.*, 2018, pp. 2004–2018. [Online]. Available: https://www.sas.com/content/dam/SAS/support/en/sas-global-forumproceedings/2018/2004-2018.pdf.
45. O. Sauer, "The digital twin – a key technology for Industry 4.0," *visIT Industrial IoT - Digital Twin*, pp. 8–9, 2018. [Online]. Available: www.iosb.fraunhofer.de.
46. M. Fullen and F. Pethig, "Digital twins for industrial alarm management," *visIT Industrial IoT Digital Twin*, pp. 10–11, 2018. [Online]. Available: www.iosb.fraunhofer.de.
47. A. Werner, N. Zimmermann, and J. Lentes, "Approach for a holistic predictive maintenance strategy by incorporating a digital twin," *Procedia Manufacturing*, vol. 39, pp. 1743–1751, 2019. doi: 10.1016/j.promfg.2020.01.265.
48. Oracle, "Digital twins for IoT applications: A comprehensive approach to implementing IoT digital twins," Tech. Rep., 2017. [Online]. Available: https://www.oracle.com/assets/digital-twinsfor-iot-apps-wp-3491953.pdf.
49. O. Maryasin, "Design of ontologies for the digital twin of buildings," *Ontology of designing*, vol. 9, pp. 81–96, 4 2019. doi: 10.18287/2223-9537-2019-9-4-480-495.
50. "Chapter 8 - building automation for energy efficiency," in *Handbook of Energy Efficiency in Buildings*, F. Asdrubali and U. Desideri, Eds., Butterworth-Heinemann, 2019, pp. 597–673. doi: 10.1016/B978-0-12-812817-6.00008-5.
51. Siemens, "Digital twin-Driving business value throughout the building life cycle," Tech. Rep., 2018. [Online]. Available: https://new.siemens.com/uk/en/products/buildingtechnologies/ whitepapers/digital-twin.html.
52. C. Boje, A. Guerriero, S. Kubicki, and Y. Rezgui, "Towards a semantic construction digital twin: Directions for future research," *Automation in Construction*, vol. 114, p. 103179, 2020. doi: 10.1016/j.autcon.2020.103179.
53. C. Panteli, A. Kylili, and P. A. Fokaides, "Building information modelling applications in smart buildings: From design to commissioning and beyond a critical review," *Journal of Cleaner Production*, vol. 265, p. 121766, 2020. doi: 10.1016/j.jclepro.2020.121766.
54. A. Khalil, S. Stravoravdis, and D. Backes, "Categorisation of building data in the digital documentation of heritage buildings," *Applied Geomatics*, 2020. doi: 10.1007/s12518-020-00322-7.
55. J. Controls, "Applying digital twins to the built environment. a digital twin is a connected, virtual replica of a physical product," Tech. Rep., 2019. Available: https://www.johnsoncontrols.com/insights/2019/bts/applying-digital-twins-to-the-builtenvironment.
56. F. C. Sangogboye, K. Arendt, A. Singh, C. T. Veje, M. B. Kjærgaard, and B. N. Jørgensen, "Performance comparison of occupancy count estimation and prediction with common versus dedicated sensors for building model predictive control," *Building Simulation*, vol. 10, pp. 829–843, 6 2017. doi: 10.1007/s12273-017-0397-5.

57. A. Jain, D. Nong, T. X. Nghiem, and R. Mangharam, "Digital Twins for efficient modeling and control of buildings: An integrated solution with SCADA systems.," in *Proc. of the 2018 Building Performance Analysis Conf. and SimBuild*, 2018.
58. J. Drgonˇa, J. Arroyo, I. C. Figueroa, *et al.*, "All you need to know about model predictive control for buildings," *Annual Reviews in Control*, vol. 50, pp. 190–232, 2020. doi: 10.1016/j.arcontrol. 2020.09.001.
59. A. Zaballos, A. Briones, A. Massa, P. Centelles, and V. Caballero, "A smart campus' digital twin for sustainable comfort monitoring," *Sustainability*, vol. 12, p. 9196, 2020. doi: 10.3390/su12219196.
60. J. Ridley, "Our mission is therefore not merely to liberate data, but to filter it. Our job is to extract meaning from the noise. To turn data into insight and insight into action.," *Digital twin: towards a meaningful frameworksubtitle. Report. ARUP*, pp. 88–91, 2019. [Online]. Available: www.arup. com/digitaltwinreport.
61. "Ergonomics of the thermal environment analytical determination and interpretation of thermal comfort using calculation of the pmv and ppd indices and local thermal comfort criteria," International Organization for Standardization, Standart, 2005.
62. K. Dohrmann, B. Gesing, and J. Ward, "A DHL perspective on the impact of digital twins on the logistics industry DHL trend research digital twins in logistics," DHL Customer Solutions & Innovation, Tech. Rep., 2018. Available at: https://www.dhl.com/global-en/home/insightsand-innovation/thought-leadership/trend-reports/virtual-reality-digital-twins. html.
63. 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. of Adv. Manufacturing Techn.*, vol. 94, pp. 3563–3576, 9-12 2018. doi: 10.1007/s00170-017-0233-1.
64. R. Vrabiˇc, J. A. Erkoyuncu, P. Butala, and R. Roy, "Digital twins: Understanding the added value of integrated models for through-life engineering services," in *Procedia Manufacturing*, vol. 16, Elsevier B.V., 2018, pp. 139–146. doi: 10.1016/j.promfg.2018.10.167.
65. H. Aiki, K. Saito, K. Domoto, and H. Hirahara, "Boiler digital twin applying machine learning," *Mitsubishi Heavy Industries Technical Review*, vol. 55, 4 2018. Available at: https://www.mhi.co.jp/technology/review/pdf/e554/e554130.pdf.
66. T. S. Cognizant, "Nurturing digital twins: How to build virtual instances of physical assets to boost performance," Tech. Rep., 2019.
67. C Wagner, J Grothoff, U Epple, *et al.*, "The role of the Industry 4.0 asset administration shell and the digital twin during the life cycle of a plant," in *2017 22nd IEEE International Conference on Emerging Technologies and Factory Automation (ETFA)*, 2017, pp. 1–8. doi: 10.1109/ETFA.2017.8247583.
68. A. Roxin, W. Abdou, D. Ginhac, W. Derigent, D. Dragomirescu, and L. Montegut, "Digital building twins-contributions of the ANR McBIM project," in *15th International Conferenceon Signal Image Technology & Internet Based Systems, SITIS 2019*, 2019, p. 2420387. [Online]. Available: https://hal.archives-ouvertes.fr/hal-02420387.
69. Altran, "Digital Twins: The Altran point of view," Tech. Rep., 2019. Available at: https://www.altran.com/no/en/insight/the-digital-twin-how-to-create-value-now-andprepare-for-digital-operations-for-tomorrow/.
70. D. A. Howard, J. Mazanti, A. Agrotech, Z. Ma, and B. N. Jørgensen, "Data architecture for digital twin of commercial greenhouse production," in *The 2020 RIVF International Conference on Computing & Communication Technologies*, 2020, pp. 1–7. doi: 10.1109/RIVF48685.2020. 9140726.

Received (Надійшла) 20.03.2023
Accepted for publication (Прийнята до друку) 17.05.2023

ABOUT THE AUTHORS / ВІДОМОСТІ ПРО АВТОРІВ

Захарченко Анастасія Сергіївна – аспірантка, кафедра автоматизації енергетичних процесів, Національний технічний університет України «КПІ ім. Ігоря Сікорського», Київ, Україна;
Anastasiya Zakharchenko – Post-Graduate student, Department of Automation of Energy Processes, National Technical University "Igor Sikorsky Kyiv Polytechnic Institute", Kyiv, Ukraine;
e-mail: zakharchenko.anastasia@lll.kpi.ua; ORCID: https://orcid.org/0000-0001-5767-3028;

Степанець Олександр Васильович – кандидат технічних наук, доцент кафедри автоматизації енергетичних процесів, Національний технічний університет України «КПІ ім. Ігоря Сікорського», Київ, Україна;
Oleksandr Stepanets – Candidate of Technical Sciences, Associate Professort, Department of Automation of Energy Processes, National Technical University "Igor Sikorsky Kyiv Polytechnic Institute", Kyiv, Ukraine;
e-mail: Stepanets.Oleksandr@lll.kpi.ua; ORCID: https://orcid.org/0000-0003-4444-0705.

Роль цифрового двійника в проектуванні інтелектуальних будівель

А. С. Захарченко, О. В. Степанець

Анотація. Мета дослідження. В роботі розглядається можливості Цифрових двійників і їх потенціал для систем автоматизації. Дослідження спрямоване на розгляд та систематизацію знань в сфері двійників як через призму історії виникнення та розвитку так і сучасного погляду на концепцію. **Результати дослідження.** Значну увагу було приділено питанню класифікації Цифрових двійників, що відображає значну варіацію функціональності в залежності від їх призначення, фази життєвого циклу, масштабу фізичних близнюків, та включає наявність зв'язків з іншими Цифровими двійниками, їх ієрархія з метою побудови двійників для складних систем. Чітко сформульовані можливості та цінності даної концепції допомагають визначити можливі варіанти практичного застосування технології та демонструють потенційні вигоди від впровадження Цифрових двійників. Водночас, у цій роботі розглядається використання Цифрових двійників у сфері автоматизації будівель, які потенційно можуть стати платформою для інтеграції систем управління будівлями та технологій інформаційного моделювання будівель з рішеннями в області технології Інтернету речей. Висвітлено питання впровадження Цифрового двійника для комплексу автоматизації інженерних систем будівель та можливість інтегрувати людський фактор в систему управління за допомогою індексів задоволеності кліматом та зворотного зв'язку з користувачами через людино-машинних інтерфейси. **Висновок** Цифровий двійник має високий потенціал для підвищення енергоефективності, оскільки враховує багато факторів, інтегрує величезну кількість даних і постійно вдосконалюється за допомогою реальних даних.

Ключові слова: моделювання; контроль на основі даних; контроль в реальному часі; інтернет речей; Цифровий двійник; контроль на основі знань; автоматизація будівель.