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# Digitalization of urban multi-energy systems – Advances in digital twin applications across life-cycle phases

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ABSTRACT

Urban multi-energy systems (UMES) incorporating distributed energy resources are vital to future low-carbon energy systems. These systems demand complex solutions, including increased integration of renewables, improved efficiency through electrification, and exploitation of synergies via sector coupling across multiple sectors and infrastructures. Digitalization and the Internet of Things bring new opportunities for the design-build-operate workflow of the cyber-physical urban multi-energy systems. In this context, digital twins are expected to play a crucial role in managing the intricate integration of assets, systems, and actors within urban multi-energy systems. This review explores digital twin opportunities for urban multi-energy systems by first considering the challenges of urban multi energy systems. It then reviews recent advancements in digital twin architectures, energy system data categories, semantic ontologies, and data management solutions, addressing the growing data demands and modelling complexities. Digital twins provide an objective and comprehensive information base covering the entire design, operation, decommissioning, and reuse lifecycle phases, enhancing collaborative decision-making among stakeholders. This review also highlights that future research should focus on scaling digital twins to manage the complexities of urban environments. A key challenge remains in identifying standardized ontologies for seamless data exchange and interoperability between energy systems and sectors. As the technology matures, future research is required to explore the socio-economic and regulatory implications of digital twins, ensuring that the transition to smart energy systems is both technologically sound and socially equitable. The paper concludes by making a series of recommendations on how digital twins could be implemented for urban multi energy systems.

## 1. Introduction

The current energy system is transforming, driven by technological advances, climate and energy policy shifts, and evolving societal expectations [1,2]. The rapid advancement of decarbonization, decentralization, and digitalization has revolutionized the energy sectors [3–7]. In this context, UMES are emerging in the energy landscape due to their ability to optimally manage increasing shares of distributed energy resources (DERs) in terms of type, location, and time [8–10]. As urban areas become the epicenters of global energy consumption, the integration of multiple energy sectors such as electricity, heat, and gas is critical for demand management, increased integration of renewables, and reduction of environmental impacts. As illustrated in Fig. 1, with the increasing number of energy carriers, technologies, and actors, the complexities of socio-technical energy systems are also increasing rapidly. Due to increasing sector coupling, energy systems are becoming a decentralized interconnected system of systems, further increasing the complexity of system architecture and operation [11–13]. Such increasing complexity requires advanced digital tools to navigate it [14].

Digitalization is playing a crucial role in the changing energy landscape. Energy systems are going through rapid evolution towards

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digitalization thanks to emerging technologies such as the internet of things (IoT), artificial intelligence (AI), blockchain technology (BT), and digital twins (DTs) [15]. The increased application of information, communication, and automation technologies, as well as software, is transforming the energy system into a cyber-physical system [16–20]. These technologies facilitate more efficient energy distribution, predictive maintenance of energy assets, and better integration of distributed renewable energy sources. The emergence of digitalization and the Internet of Things (IoT) brings new opportunities and challenges for the planning and operation of the cyber-physical energy system [21].

Among these digital technologies, digital twins (DTs) have emerged as a transformative tool. A digital twin is an innovative concept that describes the management of a virtual replica of a physical object or system. Examples of digital twins are increasingly common in industrial sectors such as manufacturing, automotive, and logistics; however, the adoption of digital twins has been relatively slow in the energy sector. DTs offer virtual representations of physical energy assets, enabling real-time monitoring, simulation, and optimization across different life-cycle phases [1,22]. By integrating data from multiple sources, DTs create a comprehensive digital counterpart that represents the state and behavior of its physical counterpart, enabling improved decision-making and operational efficiency [23,24]. DTs can also optimize operations and contribute to predictive maintenance, increasing the reliability of energy systems [25]. These virtual representations in DTs include models enabling stakeholders to foresee the impact of different scenarios and strategies [26]. Data-driven modeling, optimization, and model learning processes are functionalities enabled by digital replicas [27]. At the same time, digital twins (DT) and cyber-physical systems are considered closely related concepts that can complement each other. DTs use data from cyber-physical systems to enhance predictive analytics and optimization, improving the efficiency and resiliency of energy systems. Through better insight based on real-time data from cyber-physical systems, DTs can facilitate the energy system integration of renewables [28], improve system reliability [29], and provide much-needed flexibility services [22,30] – hence allowing the transformation of the current fossil fuel-based energy system into a low-carbon one.

DTs offer a real-time connection to data, enhancing information modeling processes such as Building Information Modelling (BIM), International Foundation Class (IFC), Geographic Information System (GIS), and supporting simulation models like Functional Mock-up Interface (FMI). However, the full potential of data-driven modeling is often hindered by siloed data, a common challenge in digital transformation. The integration of semantic data as a feature of DTs can help address this issue. DTs frequently incorporate an internal knowledge graph, which, when based on semantic web standards such as Web Ontology Language (OWL), can improve interoperability and scalability [31].

In the changing energy and digital landscape, several cities and communities around the world are increasingly using or planning to adopt DTs. Below and in Section 5, we offer an overview of the potential of these initiatives. For example, Cityzenith is developing the urban DT of several cities such as Las Vegas, Phoenix, Aberdeen, etc. [32]. These DTs combine available data in a standard, easy-to-understand 3D visual model to help decision-making. Stockholm virtual city, a 3D city DT model, performs real-time fleet, traffic flows, and pedestrian mapping using different software from Bentley [33]. It provides digital contexts for designing complex scenarios for urban planning projects. Similarly, Zürich 4D is a DT for visualizing structural development in space and time, including future scenarios, which is not yet coupled with the energy system [34]. Yet, it is an effective source for the historical and future data of the urban built environment of Zürich. A digital urban climate twin, which also considers the energy system and its anthropogenic heat emissions, has been developed for Singapore [35]. It can demonstrate how measures like electric vehicles and tree cover can reduce urban heat in Singapore. For more details on some of these UMES DT applications, refer to Section 5.

In the context of UMES, DTs have attracted considerable interest for their potential to improve the entire supply chain from generation, transport, distribution, and consumption as well as to manage increasing

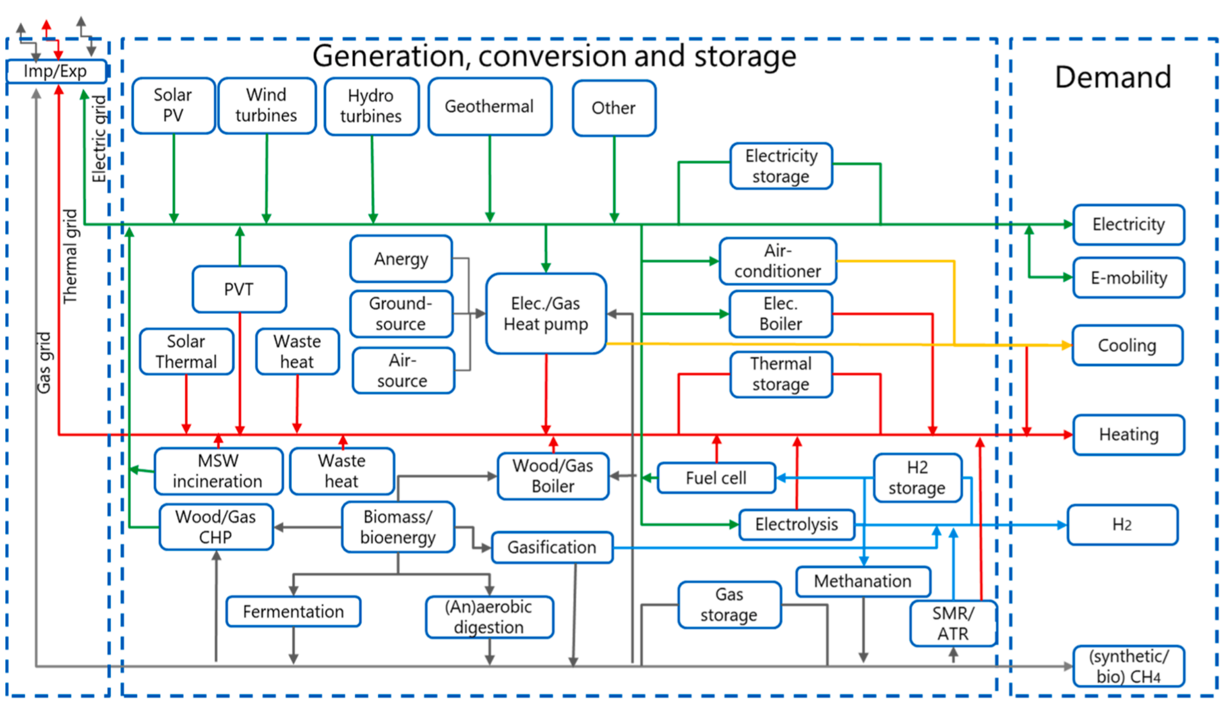


**Fig. 1.** Schematic diagram of lateral multi-energy carrier interactions in urban multi-energy systems (UMESs). The diagram illustrates a complex system architecture of UMESs covering the entire value chain from local generation, conversion, storage, transport, and demand. Different colored arrows represent multi-energy carriers flow (green: electricity, blue: Hydrogen, grey: (synthetic/bio) methane, red: heating, and orange: cooling). CHP: combined heat and power, PV: photovoltaics, PVT: photovoltaics and thermal collector, MSW: municipal solid waste, SMR: steam methane reforming, ATR: auto-thermal reforming, $H_2$: hydrogen, and $CH_4$: methane.

complexity. From optimizing energy generation units and grid operation to improving energy efficiency in buildings, DTs offer opportunities to improve the economic and environmental performance of UMES [36]. Such latest digital applications also help exploit synergies and interdependencies between different energy systems and sectors [37]. Yet, it should be highlighted here that these applications of DTs so far are mainly limited to data collection, communication, and visualization, but fully functional UMES DTs do not fully exist yet in practice. The existing applications also suffer from fragmented approaches and are not ready to act as a holistic ecosystem of DTs to make sound decisions. Ideally, the DTs from the planning stage should accompany and enhance the UMES's commissioning, operation, performance monitoring, and decommissioning. The integration of DTs in UMES represents a significant leap forward, offering unprecedented insights into system performance and facilitating more effective decision-making across the entire life cycle of UMESs. Despite these potential for scalability, the application of DTs for UMES has not been reviewed in detail. By delving into the current state of UMESs and the potential application of DTs, this review aims to understand how DTs can drive the future of UMESs comprehensively. Since UMES DTs are admittedly a new topic, this paper takes a clear stance and proposes what a UMES DT should look like. Readers are encouraged to approach this review paper with this consideration in mind.

### 1.1. Materials, methods, and research objectives

The methodological approach involves a comprehensive literature search on scholarly articles, technical reports, and industry publications. This detailed review synthesized advancements in DT architectures, energy system data categories, semantic ontologies, and data management solutions, focusing on their application across different life-cycle phases pertinent to UMES.

As UMES continue to evolve, DTs have emerged as a transformative tool, enabling data-driven decision-making and optimization of urban infrastructure. Recent advancements in UMES and DTs have paved the way for innovative approaches to urban planning, monitoring and infrastructure management. To fully leverage the potential of DTs, it is crucial to explore several key areas like the latest technological developments, the methods for data collection from physical twins, and the techniques for data management and analytics, and their application across different lifecycle stages of UMES. This review addresses these essential aspects by investigating the following main research questions:

- What are the recent advances in UMES and DTs?
- How is data **collected** from existing physical twins, including network infrastructures, technologies, sensors, and actuators? What are the data management and semantic ontologies techniques used to collect and store the data, and how can data be made accessible in the DT, ensuring interoperability across different **data sources**?
- How does DT process the data to generate insights into and information about the physical twin**, and how do** its various components **interconnect** and communicate?
- How are DTs **applied** across different life cycle phases of UMES? How is information **accessed** through user interfaces, enabling informed decision-making by the relevant stakeholders?

To systematically address these questions, this review involved the following steps:

**Systematic literature review:** A comprehensive literature review is conducted using electronic databases such as Scopus, Web of Science, and Google Scholar, with key words like "urban multi-energy systems", "digital twins," "data models," and "data management". A total of 227 sources including journal articles, conference papers, book chapters, technical reports, and relevant case studies, were reviewed to analyze advancements in UMES DT applications.

**Identification of data and knowledge management in DTs:** Various data sources for DTs, as proposed in the literature, including different twin phases, are identified and elaborated upon in Section 3. This includes the exploration of data management strategies across different twin phases.

**Evaluation of semantic ontologies and data categories:** The review assessed the use of semantic ontologies and knowledge representation techniques to enhance the interoperability and semantic integration of heterogeneous data sources within UMES. Commonly adopted ontologies for energy, buildings, and urban infrastructure are reviewed in Section 3.

**Application of DTs in UMES lifecycle phases:** Case-studies were reviewed to investigate how DTs can be applied during the planning, operation, and reuse phases of UMES. The role of DTs in facilitating collaborating energy planning, improving system operations, and managing decommissioning processes are analyzed in Section 5.

**Identification of research gaps and future directions:** Based on the findings of the review, critical research gaps and future research directions are identified and discussed in Section 7, with particular attention to scalability, data integration, and interoperability issues, the integration of emerging technologies, and the socio-economic implications of UMES DTs.

The methodology ensures a comprehensive exploration of the current state-of-the-art DT applications for UMES, providing a robust foundation for understanding and advancing this rapidly evolving field. The rest of the review paper is organized as follows to systematically examine the creation and application of UMES DT, addressing the key research gaps in this field. Section 2 introduces and defines the fundamental UMES and DT concepts, providing the necessary context for understanding how digital twins can address the complexity of UMES. Section 3 discusses the data management process within UMES DTs, focusing on data organization and promising initiatives for efficient data handling. This section highlights the need to address data integration challenges, a crucial research gap in the development of scalable and reliable UMES DTs. Section 4 reviews common methods for modelling and representing UMES DTs, highlighting which models and architectures are most suitable and how frequently DTs should be updated – areas where the lack of a standardized approach remains a significant challenge. Section 5 covers various DT applications across planning, operation, and decommissioning phases, emphasizing their interconnectedness and the need for holistic lifecycle management, a gap in current DT applications. Section 6 discusses the key findings and outlines the remaining challenges in scaling and applying digital twins to real-world UMES. Finally, Sections 7 and 8 present this review's future outlook and the key conclusions, identifying research directions that can further advance the field.

## 2. Urban multi-energy systems (UMES) and digital twins (DT)

This section establishes the important context for understanding the role of DTs within UMES, highlighting their significance in the broader scope of urban energy systems. While the primary focus of the paper is on specific applications of DTs in UMES, the literature review has been expanded to highlight recent advancement in UMESs and to explore how digital twins can help improve the transition of these systems. A clear working definition of UMES, DTs, and UMES DTs are provided to clarify their scope in this paper. The sections conclude with a discussion on the key opportunities and challenges associated with implementing UMES DTs.

### 2.1. Urban multi-energy systems (UMES)

Given the advantages of distributed energy resources, UMESs are rapidly emerging in the energy landscape [4,11]. Inspired by the JPI Urban Europe's definition of positive energy districts [38], the following definition is adopted to define the scope of this review: *Urban multi-energy systems (UMES) are efficient and flexible decentralized energy systems composed of multiple interconnected consumers and producers that* *emit low or net-zero greenhouse gases and actively manage local production and consumption of renewable energy.* Geographically, they can span groups of buildings, neighborhoods, districts, and cities. UMES holistically integrates different energy carriers, technologies, and infrastructures in interaction with the buildings, the users, and the adjacent energy systems, mobility, and ICT while securing the energy supply in line with social, economic, and environmental sustainability.

Figs. 1 and 2 illustrate that UMESs are complex infrastructural networks integrating different generation, conversion, storage, and network technologies. UMES integrates various energy sources and technologies to meet the diverse energy needs of urban areas efficiently and sustainably. Fig. 2 shows that UMESs are a complex socio-technical [39,40], interconnected system of systems [41] consisting of multiple actors, various decision-makers, and technological artifacts governed by energy policy in a multi-level institutional space [42,43]. UMES actors include households, building-owners, local communities, housing corporations, local municipalities, national government, energy suppliers, intermediaries or aggregators, system operators, energy service and technology providers, regulators, and (local) energy market operators [4,14]. By integrating multiple energy carriers, UMES goes beyond the concept of smart and microgrids, incorporating decentralized production and utilizing local synergies [44]. The integration of different energy carriers such as electricity, (renewable) gas, heating, and cooling, as well as various sectors such as buildings and transport sectors together with community engagement, is expected to contribute to more flexible, sustainable, cost-effective, and efficient energy systems [4,45]. UMESs are emerging as an essential building block for the effective decarbonization of the built environment and for dealing with the security of supply challenges.

Previous research efforts have demonstrated techno-economic modeling approaches to the planning and operation of UMES [4, 46–50]. These studies utilize optimization techniques such as linear and non-linear programming [48,51–58]. Keirstead, Jennings, and Sivakumar (2012) identified challenges of energy system modelling like model complexity, data quality, uncertainty, and model integration [59] . Nik, Prerea, and Chen (2021) highlight the need for improving the models capturing future climate variations to design resilient energy transition pathways [60]. Zheng et al. (2024) identified physical, cyber, and social energy processes layer in urban energy systems to further optimize their design and implementation [61]. The authors also highlight the need for data sharing and analytics for urban-scale energy modelling as well as policies for safety, privacy, cyber-security, and interoperability issues.

Moreover, current urban energy planning practices face significant challenges due to the vast array of modeling tools and continuously evolving data sets that are often not interlinked, compatible, or consistent. This results in a constrained, static, and isolated view of UMES, particularly in multi-actor contexts. Future energy system models will benefit from access to sensors and contextual data [21]. For instance, a digital twin composed of connected metered PV readings could lead to better forecasts of energy supply and its intermittency. With the emergence of cyber-physical systems, how data is collected, stored, analyzed, and presented is also changing. However, processing the dynamic and steadily increasing volume of data using traditional models is challenging. Sectoral integration, with increasing synergies and interdependencies, adds further complexities to the planning and operation of UMES. As a result, significant challenges and opportunities exist for improving the modeling of UMES planning and operations, driven by the need to manage growing data quantities and extract actionable insights. Non-conventional approaches will be required for the effective planning and operation of UMES [62,63], and the application of DTs is expected to help overcome these limitations.

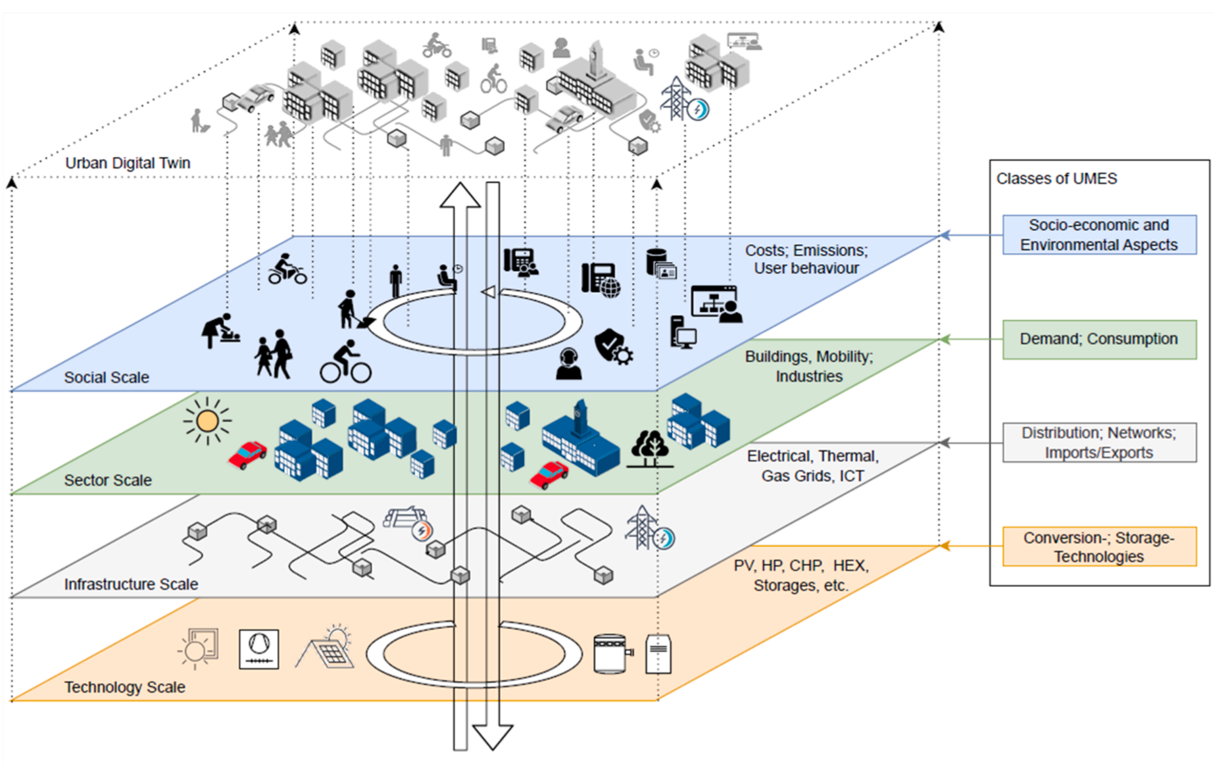


**Fig. 2.** Schematic diagram of multi-level interactions of UMES as complex multi-layer socio-techno-economic systems of systems. The UMES is decomposed into technical, infrastructure, sector, and social scales. The four physical scales are represented in the Urban digital Twin, defining the UMES DT. The latest digitalization trends, such as cyber-physical systems, the Internet of Things, and digital twins, have the potential to provide a solid information basis for decision-making and performance monitoring. The classes categorize the typical components in UMES and are discussed further in Section 3 and Table 2.

### 2.2. Digital twins (DT)

Several definitions regarding DTs are available in the literature [21,24,64–69]. For the scope of this review, the following is adopted as a working definition: A digital twin (DT) is a virtual representation of an object or system that spans its lifecycle, is updated using real-time data, and uses models and machine-learning techniques as information bases to support decision-making [70]. The digital twin is an emerging concept in research and industry [65,67]. The idea of the digital twin was first introduced by Greives in 2003 concerning product life-cycle management as a virtual and digital equivalent to a physical product consisting of three main parts: a) physical products in real space, b) virtual products in virtual space, and c) the data and information interconnection between virtual and physical products [24,65]. However, some even believe that DTs were practiced many decades earlier, e.g., in NASA's Apollo mission [71].

Moreover, there are several initiatives to make DTs of smart cities [72], whole countries such as the UK [73] and Singapore [74], and even the entire earth [75]. Rasheed et al. (2020) define the digital twin as "the virtual representation of a physical asset enabled through data and simulators for real-time prediction, optimization, monitoring, controlling and improved decision making" [76]. Hoffbauer et al. (2019) introduce several types of DTs: the digital twin prototype, the digital twin instance, and the digital twin aggregate [77]. Pileggi et al. (2019) argue that a digital twin is a simulation tool used in a specialized way, which is meant to be employed not only at the development stage but also during the operational phase of the physical system [21]. Woods and Freas (2019) emphasize that DTs are essential for understanding and managing the complex integration of multiple assets and systems, such as those found in zero-carbon communities [66]. Zhang et al. (2021) review various simulation tools, highlighting the potential of DT applications in accelerating sustainability efforts [78].

Similarly, Schooling et al. (2020) argue that DTs enhance the ability to monitor, interpret, and make more informed decisions across different infrastructure networks and sectors [79]. With the capabilities of multi-physics simulation, data analytics, machine learning, and artificial intelligence [80,81], DTs can effectively demonstrate the impact of design changes, operation scenarios, and environmental variations, thus facilitating the planning and operation processes. Multi-physics models offer interpretability, while machine-learning models contribute to the speed and efficiency of DTs [82]. The digital twins, with its ability to create dynamic, real-time representations of physical systems, serve as the foundational framework for their application within UMES, where the complexity and integration of diverse energy sources require specialized approaches..

### 2.3. UMES digital twins' definition

From the definitions and discussion of DTs above, we can consider all UMES DTs to contain or at least strive for the following elements:

1. A digital representation of a real-world physical UMES, including the data requirements and data processing module
2. A real-time data connection to the physical twin, which is updated at desired intervals
3. A mathematical model to predict specific behavior/future conditions of the physical twin, e.g., machine-learning-based, simulation, and optimization models.

Optionally, connections and mapping between digital twins of different UMES life-cycle phases and connections to other databases outside the scope of the urban energy system are needed.

Building on the foundational understanding of UMES DTs, it is essential to explore the current advancements, challenges, and ongoing initiatives in this field as identified by recent literature and projects. Ferré-Bigorra et al. (2022) reviews existing approaches on urban digital twin highlighting open issues, key challenges and requirements for future development [83]. Bettencourt (2024) highlights recent achievements and conceptual challenges for urban digital twins emphasizing size, heterogeneity and open-ended character of cities. Weil et al. (2023) indicates interoperability and semantics, computational infrastructures, data acquisition and quality, modeling and simulation, human resources as well as governance, organizational and social issues as main challenges for widespread adoption of urban digital twins [84]. Using systematic literature review and expert survey, Lei et al. (2023) also identifies interoperability and practical value as main challenges for urban digital twins [85]. Onile et al. (2021) explore DTs in energy services [22], and the +CityXchange project develops digital twin models for buildings in positive energy blocks, integrating a physics-driven simulation with operational data [86]. Peldon et al. (2024) highlights transformative role of digital twin in shaping urban futures [87]. JPI Urban Europe funded PED-ID project highlights potential uses of DTs in various aspects of UMES, such as planning, visualization, communication/stakeholder engagement, and simulation of scenarios [88]. Horizon Europe is also funding several new research projects on further developing and demonstrating DT applications in energy systems [89]. In addition, several commercial initiatives are also emerging for the development of UMES DTs [32,66]. Having reviewed the current developments and key research in UMES DTs, the next sub-section will delve into the specific advantages these systems offer, as well as the challenges that must be addressed for their effective implementation and widespread adoption.

### 2.4. Advantages and challenges of UMES DTs

The complex and multi-dimensional UMESs present significant challenges related to data integration, system optimization, and real-time operation. DTs provide innovative solutions to these challenges by offering a real-time, data-driven virtual replica of physical systems capable of simulating, monitoring and optimizing UMESs. DTs are expected to provide a robust information basis through continuous validation, integrating heterogeneous data sources, and investigating different what-if scenarios in UMESs. These capabilities will facilitate UMES's continuous integrated planning, operation, and collaborative decision-making. UMES DTs facilitate improved resource management and optimization by monitoring and analyzing asset usage, performance, and condition, including fault-detection. This allows for more efficient utilization of resources, such as energy, water, and materials. The data-driven approach enables better decision-making regarding resource allocation, maintenance scheduling, and retrofitting opportunities.

Additionally, DTs can assist in assessing environmental impacts and identifying sustainability improvements. By integrating data on energy consumption, material usage, and waste generation, DTs can provide insights into the ecological footprint of built assets. This information supports informed decision-making regarding design modifications, energy efficiency enhancements, and adopting circular practices, leading to a more sustainable built environment. The advantages of UMES DTs can be measured using the key performance metrics listed in Table 1.

Despite the above benefits, as illustrated in Table 1 below, today's UMES DTs are not without shortcomings: The technical and financial complexity of establishing a DT represents a significant barrier, necessitating a substantial commitment of resources and expertise [90]. The depth and breadth of data required to feed a DT for accurate reflection and forecasting can also cause data overload, where managing such information becomes an additional complex layer to navigate [91]. DTs simultaneously expand the potential attack surface for cyber threats [25]. Moreover, the development of DTs is bound by the quality of available data, which can be hindered by both technical data collection limitations and privacy regulations, thus impacting the veracity and utility of the DT model [92].

**Table 1**
Overview of key issues and key performance indicators of urban multi-energy system digital twins (UMES DTs).

| Key issues in UMES DTs | | | | | Key Performance Indicators | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Scalability and life cycle management | Data management, interoperability, and visualization | Stakeholder engagement | Technical. financial, and regulatory issues | Inter- and cross- disciplinary research and innovation | Efficiency (losses reduction, improved forecasts) | Reliability (down-time, fault detection) | Environmental impacts and sustainability improvements | Data quality (accuracy, timeliness) | Cost-effectiveness (design and operational cost savings) |

As UMES evolve, so must the DTs that represent them, yet scaling these solutions to model larger, more complex systems accurately remains a formidable task [62]. Additionally, discrepancies in communication standards and protocols across different UMES components pose interoperability challenges, further complicating the DTs' ability to provide a seamless and unified system model [93]. Many challenges in operating DTs, such as lack of interoperability and practical value, hinder their design and implementation [85]. Additional challenges of the existing DT for UMES are rooted in the complexity of transforming energy systems into cyber-physical systems [62,94]. As UMESs evolve to integrate more DERs and adopt advanced digital and automation technologies, there is a pressing need for robust data management and sophisticated tools to harness the potential synergies and manage the reliability and flexibility of these interconnected systems [62].

Moreover, regulatory considerations are pivotal, as existing energy regulations may not have accounted for DTs' rapid advancement and unique capabilities [95]. While DTs present an innovative tool for advancing UMES, the road to their full-scale implementation and seamless integration is marked by various technical, security, and regulatory hurdles due to data protection and privacy issues. Addressing these will require a concerted inter- and cross- disciplinary effort from researchers, industry practitioners, and policymakers to ensure that DTs can deliver on their promise to foster sustainable and resilient urban energy landscapes [2,96,97].

Having established the foundational context for UMES digital twins and explored their roles in advancing urban energy systems, the next section will delve deeper into the important aspect of data and knowledge management, which underpins the development and operation of DT models. Effective data management is key to ensure that DTs can accurately represent and optimize UMES in real-time. The following section explores the processes and frameworks required to manage the vast amount of data generated and utilized by UMES DTs, examining how data flows through the various phases of UMES DTs' lifecycle. The next section will also highlight the role of existing techniques like Building information modelling.

## 3. Data and knowledge management for UMES DTs

Data is essential for the development and operation of DT models. During its separate phases, namely pre-twin, active-twin, and post-twin, DTs often ingest and integrate data from multiple sources and require a data connection to the physical twin during its operation. Management of data is critical for the effective operation of a DT. This section explores the processes necessary to manage data required and generated by a DT. The review considers general requirements of DTs in the Architecture, Engineering, and Construction (AEC) sector and identifies specific features or requirements necessary for UMES DTs. This section highlights the difference and complementarity between DTs and building information modeling (BIM), as the latter is widely used in practice, especially in the AEC sector, and serves as an essential data source for DTs. Then, different data sources for UMES DTs in pre-twin, active, and post-twin phases are highlighted, corresponding to UMES's design, operation, and decommissioning/material re-utilization phases, respectively. This follows a comprehensive elaboration on semantic ontologies and data-schemas for UMES DTs. Finally, data transaction protocols supporting UMES DTs communications with physical twin and simulation models are highlighted.

### *3.1. The difference between DTs and BIM*

Building information modeling (BIM) is a standardized process of managing digital information about a construction project and throughout the lifetime of an asset or facility. The BIM process applies to buildings and supports the construction and operation phases. Examples of applications of BIM relevant to UMES include urban energy planning [98], planning of district energy systems [99], community energy system design [100], and site selection for a solar PV power plant [101]. BIM is typically applied in a project's planning, design, construction, operational, and decommissioning phases [102,103],. The BIM process facilitates collaborative management and decision-making throughout a construction asset or facility's lifetime.

On the other hand, DTs provide a real-time data connection and model how the physical asset will behave under different scenarios. Therefore, it can be argued that a BIM strategy is a prerequisite for a digital twin, as it provides the initial information required to build a UMES DT. The line separating BIM and DT is increasingly blurred. Dimensional extensions are used to describe the application and functionality of BIM. 3D BIM describes the modeling of the geometry in 3 dimensions. This is then extended to 4D (time), 5D (cost), 6D (safety/sustainability), and 7D (facility management); however, there is limited agreement across the industry on what these categories refer to beyond the 5th dimension [104]. Some have also proposed an 8th dimension for the sustainability and circularity of the asset during the design process [105]. Others have gone beyond this, defining the 8th, 9th' and 10th dimensions as safety, lean requirements, and industrial automation [106]. The connection of the BIM model to real-time DTs has been proposed to close the performance gap between simulated and actual energy usage; however, closing this loop is far from maturity [107].

DTs can be considered an extension or evolution of the BIM process, enabling ongoing operational decisions due to the real-time data connection. It could be argued that they represent or extend a dimension of the BIM process; however, it will take time until a consensus is established on this definition. BIM models have been considered insufficient for lifecycle asset management, and a shift to DTs that incorporate artificial intelligence, machine learning, and dynamic digital models has been proposed to address this shortfall [108]. DTs extend static BIM models to enable real-time analysis, visualization, and control of the built environment [109]. There are proprietary and nonproprietary data formats to exchange BIM information. In addition to modeling construction assets, several opportunities from BIM-GIS integration have been hypothesized to expand the range of applications [110]. The use of BIM as a data source in GIS is particularly relevant for multi-energy systems as the spatial context of an energy system is vital in determining infrastructure synergies, resource availability, and demand flexibility. Conventional BIM models, however, are considered challenging for energy analysis of buildings due to the inability to extract space boundaries of buildings for energy analysis [100]. A review of the use of BIM in energy simulation has also been carried out by [111]. One of the main non-proprietary data formats for exchanging BIM information is the Industry Foundation Classes (IFC) format. The IFC format is a reference format designed to share information between project stakeholders. The focus is on interoperability, and the model has been criticized for not containing sufficient semantic information for DTs; the authors propose a "no model architecture" to connect BIM and DT [112].

In this work, we define and align the UMES DT Lifecycle Phases with the established BIM project phases, see Fig. 3. The pre-twin phase corresponds to a BIM project's Design, Planning, and Construction phases and UMES's planning phase. During this phase, schematics and descriptions of the system are created through an iterative process with engineers and other stakeholders. These data types can later be used to develop DTs that only become active once updated by the physical twin/real-world facility; therefore, DTs are only active during the operational phase of a project. During the post-twin, the information collected by the active digital twin can assist in decommissioning and material and asset reuse.

### 3.2. Data sources for UMES DTs

A conceptual framework for UMES DTs for the urban area shows the necessity of integrating domain knowledge from infrastructure systems such as water, energy, and transportation [113]. In addition, other data, such as occupancy and economic activities, might also be relevant. This sub-section explores the different data types required by and produced by UMES DTs.

#### 3.2.1. Pre-twin data sources

The pre-twin phase corresponds to the design-build phase of the physical object and refers to a period where there is no real-world physical counterpart to establish a data connection. Data is subject to frequent updates and refinements as designers build the DT during this period. Designers are focused on optimizing the system's design, modeling performance, and procuring the equipment and expertise required to construct the real-world physical counterpart.

Fig. 4 shows the data types used during the pre-twin phase. The pre-twin phase corresponds to a BIM model's design, planning construction phases, and UMES's planning phase. In these phases, 3D BIM models are created containing architectural, structural, and system data, city scale geometry models, and geo-coded sensor data. This is then often extended to 4D (time) and 5D (cost) to perform what-if scenario analysis during the design phase. The data sources used in DTs are strongly tied to the scale of the physical entity they represent. For example, DTs of buildings rely on detailed information about the construction and geometry of the building, which is often contained in a BIM model; city-scale DTs, on the other hand, are usually built using open geospatial data, network topologies, and statistical data. DTs of UMES need to integrate data from multiple sources that cover the different physical entities that influence the model. As discussed earlier, the information in a BIM model could be a starting point for building digital twin models. Some approaches aim to convert all the data stored in an IFC into a knowledge graph [114]. Others believe that the IFC schema is complex and unable to cover the operational phase of the building lifecycle sufficiently; as a result, a modular data integration framework is proposed that relies on several ontologies for data integration [115]. In the literature, it is accepted that knowledge graphs are inefficient for storing time series, and it is recommended that they be stored in a dedicated time series database [116].

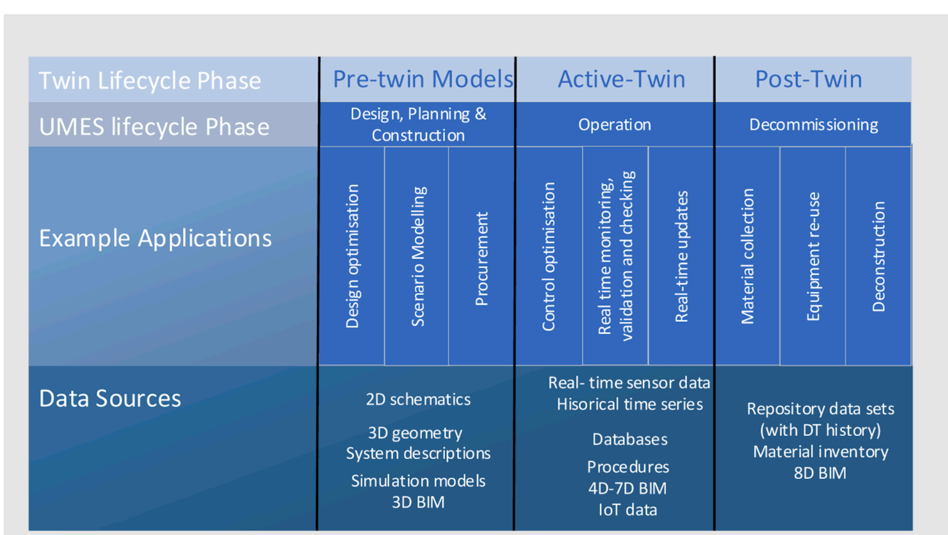


**Fig. 3.** The diagram outlines the phases of a digital twin (DT) concerning the lifecycle phases of the real-world urban multi-energy system (UMES) asset and BIM processes, providing examples of applications and data sources that change throughout the UMES and DT asset's lifecycle. The lifecycle is divided into pre-twin models, active-twin, and post-twin phases, highlighting design, operation, and decommissioning/material re-utilization, respectively. While pre-twin and post-twin phases rely heavily on static historical data, active twin relies on real-time sensor data.

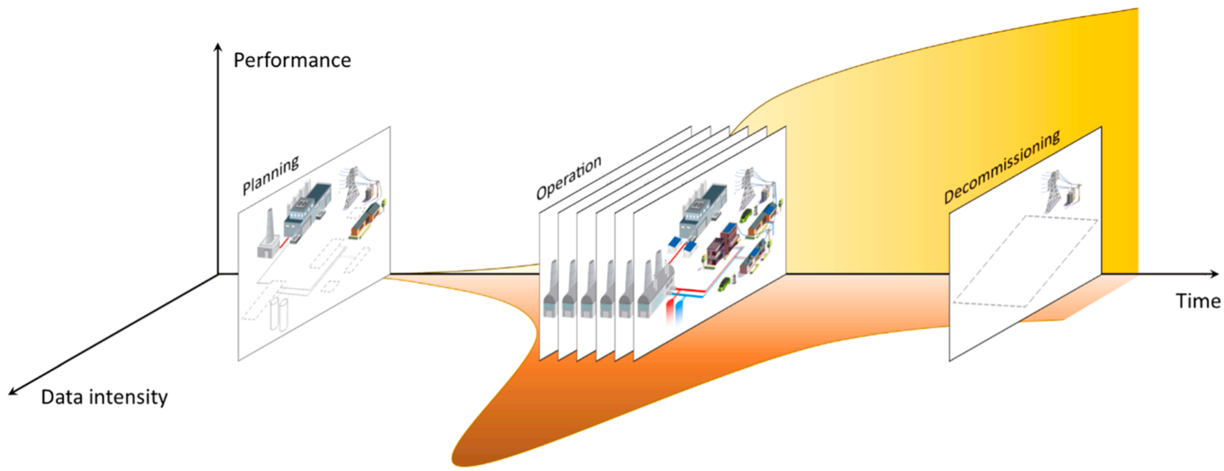


**Fig. 4.** A digital twin of urban multi-energy system (UMES). Each image is a snapshot of the physical twin at a specific time. The snapshots represent the update cycle of the digital twin during distinct phases of its life. Snapshots are less frequent during the planning and decommissioning phases and more intensive during the operation phase. The performance of a UMES improves throughout its life as additional data is gathered and processed from the physical counterpart.

As illustrated in Fig. 2, UMES DT sources data across multiple scales of the physical system, encompassing technological components, infrastructure networks, and sectorial interactions. In the use cases reviewed in this work, DTs can be created to represent assets and systems spanning different spatial and temporal scales. The complexity of handling multiple scales in a single twin establishes the need for a network of interconnected DTs instead of a single monolithic digital twin [117]. This means the digital twin developers must know the data models available to represent the domains and scales relevant to their DT. An in-depth discussion of DTs for the built environment, their requirements, abilities, and spatial scales is provided in [113].

#### 3.2.2. Active-twin data sources

Real-time data connection often provides updates about a system's state. The update cycle between a UMES DT and its physical counterpart is illustrated in Fig. 4. The UMES DT must be able to handle data with different modalities and contexts, which are collected at heterogeneous temporal and spatial scale resolutions. Furthermore, UMES DT should match and refine data along different modalities to provide comprehensive and reliable information to the corresponding decision-makers. It must then understand how this data influences long-term forecasting.

#### 3.2.3. The post-twin as a data source

Supposing that a DT is maintained throughout the life cycle of UMES, asset managers can use the available information on assets and materials to connect to other applications and databases for reuse and second-life applications. Furthermore, the comprehensive data repository encompassing the entire lifespan of a DT can serve statistical purposes or be employed to train future DT models. This utilization facilitates leveraging historical and operational data to enhance predictive analytics and refine other DT frameworks, ensuring continual improvement and knowledge transfer across models. The post-twin as the data source for the decommissioning and re-use phase of UMES is further elaborated in Section 5.3.

### 3.3. Data handling and interface integration

Aheleroff et al. (2021) describes a DT Reference Architecture Model for Industry 4.0 [118]. This reference architecture sets DTs apart from standard models due to a time data connection. The reference standard defines the level of integration based on how this real-time connection is implemented. The levels of integration defined in the reference architecture include: Digital Model (no real-time), Digital Shadow (one way), Digital Twin (bi-directional), and Digital Predictive (bi-directional powered by distributed computing technologies). When considering the importance of real-time connection of UMES DTs, live data connection will mostly be obtained from meters and sensors installed across the UMES system.

Data is at the heart of the functionality of DTs. Effective handling of diverse data types—such as real-time sensor data, historical datasets, and forecast data—is essential to the operational success of DTs. Digital twins utilize advanced data fusion techniques to integrate these heterogeneous data sources into a coherent model, allowing for real-time monitoring and predictive analytics [119,120]. Data preprocessing steps, such as normalization, missing data imputation, and filtering [121], are employed to ensure data quality before use in the digital twin. The ability to process and manage these data efficiently ensures that the virtual twin remains an accurate and up-to-date representation of the physical energy system.

The integration of various modules within the digital twin is facilitated by a middleware layer using standardized communication protocols such as OPC-UA [122] and MQTT [123,124]. This layer ensures seamless interoperability between different system components and external data sources. These interfaces play an important role in achieving a modular and scalable architecture in UMES DTs. In addition, different methods are needed to address and overcome data gaps, which can arise due to sensor faults, communication failures, or data sparsity. Techniques such as interpolation, machine learning-based data reconstruction, and data augmentation from historical datasets are applied to minimize the impact of missing data [125]. Additionally, real-time redundancy checks and fallback mechanisms can be implemented to maintain the continuous operation of the digital twin.

### 3.4. Ontologies and data schemas for UMES DTs

The contextual understanding of the integration layers of a digital twin can be augmented through the use of ontologies and established data models. DTs can be implemented to work in communication with a data architecture built on schemas that comply or make reference to such data models. The challenge data architects face when building a comprehensive DT framework, is enabling the twin to access the required data access without compromising performance. Domain models provide a basis for the physical representation of the system, allowing advanced querying and analytics, and meta-models can provide functional processes such as scenario and provenance tracking. This section gives an overview of data models that could be implemented to represent the key processes necessary for an UMES DT.

Over the past few years, ontologies have been seen as a critical technology for addressing heterogeneities and mitigating misunderstandings and isolation, which can lead to a lack of clarity about activities, data, and information in a particular domain. Moreover, ontologies enable semantics-driven knowledge processing, which converts knowledge into tangible assets. Thus, ontologies are formal structures enabling acquiring, maintaining, accessing, sharing, and reusing data, information, and knowledge.

Knowledge management systems benefit from ontologies that semantically enrich information and precisely define the meaning of various information artifacts. Ontologies have been developed to facilitate knowledge sharing and reuse among different disciplines and research communities, such as advances in medicine, knowledge engineering, natural language processing, cooperative information systems, information integration, and software agents. We can conclude that ontologies provide the following:

- A common and shared understanding of a specific domain and context.
- A human and machine-readable approach to knowledge management.
- An explicit conceptualization describing data meaning.

Adherence to standardized ontologies and data schemas enables interoperability and scalability of UMES DTs. Ontologies define the

**Table 2**
An overview of ontologies and their capability to represent the necessary elements of an urban multi-energy system digital twin (UMES DT). Green/tick: the majority of concepts are covered by the ontology. Yellow/dash: partial coverage. Red/cross: Limited coverage, in combination with an additional ontology, is necessary. *Includes extensions and submodules. Note that a limited or absent capability does not mean the ontology is inferior; it is just specialized in other areas.

| Ontologies and data models | Energy conversion and storage technologies | Distribution networks/ imports and exports | Demand and Consumption | Socio-economic and environmental aspects | Type and status | Relevance for UMES DTs |
|---|---|---|---|---|---|---|
| OEO | √ | √ | √ | - | Open source, regularly updated | It can represent the process and state of the system. |
| SAREF* | √ | √ | √ | √ | Standards driven, periodically updated by working group | A comprehensive library of terms and extensions relevant to UMES. |
| SSN | - | - | - | - | W3C Recommendation, periodically updated by the working group | Semantic processing of real-time data. |
| CIM | √ | √ | - | - | Industry Standard, periodically updated by the working group | Network stakeholders follow labeling conventions. |
| CityGML* | √ | √ | √ | - | Standards-driven, periodically updated. | Extensible open data model. Existing urban infrastructure is published in the format. |
| SEMANCO | √ | √ | √ | √ | Stemmed out of research and is not regularly updated | Comprehensive ontology containing terms relevant to UMES systems. |
| REC | - | x | x | x | Open-source, regularly updated | Represent buildings and their equipment. |
| Brick | - | x | - | x | Open-source, regularly updated | Building energy systems and technologies. |
| DABGEO* | √ | - | √ | - | Research output, periodically updated by contributors. | A comprehensive library of terms and extensions relevant to UMES. |
| AIO | √ | √ | √ | √ | Open-source, but most features are infrequently updated | Incorporate many of the important domain ontologies for UMES. |
| FIWARE | √ | √ | √ | - | Open-source, and frequently updated | FIWARE models harmonize formats and representations of domains relevant to UMES DTs. |

classes and properties that make up a domain, enable contextual understanding of data ingested by the twin, and can handle assumptions when simulating future scenarios. Ontologies can be used to organize the ingestion and querying of real-time and historical measurements of the physical twin. They handle the spatial hierarchies of the equipment, e.g., sub-meters and temporal aggregations, e.g., daily, hourly, minutely, etc. The individual domain ontologies and their relation to the components of UMES systems are discussed below.

#### *3.4.1. Ontologies and data models relevant to UMES DTs*

In the context of UMES, integrating ontologies and data models is pivotal to creating effective Digital Twins (DTs). No single ontology or data model can fully represent all the elements and functions of UMES DTs. The choice will depend on the specific functionality and requirements of the twin. Therefore, a comprehensive and integrated approach is necessary to effectively select and utilize ontologies and data models that represent the relevant features of the UMES DTs. This section reviews the ontologies and data models relevant to domains containing the UMES classes shown in Fig. 2. Table 2 provides an overview of different semantic ontologies and their capabilities to represent the necessary elements of a UMES DT.

The **Open Energy Ontology (OEO)** is an example of domain ontology that supports energy system modeling by categorizing entities as either continuants or occurrents [126]. This classification allows for capturing dynamic processes and the impact on systems components integral to UMES's function and operation. Similarly, the **Smart Appliances Reference Ontology (SAREF)** provides a framework for interoperability between smart appliances [127], focusing on device-centric approaches and extending to energy (SAREF4ENER), smart grids (SAREF4GRID) and smart city (SAREF4CITY) applications relevant to UMESs.

Another important ontology is the **Semantic Sensor Network (SSN),** which describes sensors and actuators regarding capabilities, measurement processes, observations, and deployments [128]. This ontology helps integrate sensor data from multiple sectors into UMES DTs [129]. The **Common Information Model (CIM)**, a Unified Modelling Language (UML)-based standard developed by the International Electrotechnical Commission (IEC), offers a standardized approach for network modeling [130], aligning data structures used in UMES DTs with industry standards and facilitating integration across different operators. UML is a standardized modelling language used to specify, visualize, construct and document the artifacts of software and non-software systems.

**CityGML,** an open-data model from the Open Geospatial Consortium (OGC), represents urban infrastructures in 3D models, making it a valuable resource for detailed simulation of UMES [131]. CityGML 3.0 contains a more extensive set of classes for semantic models to enable more accessible connections to different ontologies [132]. It has been used to support energy simulation of urban data models and store simulation configurations, highlighting its potential applications within UMES DTs [133]. Similarly, the **SEMANCO** ontology facilitates the creation of models of UMES [134,135], although its adoption beyond the initial project remains unclear.

The **RealEstateCore (REC)** and **Brick** ontologies focus on building systems and assets, providing uniform metadata representation within UMES [136,137]. Both ontologies are modular and interoperable, aligning with standards like Shapes Constraint Language (SHACL) and the Digital Twin Definition Language (DTDL) to ensure consistent modeling. **Domain Analysis-Based Global Energy Ontology (DABGEO)** addresses the heterogeneity in energy ontologies, offering a comprehensive and modular framework for various energy domains [138].

**Azure Industry Ontologies (AIO)**, part of Microsoft's digital twin platform, incorporates domain-specific ontologies into their Digital Twin Definition Language (DTDL). At the time of writing, four ontologies are developed in open-source repositories: intelligent buildings, smart cities, energy grids, and manufacturing [139]. Despite some update frequency and format complexity limitations, AIO aligns well with established ontologies like Brick and CIM, demonstrating its relevance for UMES DTs. Lastly, FIWARE Data Models provide open-source components and data models for developing applications across smart cities and other domains, proving their suitability for UMES DT implementations [140].

Next, as a summary of the above-mentioned ontologies, Table 2 presents different semantic ontologies, their capabilities, and considerations for integrating them into UMES DTs, considering different classes presented in Fig. 2. It highlights each model's scope, features, licensing, and development status, offering insights into their relevance and applicability within the UMES context. This integrated approach underscores the necessity of combining multiple ontologies and data models to create robust and effective UMES DTs.

### *3.5. Data transaction protocols supporting UMES DTs communication*

UMES DT requires a hosting platform that manages the data communication between various data sources and data processing modules. Executing a DT is often managed by a primary solver that handles the communication between various secondary modules based on a standardized protocol. DT encompasses the concept of the IoT in connecting virtual and physical spaces [36,141–143]. IoT refers to interacting with objects without human intervention, providing intelligent services [144–147]. ISO 23,247 can be considered when considering protocols for network communication in UMES DT [148–150].

#### *3.5.1. DT and real-world communication*

UMES utilizes multiple sensors to manage effective energy balance [88,89],. These sensors monitor the system's status and performance and collect the necessary data to control energy production, storage, and usage. UMES sensors are bound to lightweight IoT network protocols (e.g., Zigbee [151–153], LoRaWAN [154–156], Bluetooth, etc.) in the physical twin representing the real-world layers. UMES DTs can consider the IoT platforms (e.g., oneM2 M [157,158], NGSI-LD [159,160], etc.) for collecting vast and diverse data. In addition, network communication protocols such as low-power, lightweight MQTT [123,124], HTTP, and CoAP [161] can also be considered.

#### *3.5.2. DT and simulation model communication*

Given that seamless communication between the simulation modules is an integral part of UMES DTs, the Functional Mockup Interface (FMI) [162] has also been the popular choice for standardizing communication within the DTs. FMI is a tool-independent standard for the exchange of dynamic models and co-simulation. These standards resolve communication issues by allowing various simulation modules to interact and exchange information efficiently, ensuring interoperability and cohesive operation within the UMES DTs. Resorting to FMI for co-simulation or model-exchange allows FMUs (functional mockup units) to communicate promptly based on a standardized protocol. Such a setup facilitates interoperability between different simulation platforms. FMUs can be imported into a variety of simulation environments, which can be divided into two categories:

(1) commercial toolboxes such as Dymola [163], Simulink [164], COMSOL Multi-physics, Ansys Twin Builder, and SimulationX [165];
(2) non-commercial toolboxes such as openmodelica [166], and Mosaik [167]

### *3.6. Summary of data management for UMES DTs*

This review of data management shows that DTs can be built from various data sources. The data requirements will depend on the twin's purpose and the physical counterpart's condition. The approach also depends on whether the physical counterpart exists or whether the UMES is in the planning phase. It is argued that a digital model of a conceptual future system cannot be twinned until the physical counterpart is built. Nevertheless, existing processes, such as BIM, can be utilized to collect the information to create the Digital Twin during the planning phase.

Once the objectives and the case for a UMES have been established, several ontologies will be used to represent the functionality and knowledge generated by the DT. Adherence to standardized ontologies will facilitate interoperability and scalability; however, care must be taken to select and reuse the relevant ontologies wherever possible. The limited adoption of published ontologies implies that this is a challenging endeavor. The same message is valid for communication protocols; a mandatory feature of DTs is synchronization between the digital model and the physical counterpart. Without this, it is not a twin. Using documented communication protocols enables effective, secure, and efficient operation of DTs. Moreover, further development in data-sharing protocols is needed to ensure interoperability across diverse systems, data security and privacy, scalability, real-time processing and synchronization, and standardization of data formats. Ontologies and communication protocols were not created solely to serve the data needs of DTs; however, DTs could demonstrate the value, building upon a semantically robust foundation using established ontologies and data models.

Having established the importance of data and knowledge management in UMES DTs, the next important aspect involves understanding the architectural frameworks that underpin these systems. The architecture of UMES DTs is central to their functionality, as it defines how data is processed, interpreted and utilized to support collaborative decision-making. The following section explores the various data processing modules that form the foundation of UMES DT architectures, ranging from highly interpretable open-box models to more opaque closed-box models, along with hybrid approaches. Next section will provide insight into the different modeling techniques and their roles in achieving accurate and efficient UMES DTs.

## 4. UMES DT architectures

In the core of UMES DT architecture sit several data processing modules, forming an ecosystem of various digital services that address the purpose of the DT. The architecture of these data processing modules can be divided into four categories, i.e., (1) open-box (white-box) models, (2) semi-open-box (grey-box) models, (3) closed-box (black-box) models, and (4) a combination of the models (hybrid) [168]. At one end of the model interpretability spectrum sit the open-box models. Open-box models (also referred frequently as equation-based or physics-based models, e.g., TRNSYS, EnergyPlus) are developed based on clear and explainable theoretical structures that represent physical phenomena (e.g., laws of heat and mass transfer) and can be deployed without observations of a system's performance. Around the center of the model interpretability spectrum lie semi-open-box models (e.g., CityEnergyAnalyst [169]). Semi-open-box models rely on a partial theoretical structure and require data for completion; hence, resistance-capacitance (RC) models are frequently used for semi-open-box modeling [170]. The theoretical structure of semi-open-box models is coupled with observations (data) to identify and enhance prior knowledge about the model parameters. Modelica is one of the leading platforms for creating semi-open box energy models [171]. Closed-box models (e.g., Buildingenergy.ninja [172]) sit at the far end of the model interpretability spectrum, with limited transparency. Closed-box models solely rely on observations of a system's performance and do not necessarily provide explainable knowledge about their internal workings.

The distinction between open, semi-open, and closed-box models can be attributed to the abstraction level employed in each method. In the context of UMESs, this translates to the desired level of interpretability. However, high-level abstraction is conditioned on the availability of measurements during the systems' operation.

- Open-box models are based on equations and are more detailed and transparent. They aim to provide a deep and complete understanding of the system. Each component or equation of an open-box model can be viewed, modified, updated, and extended. On the contrary, closed-box models are abstract and obscure, often based on simple and modular transfer functions that collectively mimic the behavior of a complex system.
- Closed-box models are beneficial when the inner-workings of the system are not well-understood or when the focus is on prediction rather than understanding the underlying mechanism of the system.
- Semi-open-box models share qualities of open-box and closed-box models, providing a tradeoff between the interpretability of open-box models and the computational efficiency of closed-box models. Users of semi-open-box models can access some internal details of the system, but not all.

Despite the general descriptions above, the distinction between the three modeling approaches has diminished in recent years. Open-box models can be fine-tuned with measurements when there is a lack of confidence in the prior knowledge. On the other hand, semi-open-box models can host various levels of abstraction, from fully detailed models to encapsulated equations. Similarly, it has long been believed that closed-box models often provide a high-level of abstraction and mask the system's internal working, which they mimic. However, with the advancements in physics-constrained closed-box models, the distinction between semi-open and closed-box models has faded [173].

No single model is the perfect solution for all UMES DT applications, as each model architecture has certain purposes with advantages and drawbacks. For instance, open-box models provide insights into every part of a system, even where physical data loggers are not installed. Meanwhile, closed-box models can only provide predictions if measurements are already available and representative. Open-box models can be executed at different temporal resolutions, including those different from the measurements [174]. Semi-open-box models provide more accurate predictions than open-box models while being more robust to unforeseen events than closed-box models. Closed-box models can offer higher accuracy in forecasts when compared to open and semi-open-box models [175].

Regardless of the chosen architecture, it is imperative that the model performs well in real-world setups and is capable of generalizing to unforeseen events. This capability is often called high-fidelity performance and is crucial for evaluating system performance (e.g., robustness, flexibility, and resiliency) in extreme scenarios [176]. It is important to note that high-fidelity performance is an imprecise description of a model's function. Thus, case-specific quantitative metrics are vital in choosing the proper model architecture for each use case. Such criteria are often chosen based on the application of the digital twin [174]. For instance, models with high-levels of uncertainty can be unsuitable for implementing and benchmarking MPC (model predictive controllers). Thus, rule-based controllers (RBC) will inevitably become the preferred choice for such scenarios [177]. This issue affects explicitly pure open-box models that are not calibrated to measurements and, thus, suffer from the "performance gap" phenomenon. In such cases, semi-open-box and closed-box models – developed and fine-tuned based on measurements – can mimic the physical counterpart accurately and, therefore, appear to be the preferred solutions for digital twin model architectures [178]. A comparison of different architectures and their features is provided in Table 3.

Although many articles discuss the high-fidelity feature of the digital twin, the execution time of the underlying modeling process is rarely mentioned. Occasionally, there are incompatible needs for the fidelity of the virtual representation, and therefore, multiple DTs of different abstraction levels are recommended [179]. Other means to reduce

**Table 3**
A comparison of distinctive features and characteristics of urban multi-energy system (UMES) digital twin (DT) architectures, open-box, semi-open-box, and closed-box models.

| | Open-box | Semi open-box | Closed-box |
|---|---|---|---|
| Inputs | System characteristics, time-series data | System characteristics, Time-series data | Time-series data |
| Outputs | Time-series data | Time-series data | Time-series data |
| Transparency and abstraction | Transparent | Customizable | Abstract |
| Spatio-temporal Resolution | Limited by the simulation tool | Limited by the simulation tool | Limited by the measurements |
| Manual labor | Medium-High | Low-Medium | Low-Medium |
| Simulation time | Medium-High | Low-Medium | Low-Medium |
| Computing resources | Low-Medium | Low-Medium | Medium-High |
| Accuracy of model | Low-Medium | Medium-High | Medium-High |
| Performance fidelity | Medium-High | Medium-High | Low-Medium |
| Generalization capabilities | Medium-High | Medium-High | Low-Medium |

computation complexity include using machine learning techniques to build a surrogate model [180]. However, interpretability and extrapolation with machine learning techniques are often considered insufficient. Incorporating known physical equations into the black-box neural network can provide a favorable balance between both sides and ensure trust when managing critical infrastructure [181].

Two aspects differentiate UMES DTs from classical UMES simulation platforms: (1) the capability of data communication between different DT modules and the physical counterpart and (2) the capability to actively override the input variables to the DT modules during data processing [182]. UMES DTs can be developed from open to closed-box models, often consisting of different engines (solvers) that may run at dissimilar temporal resolutions.

The literature is rich with studies that adopt various configurations of the abovementioned model architectures. DTs of energy systems have been devised and trialed at building to urban scales by integrating data streams with open, semi-open, and closed-box models or a combination.

### 4.1. Open-box models

Open-box models require validation against measurements to assess their reliability. The validation is often followed by a calibration process to reduce the performance gap as much as possible. While calibration can be applied to both the model and the inputs, fine-tuning the latter is more common. Studies have coupled real-time (as well as future) weather data with EnergyPlus through co-simulation to visualize energy demand, water consumption, and the global warming potential [183]. In another case study, fine-tuned open-box models were developed in MATLAB and then coupled with TRNSYS and CONTAM software to create a digital twin of a complex pipe-integrated shell roof system. Another great platform is the spawn of EnergyPlus (SOEP), which couples Modelica with EnergyPlus tools [184,185]. This coupled modeling allows data communication between different software, where each software is tailored for simulating one module of the overall integrated system [186].

### 4.2. Semi-open-box models

Semi-open-box models are often sought when the excessive computational load of pure open-box models must be avoided, yet model interpretability is highly desired. Vering et al. (2019) opted for semi-open-box models [163] in the Modelica simulation environment for developing and simulating dynamic systems, given the modularity of Modelica Libraries [187]. The model was executed in a Docker virtual environment to ensure interoperability with different operating systems [188]. Similarly, Clausen et al. (2021) used the Modelica environment to create semi-open-box modules for building systems and executing simulations [189].

### 4.3. Closed-box models

In cases where the physical environment is too complex to model and interpretability is less important, studies opt for pure closed-box models. The application of closed-box models with online updates based on real-time data streams has proven suitable for replicating the performance of HVAC systems and evaluating alternative operation scenarios [190]. Given that closed-box models benefit from a generic architecture, transferability to different energy sectors is facilitated when opting for end-to-end data-driven architectures [172].

Given that the DTs may consist of various modules with dissimilar levels of complexity, hybrid models are becoming more prevalent [191, 192]. For instance, a combination of semi-open and closed-box models has been utilized to benchmark the load-shifting potential of MPCs through storage systems [190]. It has been argued that a combination of open and closed-box models yields more robust DTs and, therefore, is a more suitable solution for benchmarking the operation and control of energy systems [193]. On an urban scale, Srinivasan et al. (2020) resorted to an open-box model for seamless data transfer for real-time demand response. In this study, open-box modules have also been fed with future weather data as a surrogate simulation engine to support decision-making through closed-box models [194].

As a subcategory of closed-box models, Artificial Intelligence (AI) has displayed exciting potential for designing and operating digital twins for UMES. The utilization of AI in developing digital twins for urban energy systems spans from the microscale of individual buildings to the macroscale of districts and entire cities. At the building level, digital twins utilize AI to enhance energy efficiency, predict maintenance needs, and facilitate the integration of renewable energy sources, as demonstrated by Testasecca and Lazzaro (2023) in their exploration of smart energy networks [195]. Expanding to the district and city scales, AI-enriched digital twins offer sophisticated management of energy networks, promoting sustainability through predictive analytics and boosting resilience against environmental challenges [15]. Furthermore, the incorporation of AI with digital twins for the development of hybrid and sustainable energy systems is explored by Khan et al. (2022), illustrating the potential for optimization and sustainability in energy systems [196].

The utilization of AI in the development and management of digital twins for urban energy systems also presents several limitations. One of the primary concerns is data privacy and security, as the integration of AI with digital twin technology requires handling sensitive data, potentially exposing it to cybersecurity risks [197]. The complexity of accurately modeling and simulating the intricacies of urban energy systems poses another significant challenge, demanding advanced computational resources and sophisticated algorithms [198]. Moreover, these digital twins require continuous data collection and processing to reflect real-world changes accurately, which can be resource-intensive [199]. The quality and availability of data become crucial factors in the effectiveness of these systems, particularly in complex urban environments with layered infrastructure networks [200]. Lastly, the potential for algorithmic biases in AI models can lead to skewed outcomes, necessitating careful calibration and oversight. The accuracy of AI models is often called "impressively high," with accuracies over 95 %. However, AI systems would render unreliable compared to safety-critical systems that are certified out to 5–6 decimal points (i.e., 99.99999 %) [201]. Most of the limitations specified here for the AI-driven DTs also apply to DTs in general, particularly data privacy and security, computational expenses, sophisticated algorithms, and resource intensity.

To summarize, the UMES DTs architecture consists of several data processing modules categorized into open-box, semi-open-box, closed-box, and hybrid models. Open-box models are transparent, based on theoretical structures, and require no system performance observations. Semi-open-box models combine theoretical structures with observational data for enhanced parameter identification. Closed-box models rely solely on system performance data with limited transparency. Each model type has strengths and limitations regarding interpretability, computational efficiency, and accuracy. The distinction between these models diminishes with technological advancements, allowing for more robust and flexible digital twin implementations. Regardless of the chosen model, ensuring high-fidelity performance in real-world scenarios remains crucial. The integration of AI further enhances the capabilities of digital twins, although it introduces challenges related to data privacy, computational resources, and potential algorithmic biases.

With a solid understanding of UMES DT architectures, the next section focuses on how digital twins can be applied to different life-cycle phases of urban energy systems. From initial planning and design to ongoing operation and eventual decommissioning, digital twins offer a wide range of applications to optimize each phase of UMES. However, it is essential to recognize that the integration of DTs across lifecycle phases is still evolving, and greater interoperability between these phases can unlock further potential. Next section explores how DTs contribute to improved energy planning, operation and decommissioning, providing insight into both the opportunities and challenges that arise with it.

## 5. UMES DT application to lifecycle phases

By leveraging DTs, UMES can improve strategic energy planning, dynamically manage energy supply and demand, enhance energy efficiency, and increase the resilience of urban infrastructure. Applications of DTs in different lifecycle phases of UMES, from planning and design to operation and decommissioning, can exploit distinct opportunities and challenges, as discussed in the sub-section below. They are also expected to offer higher flexibility, scale, and interoperability beyond existing solutions such as Building Information Modelling (BIM), Computer-Aided Design (CAD), Geographic Information System (GIS), Energy management systems (EMS), and Building Management Systems (BMS) [32]. UMES DTs build on these existing solutions by integrating and enhancing data exchange and decision-making capabilities across these platforms. It should be noted that today DT applications for design, operation, and decommissioning phases are not interoperable silos. Data science and analytics development are needed to connect between different life cycle phases, further maximizing the benefits of DT applications. By applying DTs in different UMES lifecycle phases, energy system actors, such as urban planners, policymakers, engineers, citizens, and energy communities, can better understand the complexities and opportunities of such systems.

### 5.1. Planning phase

During UMES planning, DTs can help consider energy system architecture, technology selection, and stakeholder engagement. With the widening applications, UMES DTs can act as a “base truth” and “visual basis” to enhance the collaborative planning process, addressing the inputs of various energy system actors such as city, utilities, energy planners, and project developers as well as facilitating their evaluations and decision-making process in UMES design. The UMES DTs will act as an unbiased basis to test the alignment of proposed socio-techno-economic and institutional design choices in different transition trajectories and scenarios with the energy and emission performance objectives.

However, the DT application in UMES planning is new [64,65]. Table 4 summarizes some examples of applications of DTs in the planning phase of UMES. The table lists digital twin projects from diverse locations, including the Orkney Islands, Anzio port, Docklands, Zürich, and Singapore, each serving distinct purposes like reducing carbon footprint, achieving zero energy districts, urban planning, and collaborative decision support. The projects utilize various platforms such as IES, Green building studio, Unity3D, GIS, and Virtual Singapore to effectively implement and visualize the UMES DTs.

Orkney Islands DT represents a complex environment of buildings, energy systems, and other infrastructures, including their interrelationships and the impact of changes on system performance. Using scenario analysis, the UMES DT helps to understand how a combination of energy efficiency measures and local renewable energy resources could create conditions for a zero-carbon community [66]. The challenges associated with the Orkney Island DT were installing new heat meters, oil meters, electricity meters, and weather sensors to provide a clearer picture across the island portfolio. The main limitation of the Orkney Islands DT is that it is not built in an open-source environment.

Anzio port DT supports the transformation of port areas to zero-energy districts in the Lazio region of Italy. The focus is on energy-saving procedures and strategies as well as renewable energy integration for sustainable mobility [202]. The DT supports decision-making among port stakeholders using integrated multi-scale digital data sources from BIM and GIS to simulate strategies for energy performance improvement at the port area. Anzio port DT’s limitation is the integration of multi-scale digital simulations into real-time data. Further expansion of DT extending the harbor representation can improve its environmental and economic management.

Docklands DT is an open-source platform that can be used to gather citizens’ feedback on urban planning and policy decisions [203]. It has six layers: terrain, buildings, infrastructures, mobility, digital layer

**Table 4**
Examples of digital twins (DTs) application to the planning phase of urban multi-energy system (UMES). It covers various digital twin projects across multiple locations, highlighting their geographical scale, purpose, and platform/middleware used.

| Location | Geographical scale | Purpose | Platform/ middleware | Reference |
|---|---|---|---|---|
| Orkney Islands | District | Reduce carbon footprint and energy consumption and maximize renewables | Integrated Environmental Solutions (IES) | [66] |
| Anzio port | District | Zero energy district, energy savings, renewables integration, sustainable mobility | Green building studio, In-sight, Revit, Archi CAD, Infraworks, CFD | [202] |
| Docklands | District | Urban planning, energy usage | Unity3D, WebGL | [203] |
| Zürich | City | Geodata repository for urban planning, platform for visualization and collaboration | GIS, geoportal, Virtual Zürich | [34,204,205] |
| Singapore | City | Collaborative decision support system, Urban planning, analysis of the potential for solar energy production, communication, and visualization | Virtual Singapore | [206,207] |
| Helsinki | City | Urban planning | CityGML, Virtual Helsinki | [207–209] |

(smart city), and virtual layer (digital twin). The Docklands DT offers an online interaction platform for citizens, researchers, and city councils. It helps citizen engagement as citizens can easily tag problem areas in the city and request changes, providing valuable feedback for urban planning. Some datasets are interpolated due to the availability of only aggregated data at Dublinked open data source [210], leading to less accurate simulations. Further limitations of current DT include poor representation of older buildings, open spaces, and some infrastructures and the exclusion of some urban mobility.

Zürich 4D is a DT for visualizing structural development in space and time, including future scenarios, and acts as a source for historical and future data [34]. The City of Zürich uses its DT in the areas of environment (noise, air pollution), energy (solar potential analysis), and urban planning [204]. It is also used explicitly to develop the municipal development plan of Zürich. It can be used for location-based collaboration with internal (city departments) and external partners. The data sets of Zürich 4D are also available at Open Government Data. The Zürich DT also enables digital participatory processes in Urban planning, e.g., Minecraft computer games and web-based 3D interactive tools. It offers new possibilities for collaborative discussion and decision-making in urban planning. The limitation of Zürich 4D is that it is not yet integrated to the energy system. Nevertheless, it demonstrates the key components of a digital twin relevant to UMES, specifically the visualization of structural development over space and time, which could potentially evolve to incorporate energy systems.

Singapore's digital urban climate twin, which also considers the energy system and its anthropogenic heat emissions, has been developed to demonstrate how measures like electric vehicles and tree cover can reduce urban heat [35]. It integrates computational models such as environmental, land surface, building energy, etc.) as well as regional and micro-scale climate models. Exploring what-if scenarios, it can be exploited by urban planners and policymakers in their decision-making processes. Challenges include validating the DT through environmental monitoring to develop reliable model simulations in an urban context.

The digital twin of Helsinki is a virtual replica of the city's environment, operation, and changing circumstances. It combines information technology services, open data, and continuous updates of information. Helsinki DT contains information about renewable energy potentials, possibilities for energy renovations, water consumption, district heating and electricity throughout the region. City planners, housing companies, residents, and energy service providers can benefit from its energy data on buildings, simulated building heating demand, solar energy, and geothermal potential. It is being used to illustrate upcoming plans and to co-create new city functions in collaboration with citizens [207]. Despite the potential of DT for urban planning, organizational, technical, and data integration issues hinder its extensive deployment [208].

The DTs reviewed here offer insights into both the capabilities and limitations of current platforms in supporting UMES planning. For DT to fully support UMES, it must integrate not only urban infrastructure data but also energy system data. DTs of Orkney Islands, Docklands, and Singapore demonstrate the importance of this integration, enabling decision-making that accounts for energy consumption, emissions, and system performance. Singapore DT illustrates the importance of scalability and the ability to integrate a wide range of data sources. A UMES digital twin must be flexible enough to evolve with changing urban energy needs and technological advancements. In summary, while existing digital twins have made substantial progress in supporting UMES planning, there are still gaps regarding full UMES integration. Future development should focus on enhancing energy system data integration, improving scalability, and fostering collaboration to realize the full potential of digital twins for urban energy system transformation.

### 5.2. Operation phase

UMES DT application in the operation phase emphasizes real-time monitoring, management, and optimization to maintain system performance according to design targets. UMES increasingly integrates distributed generation, sensing, and actuation at technology and infrastructure levels. The efficient operation of these systems necessitates significant flexibility, which can be sourced from sector coupling [12] and active engagement of energy usage. The latter requires incorporating the interaction between humans and technical systems in UMES DTs. Extreme events, such as geopolitical tensions, can significantly change human perceptions and behaviors regarding energy systems, leading to sudden changes in energy consumption patterns. This needs to be considered holistically in the UMES DT. In addition, future UMES will feature high automation levels and complexity, which raises the question of how humans, at the heart of UMES, interact with such systems efficiently and transparently. In both cases, the human dimension should be holistically incorporated into DTs to ensure that human responses and decision-making processes are accurately represented, allowing for more resilient and adaptable UMES.

To this end, we provide a detailed comparison of various applications of DTs in terms of system boundaries, the purpose of the application, the inclusion of humans, the update frequency of information, and the estimated technology readiness level (TRL) [211], as shown in Table 5. These use cases focus on the operation phase of UMES across multiple locations and geographical scales, including projects in Salamanca, Montreal, Dübendorf, Grafton, Florida, and Gelderland.

Table 5 shows that many of the envisioned values of DTs are closely linked to the operation of cyber-physical UMESs and the extent to which human interaction is incorporated. These applications include, but are not limited to, predictive maintenance or control, testing of new operational strategy [213], reliability, fault detection and diagnostics (FDD) and cyber-security assessment [214], education and training, and disaster management [22]. Although the term "digital twin" is not always explicitly mentioned in th~~o~~se use cases, core concepts of DTs are captured. A UMES DT prototype has been developed in [213], aiming at state estimation for power system operations, addressing the bottleneck caused by the need for extensive real-time data collection. The prototype was used to generate pseudo-measurements, which can be used to optimize DER operations for distribution voltage regulation. A digital twin has been developed [214] to detect coordinated cyber attacks on increasingly digitalized networked microgrids. When combined with a resilient control algorithm, this approach helps mitigate the impacts of such attacks on the system. Beyond sensing and actuation of the physical system, the integration of humans is addressed in [215], which introduces a game-based approach to facilitate human-machine interaction and promote behavioral changes that enhance energy efficiency. The digital twin in [216] focuses on thermal comfort study by leveraging real-time sensing and virtual reality to engage humans in an immersed environment. Moreover, the digital twin developed in [217] focuses on benchmarking advanced control algorithms and enables the evaluation of performance gaps under realistic conditions. Reference [218] investigates demand response mechanisms for distribution network management, utilizing a hardware-in-the-loop test platform based on real infrastructure to evaluate the effectiveness of control algorithms and their practical implications. Lastly, a disaster city digital twin has been envisioned in [219], representing a unifying framework to integrate data collection, analysis, and decision-making for disaster management. The proposed framework not only considers data collection on the physical infrastructure but also integrates humans via social sensing.

Despite the~~ir~~ varied use across scales and regions, DTs often show low TRLs, ranging from conceptual proposal [219] to prototyping at the district level [213]. A notable gap in many cases is the lack of consideration for human factors, although emerging interaction mechanisms, such as social sensing, are proposed in [219]. Information from such mechanisms can be asynchronous and does not necessarily need to be

**Table 5**
Overview of digital twin (DT) applications in the urban multi-energy system (UMES) operation phase. Different UMES DTs are contrasted based on geographical scale, purpose, human interaction, models, and TRL level.

| Location | Geographical scale | Purpose | Human in the loop | Communication | Model | TRL | Ref. |
|---|---|---|---|---|---|---|---|
| Salamanca, ES | Building | Behavioral change for energy saving | Yes | Both synchronous and asynchronous | Closed box | 3-4 | [211] |
| Montréal, CA | Building | Thermal comfort assessment | Yes | Synchronous | Semi-open box | 3-4 | [212] |
| nestli, Dübendorf, CH | Building | Controller benchmarking and flexibility quantification | No | Synchronous | Open box | 3-4 | [167, 213] |
| ProDROMOS, Grafton, USA | District | Monitoring and testing | No | Synchronous | Open box | 4 – 6 | [214] |
| Florida, USA | District | Cyber security testing | No | Synchronous | Open box | 2-4 | [215] |
| GECN, Gelderland, NL | District | Primary voltage control | No | Synchronous | Open box | 3-4 | [216] |
| - | City | Disaster management | Yes | Asynchronous | Closed box | 1 | [217] |

communicated simultaneously, as is required in physical system use cases [214,218].

Moreover, the geographical boundary of existing applications of UMES DTs in the operation phase is mainly at the building and district levels, indicating potential scalability challenge. These challenges are likely related to the difficulty in collecting system-related information and efficient modeling pipelines. For example, the open-box modeling approach in [167] requires construction details and year-long time series data. Such observations suggest that future research must provide tools to streamline information collection and scalable and computationally tractable modeling procedures. Additionally, there is often a siloed approach within disciplines, where one field may oversimplify another. This discipline-specific approach may hinder a holistic integration of DTs at different levels and a full representation of the operational stage. For example, real-time simulators with high-fidelity models have been used to mirror the operational environment, providing a virtual testbed for advanced control and system management strategy [212]. However, the infrastructure-level simulators surveyed in [212] tend to abstract buildings and districts as nodes, which creates a barrier to incorporating human interactions. Further research is needed to bridge the gaps between disciplines and their traditional representations of each other, ensuring a more comprehensive integration of DTs that includes both the technical and human dimensions.

The applications of DT in UMES differ notably between the planning and operation stages. DTs can be used for long-term forecasting and infrastructure design in the planning stage. In contrast, they are more commonly utilized for real-time system monitoring and management in the operational stage. Also, the availability and data types used to update the DTs differ in both cases. In the planning stage, there is often a reliance on hypothetical or projected data, leading to a greater need for approximation and extrapolation. By contrast, the operation stage typically involves real-time or near-real-time data, allowing for more precise and accurate updates to the DT.

Furthermore, the response to the latest information in the planning stage has a significantly larger time lag, whereas DT in the operation stage responds on a much smaller time scale. It is necessary to point out that current DT development in the planning and operational stages are typically treated separately. However, this approach can lead to inefficiencies and missed opportunities for insights that could be gained from a more integrated approach. Future research should strive to connect the flow of data collection and decision-making in both stages to achieve higher synergies. For example, data and insights gathered during the operational phase could inform adjustments in long-term planning.

### *5.3. Decommissioning, reuse, and circular economy*

The focus of UMES design so far has been on planning and operating new infrastructures. However, to enhance resource recovery and integrate circular engineering principles, the decommissioning of UMES should already be considered in the design phase [218–222]. In reuse and decommissioning, various data sources are commonly used, including water networks, sewage plants, telecommunication systems, power networks, BIM models containing architectural, structural, and system data, city-scale geometry models, and geo-coded sensor data. The application of DT during the operational stage significantly facilitates the end-of-life phase. DT applications for reuse and decommissioning play a crucial role due to the following reasons:

- For end-of-life management, information on how the assets were used and to what capacity is needed [219]. DT can be used in predictive maintenance, which is state-dependent and implies that at the designated end-of-life, it is possible to predict the asset's state. For example, companies in several countries, including Switzerland, offer PVs for leasing and buy-back programs. It is vital to know the state of the product-service models for reuse.
- The challenge concerning UMES is that the DT is federated or aggregated of multiple assets and asset classes. So, it is essential to tie in operations and end-of-life or decommissioning. For example, suppose you are modeling local grid energy and know that 20 % of your PVs must be decommissioned or replaced. In that case, you need the model to adjust and reallocate energy demands.
- DT can contribute to tracking, recycling, and management of construction waste [221].

There are no concrete instances where DTs have been employed for reuse. There are two significant obstacles in this regard. Firstly, DTs are still relatively new, and the existing examples primarily concentrate on energy rather than materials. Since reuse is a developing practice, it will likely take some time before real-life DT implementation occurs, as reuse and DTs must evolve independently. Nevertheless, DT implies high-fidelity/volume of data. If a DT is maintained at the end-of-life, asset managers can use the information to connect to other applications and databases (like a reused material marketplace).

DTs also contribute to the circular economy by promoting the reuse and repurposing of assets. By capturing detailed information about a building or infrastructure, including its design, materials, and components, DTs can facilitate the identification of potential reuse opportunities. This includes assessing the feasibility of deconstructing and repurposing components or entire structures, promoting a more sustainable construction approach, and reducing waste generation.

Moreover, DTs enable improved collaboration and communication among stakeholders in the built environment. With a shared digital representation, designers, architects, engineers, facility managers, and other professionals can collaborate more effectively, exchange information, and simulate different scenarios. This enhanced collaboration streamlines processes, optimizes resource allocation, and supports implementing circular principles at various stages, from design to operation and maintenance. Moreover, the life-cycle data set of DTs can be used to train future DT applications.

After examining the various lifecycle applications of UMES DTs, it is important to reflect on the broader implications and the challenges that arise from their deployment. The discussion in the next section will delve into the complexities associated with advancing UMES DTs, considering socio-technical dynamics, interoperability, cybersecurity, and scalability. It will also explore how data management across lifecycle phases plays a critical role in ensuring seamless real-world integration, and how digital twins can facilitate the transition toward decarbonized and resilient urban energy systems. The following section will provide a critical assessment of the current state of UMES DTs, outlining the advancements and identifying gaps that need to be addressed for future developments.

## 6. Discussion

The advancement of DTs for UMES requires a comprehensive approach that considers the multi-faceted nature of such systems, including socio-technical complexities, interoperability, cybersecurity, and scalability challenges. As UMES DTs evolve, the need for system-of-systems approaches becomes imperative, demanding coordinated and collaborative efforts across sectors and disciplines. DTs must align with real-world data connection requirements, ensuring the accuracy of virtual representation and facilitating seamless information exchange among subsystems.

Data collection and management are pivotal across UMES lifecycle phases and corresponding pre-twin, active, and post-twin phases of its DTs. While operational phases require real-time data connections, planning and decommissioning phases benefit from static and historical data sets. This review highlights advancements in integrating and processing data in UMES DTs, encompassing data gathering, modeling, simulation, optimization, and visualization. DTs provide information for UMES through continuous validation and integration of heterogeneous data sources. Different DT components capture, analyze, and interpret data to enable collaborative and informed decision-making. The UMES DT should also be able to notify when the physical twin must be decommissioned. Yet, continuing updates throughout the decommissioning process might not be feasible. Even if possible, what data should be updated and how this connection should be maintained must be further explored. DTs also should develop the inherent ability to complement poor and low-quality data.

The interoperability of DTs across UMES lifecycle phases is crucial for future development. No single model fits all applications; choosing between open-box, closed-box, or semi-open-box models should align with specific operational needs. Closed-box models are favored for their efficiency and predictive accuracy. UMES DTs also play a pivotal role in steering energy systems toward decarbonization goals, offering opportunities for enhanced efficiency, sustainability, and resilience through improved planning and optimized operations. DTs-enabled co-simulation frameworks can also facilitate the reuse of sophisticated tools across multiple sectors.

However, the digitalization of UMES introduces cybersecurity challenges, necessitating robust assessments of cyber threats as systems become increasingly interconnected. Addressing these concerns requires standardized and secured interfaces. Furthermore, as the scale of the physical system extends, the computational demands necessitate a distributed cloud computing approach to manage the growth effectively. Fully digitalized energy systems can be costly, and they often must go through the resistance of utilities and customers.

Furthermore, integrating social dimensions into UMES DTs is crucial for understanding user behavior, ensuring public acceptance, and aligning with societal expectations. This holistic approach aligns technical potential with community engagement and societal expectations.

While recent advancements in platforms and tools show promise, particularly in operational and planning phases, there remains a need to explore reuse and decommissioning phases comprehensively. Establishing clear standards and definitions for UMES DTs is essential for maximizing their potential across diverse urban energy scenarios. In conclusion, continuous refinement and development of UMES DTs are necessary to effectively accommodate the evolving landscape of urban energy systems and their management complexities.

After discussing the range of critical issues on development and integration of UMES DTs in this section, it is important to consider the future direction of UMES DTs and its broader implications. As UMES DTs continue to mature, the challenge will be in maintaining alignment between digital and physical system growth, especially as these systems become more complex and interconnected. The following outlook section delves into the key trends, challenges, and opportunities that will shape the future development of UMES DTs, emphasizing the need for interdisciplinary collaboration, standardized communication protocols, and system-of-systems approaches to ensure the seamless integration of digital twins across diverse sectors.

## 7. Outlook

Digital twins (DTs) offer a comprehensive framework for analyzing Urban Multi-Energy Systems (UMES). As UMES DTs evolve, maintaining pace with physical system expansion necessitates a system-of-systems approach involving novel technologies, multiple sectors, actors, and collaborative decision-making. Achieving consensus and standardization of interfaces between technical and social systems requires interdisciplinary collaboration. Effective communication between DTs and standardized approaches to their development is essential for seamless data exchange with other digital twins.

This review has highlighted a range of critical research questions on development and integration of UMES DTs that are pivotal to the future of intelligent energy systems. Addressing these questions is essential not only to push the technological boundaries but also to ensure the seamless integration of UMES DTs into complex urban environments. The following research outlook delves into key challenges surrounding data management, interoperability, modeling, economic and regulatory impacts, socio-technical dynamics, lifecycle management, cybersecurity, and scalability. These questions aim to inspire new innovations and collaborative efforts across disciplines, driving the evolution of UMES DTs and their role in transforming urban energy landscapes:

1. **Data Management**: What data management techniques can handle the volume, velocity, and variety of UMES data without overwhelming DT capabilities or end-users? What are the optimal methods for integrating real-time sensor and meter data into UMES DTs? How frequently should these data be updated to balance system accuracy with computational efficiency?
2. **Interoperability and Standardization**: How can we develop universal protocols and standards to facilitate the seamless integration of DTs across different energy systems and sectors? What standards and protocols are necessary for seamless interaction between various digital twin platforms and UMES components?
3. **Modeling Approaches**: What strategies are the most effective for creating open and semi-open box models for UMES that balance transparency, adaptability, user interaction, system performance, and security? How can artificial intelligence and machine learning (closed-box models) enhance the predictive and operational capabilities of UMES DTs?
4. **Economic and Regulatory Impacts**: What economic models and regulatory frameworks are required to support the adoption and scaling of DTs in UMES, encouraging innovation while protecting stakeholder interests? How can DTs improve the reliability and resilience of UMES, particularly in response to environmental and human-caused challenges? How can DTs shape regulatory and policy frameworks to promote equitable, cost-effective, and sustainable development of UMES?
5. **Socio-technical Dynamics**: How do social dynamics and stakeholder engagement influence the design and acceptance of DTs in

different life-cycle phases of UMES? What methods can effectively integrate socio-technical aspects in UMES DTs? How can DTs improve human-machine interfaces and stakeholder engagement in UMES management?
6. **Lifespan Availability, Decommissioning, and Reuse**: What are the best practices for using DTs to manage UMES assets' decommissioning and reuse phases, ensuring environmental compliance and cost efficiency? What strategies and technological innovations are needed to ensure the accessibility and functional relevance of UMES DTs throughout their lifecycle?
7. **Cybersecurity Measures**: How can DTs be fortified against emerging cyber threats associated with UMES's increased connectivity and complexity? Which best practices and security measures are critical for protecting UMES DTs?
8. **Scalability Challenges**: As UMES grows in scale and complexity, what computational architectures will ensure that DTs remain effective and responsive to real-time data and simulation needs? How can DTs be designed to scale from individual system components to the full extent of UMES without compromising functionality?

Addressing these pivotal questions demands an interdisciplinary approach integrating technological innovation with policy, human factors, and economic considerations. Insights gathered from these future research will critically influence the emergence of UMES, making them more adaptive, secure, and integrated into society. This comprehensive exploration will enhance the deployment and utility of UMES DTs, driving the transition toward smarter, more sustainable urban energy systems.

## 8. Conclusion

As cities increasingly adopt distributed energy resources and integrate renewables into their energy infrastructure, the complexity of these systems demands sophisticated solutions for real-time monitoring, optimization, and data management. This review has underscored the vital role of digital twins as virtual replicas of urban multi-energy systems, enhancing system design and operation. Yet, the success of UMES DTs hinges on effective data handling and system integration. Advanced data fusion techniques and middleware enable seamless interoperability between various system components and external data sources. Digital twins exemplify the innovative approach for closing the gap between transactional data systems and system analysis, significantly contributing to the entire urban multi-energy systems lifecycle phases of planning, operation, decommissioning, and reuse by aligning continuous validation and integration of heterogeneous data sources with model and optimization-based analysis digital twin support collaborative and well-informed decision-making processes for urban multi-energy system stakeholders. The application of urban multi-energy system digital twins has shown potential for enhancing performance, sustainability, and resilience, improving energy efficiency, optimizing operations, and reducing emissions and costs.

The strategic value of digital twins extends beyond operational analytics to encompass long-term planning, making them critical tools for achieving decarbonization objectives. The predictive accuracy of digital twins is vital. Yet, the preference for closed-box models underscores the need for context-specific data management strategies to optimize digital twin applications throughout the urban multi-energy system lifecycle. There is growing recognition of the advantages of open and semi-open box models, which provide transparency in system operations and the flexibility for ongoing modification. These models are advantageous in scenarios that require user intervention and iterative learning, facilitating greater adaptability and system evolution.

Despite the promising potential of DTs, achieving mature implementation is challenging, especially regarding scalability and data update methodologies in later lifecycle stages. Scaling digital twins to handle the complexity and heterogeneity of urban energy systems, ensuring data interoperability through standardized ontologies, and addressing socio-economic and regulatory implications are all areas requiring further attention. At the same time, ensuring the feasibility of continuous data updates requires robust data governance frameworks and scalable computing solutions. Future research should focus on developing standardized ontologies and protocols to enhance data interoperability across different urban systems. Additionally, exploring the integration of emerging technologies, such as blockchain for secure data sharing and edge computing for real-time analytics, can further enhance the functionality and resilience of UMES DTs. Addressing these areas will ensure that digital twin technology continues to support sustainable and inclusive urban energy transitions.

## Glossary

Below is the summary of the definition of key terms used in this review article.

| Term | Definition | Ref. |
|---|---|---|
| Urban multi-energy systems (UMES) | Urban multi-energy systems (UMES) are energy-efficient and energy-flexible urban areas or groups of connected buildings that emit low or net-zero greenhouse gas and actively manage local production and consumption of renewable energy | [38] |
| Digital twin (DT) | A virtual representation of an object or system that spans its lifecycle is updated using real-time data and uses simulation, machine learning, and reasoning to help decision-making.<br>Or<br>Digital representation of assets, processes, and systems within a built environment with the two-way connection between the physical and digital world. | [70]<br>[223] |
| Distributed energy resources (DERs) | "Energy resources composed of generation, storage and controllable load which is connected at the low or medium voltage distribution level " (IEC 61,850) | [224] |
| Cyber-physical system | "Interacting digital, analog, physical and human components engineered to provide functionality through integrated physics and logic." | [67] |
| Internet of Things (IoT) | "An infrastructure of interconnected entities, people, systems and information resources together with services which process and react to information from the physical world and the virtual world" ISO/IEC 20,924:2021 | [225] |
| Building information modeling (BIM) | "A collaborative way for multi-disciplinary information storing, sharing, exchanging, and managing throughout the entire project lifecycle including planning, design, construction, operation, maintenance, and demolition phase | [226] |
| Semantic ontologies | A common language that enables mapping between functional and architectural components. | – |
| Physical Twin | The physical, real-world entity that the digital twin represents. | – |
| Technology readiness level (TRL) | The most widely used scale for a maturity assessment allows a consistent comparison of maturity between diverse types of technologies. | [227] |

## Declaration

During the preparation of this work, the authors used language editing tools such as Grammarly, DeepL and ChatGPT to improve language and readability. After using these tools, the author reviewed and edited the content as needed and take full responsibility for the content of the publication.

## CRediT authorship contribution statement

**B. Koirala:** Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **H. Cai:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization. **F. Khayatian:** Writing – review & editing, Writing – original draft, Investigation. **E. Munoz:** Writing – review & editing. **J.G. An:** Writing – original draft, Investigation. **R. Mutschler:** Writing – review & editing. **M. Sulzer:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Funding acquisition, Conceptualization. **C. De Wolf:** Writing – original draft, Investigation. **K. Orehounig:** Writing – review & editing, Investigation, Funding acquisition, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Data availability

No data was used for the research described in the article.

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