Article type: Review paper

- Text revised 27 August 2024
- 5105 words, 3 Figures

Review of Digital Twins enabled applications for demand response

Author 1 Corresponding author

- Yuan Xie
- Yuan.xie.19@ucl.ac.uk
- Institute for Environmental Design and Engineering, University College London, London, UK, WC1E 6BT
- 0009-0004-6151-1303

Author 2

- Zigeng Fang, PhD
- zigeng.fang@nottingham.ac.uk
- Department of Civil Engineering, University of Nottingham, Nottingham, UK
- 0009-0006-3777-3148

Author 3

- Ivan Korolija, PhD
- i.korolija@ucl.ac.uk
- Institute for Environmental Design and Engineering, University College London, London, UK, WC1E 6BT
- 0000-0003-3153-6070

Author 4

- Dimitrios Rovas, PhD
- d.rovas@ucl.ac.uk
- Institute for Environmental Design and Engineering, University College London, London, UK, WC1E 6BT
- 0000-0002-5639-6783

Abstract

Digital Twins (DT), as one of the emerging trends in digitalisation, has attracted a large amount of research in the past few years due to its ability to provide more accurate models and better predictions for various energy-related applications. In the context of demand response (DR), the real-time bidirectional communication characteristic of DT allows for functions such as real-time energy forecast and decision making aid, which provided high potential in DR applications due to the nature of DR being highly time sensitive. The objective of this paper is to explore the concept and application of DT in the domain of DR, as there are currently limited numbers of review on this topic. It was identified that most work in this area shows promising results but is still exploratory. The main application of DT in the domain of DR is using DT as an enabling tool by leveraging the real-time and data processing function of DT for monitoring and decision-making, and providing a medium for better visualisation. Future studies can experiment with applying DT frameworks to larger case studies, and apply more elaborate DT with higher maturity levels.

Keywords chosen from ICE Publishing list

Digital twin; Building Information Modeling (BIM); Built environment

Introduction

The current energy crisis has led to soaring energy prices, this has attracted more attention on the urgency of efficient building energy management. For the existing housing stock, the options to improve its energy efficiency without retrofitting are limited. Demand flexibility, also relating to demand side management (DSM), involves the technologies, programs and policies that enable the potential and capability of energy consumers to alter their energy consumption patterns. Demand response (DR) is a measure of DSM that reduces energy consumption or improves energy consumption efficiency by controlling and scheduling the energy consumption pattern of the consumer (Onile et al., 2021). This is achieved by shifting or reducing their energy usage during the peak energy consumption period (Ali and Choi,2020). Improving demand flexibility and applying DR can allow the grid to be more reliable by reducing the stress at peak demand periods and utilising renewable energy.

DR is highly time-sensitive, the two commonly used DR schemes: price-based and incentive-based schemes (Asadinejad A and Tomsovic, 2017), both require responsible parties' active participation at a timely manner. In order to improve the demand flexibility and enable DR, there has been a focus on the development of various digital technologies. Digitalisation has been among the priorities, and investment has been seen increasing in the past few years. Digital Twins (DT), as one of the emerging trends in digitalisation, has attracted a large amount of research in the past few years due to the readily available data, advancement in computational power, and common implementation of sensors.

Although the universal definition for DT is yet to be agreed upon, the Centre for Digital Built Britain (CDBB) provided a general definition for DT using the Gemini principles as an effective functioning and trustworthy digital model that serves a clear purpose (Bolton et al., 2018). Compared to other digital models, the main feature of a DT is that the digital model is connected to their physical counterpart via various remote sensing technologies. DT provides a dynamic virtual representation of an asset in real life, with real-time monitoring of the physical building and synchronising the associated events data (Austin et al.,2020).

In the application of DR, DT allows for real-time remote monitoring and control of the targeted system, continuous data can be monitored and collected (Djebali et al., 2024). By including data-driven methods (Song et al., 2022) (Behl et al., 2016), DT could also provide functions that aid decision-making, which is crucial in DR applications. Depending on the purpose of the DT, the scale of the DT could range from a single system to the whole grid, with the critical components of the DT remaining the same: physical system, virtual representation, data acquisition, data integration, modelling and simulation, and visualisation (Djebali et al., 2024). In the past few years, numerous reviews have analysed the application of DT. Zhang and Lv's (2022) review focused on the application of DT in the distribution grid. They suggested that DT shows promising potential in the application in the area, allowing remote-friendly interaction with equipment, equipment clustering management and collaboration of the whole chain. The review done by Onile et al. (2021) focusing on the use of DT in energy services has noted the small number of publications associating DT to recommendation systems and DSM. However, a rising trend was observed between 2016 and 2019. Onile et al. (2021) concluded that data-driven twin technologies have the ability to determine the energy behaviours of consumers and showed promising results to be applied in DSM.

The increasing attention to DT in the domain of DR is closely related to the positive results reported. Key characteristics of DT, such as real-time, bidirectional data communication, detail and accurate models, and integration of data-driven functions, all shows tremendous benefit in the application of DR. However, only limited reviews have been conducted for DT in the domain of DR. Moreover, due to the lack of unified definition of DT, the DT model applied buy different study may differ in structure, function and maturity. The scope of this work is to conduct a systematic literature review of recent research on DT and similar modelling systems within the context of DR applications, including the exploration of the differences in the DT structure and function applied by various studies. The following research questions are proposed:

- How is a DT defined in the context of DR applications?
- What is the state-of-the-art research and application of DT in DR?
- What is the future possible work to be conducted in the application of DT in DR?

The rest of this paper is structured as follows. Section 2 presented the methodology used in conducting the systematic literature review. Section 3 investigated the current definitions of DT, DT's maturity level model, and the definition of DT when applying in DR. Section 4 presented the literature review on the application of DT in the domain of DR conducted. Section 5 discussed the findings from the review presented the previous section. Lastly, section 6 concludes the main discoveries of this study.

2. Methodology

This study adopted the PRISMA method (BMJ, 2021) to conduct a systematic literature review. First, through the iterative search of various combinations of keywords and discussion between authors, the keywords determined for the search are shown in Table 1. The three main domains covered are DT, built environment and DR. The search keywords of each of the main domains are connected using the 'AND' statement. As DT did not yield enough results, Building Information Modelling (BIM) and Artificial intelligence (AI) were included as the keywords to broaden the search, this is also because BIM and AI are often closely associated with innovative building models. For example, the review done by Ali and Choi (2020) investigating the AI technics used for distributed smart grid, is highly relevant to the content of this study, yet DT was not mentioned in the abstract of the paper. The target keyword search components of articles were title, keyword and abstract.

Table 1 Summarised keywords for the literature search.

Main Domain	Search Keywords
Digital Twins	'digital twins' OR 'cyber physical systems' OR 'digital shadow' OR 'BIM' OR 'artificial intelligence'
Built environment	'building' OR 'city' OR 'built environment' OR 'infrastructure' OR 'construction' OR 'facility'
Demand response	'demand side management' OR 'demand response' OR 'energy flexibility' OR 'demand flexibility' OR 'recommender system' OR 'decision support system' OR 'energy management' OR 'energy storage' OR 'building to grid' OR 'microgrid'

The search was conducted on Web of Science and Scopus databases, including journal papers and conference papers from 2010 to 2024. Figure 1 illustrates the process used for the literature screening based on the PRISMA method (BMJ, 2021). After removing duplicates, 4006 papers were found in total. The articles found were screened and further selected based on their title and abstract. 82 papers were finally selected for full-text review. A rating system of 1 to 5 stars was given to each article based on the relevance of the literature to the research questions by using keyword check boxes and assessing the quality of the paper. In the end, a total of 34 pieces of literature were covered in this review.

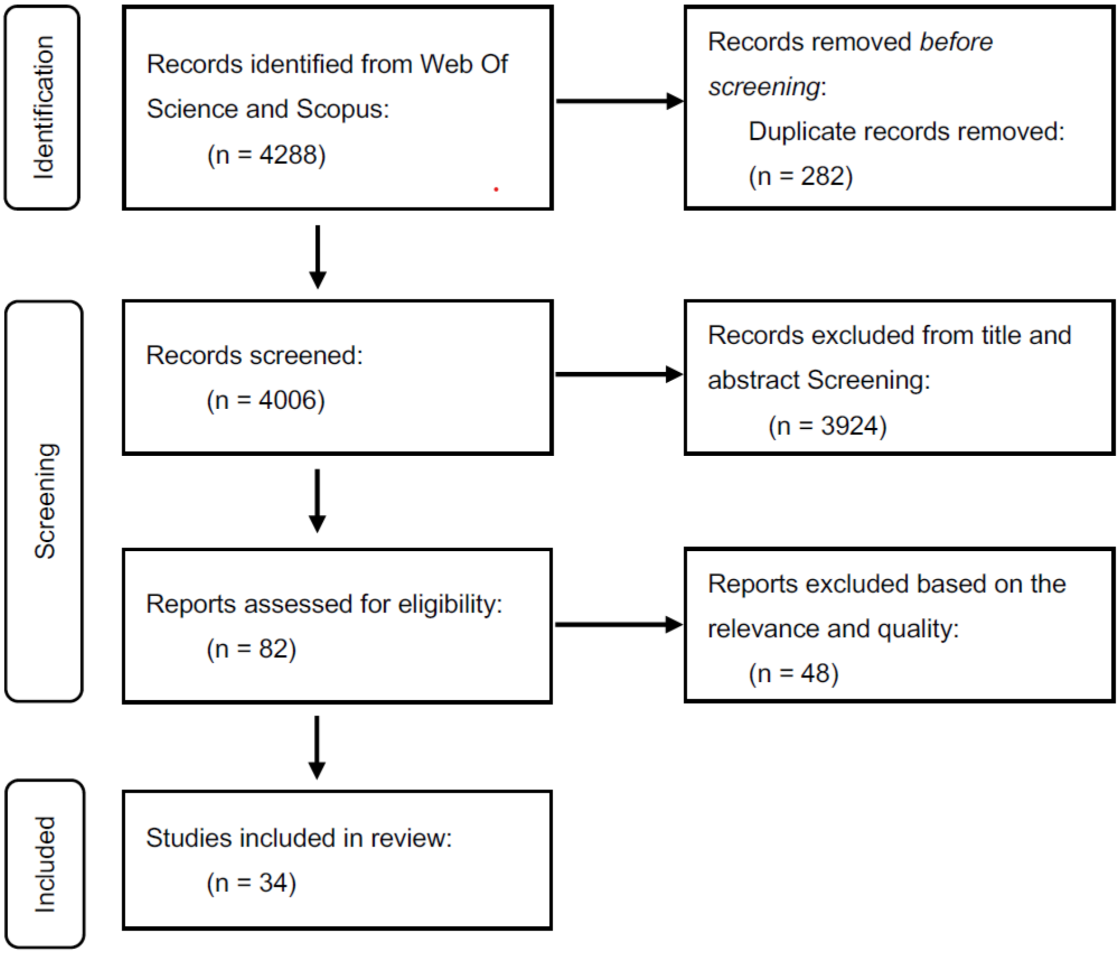

Figure 1. Literature screening flowchart.

3. DT from definitions to different maturity levels

This section will explore the current definitions of DT, and what DT means in the context of DR. It is important to recognise that for different applications, the DT may consist of different components and have different structures. CDBB defined DT as an effective functioning and trustworthy digital model that serves a clear purpose following the Gemini principles (Bolton et al., 2018). CDBB also emphasises that a DT is an accurate digital representation of physical assets, processes, or systems to the extent of detail appropriate to its purpose. This is a generic definition that fits well for all studies in the DT domain despite the type of application and provides a sound basis for the operation definition to be applied in this research.

To explore the definition of DT further, a general framework of DT, as identified by Compos-Ferreira et al. (2019), includes three main components: the physical asset, the virtual counterpart, and the connectivity between the two, allowing the physical asset and the virtual asset to have bidirectional communication. In addition, Lu et al. (2020) proposed a DT architecture consisting of 5 layers: data acquisition layer, transmission layer, digital modelling layer, data/model integration layer and service layer. This architecture will serve as a foundational reference for the subsequent analysis, where the literature will be examined in relation to the specific layers and aspects of framework development it addresses.

Moreover, Evans et al. (2019) defined the maturity levels for DT on a scale of 0 to 5, as shown in Table 2, with level 0 being reality capture and level 5 being autonomous operations. At level 3, the model is enriched with real-time data from sensors and IoTs, and this is where most of the models from the reviewed articles lie. The concept of maturity level provides a more quantitative measurement of DT's implementation level. There are other researchers like Sharma et al. (2022) who distinguished the difference between the integration level of a digital model, digital shadow and DT. A digital model does not have an information flow between the physical and virtual assets. In contrast, digital shadow has a unidirectional information flow, and DT has a bidirectional information flow. Sharma et al. (2022) also concluded in their review that there is a need for a quantitative measure for evaluating DT. Therefore, the combination of maturity level with integration level can provide a suitable scale that distinguish the existing DT definitions and applications. The literatures explored in later sections will be analysed based on the model’s maturity and integration level as the quantitative scale can provide a better comparison between the literatures.

Table 2 DT maturity level with integration level (Evans et al., 2019) (Sharma et al., 2022)

Maturity level	Key characteristic	Integration level
0	Reality capture	Digital model
1	2D map/system or 3D model	Digital model
2	Connect model to persistent (static) data, metadata and BIM Stage 2	Digital model
3	Enrich with real-time data	Digital Shadow
4	Two-way integration and interaction	Digital Twin
5	Autonomous operations and maintenance	Digital Twin

For application in DR, the scale of DT may range from a single system to the whole grid. Onile et al. (2021) summarised the key components of the DT framework when applied in DR as IoTs framework, where IoT devices can collect real-time data; data analysis function, where the collected data can be processed into more meaningful information and extract important features; and energy forecasting, where short to long term forecast could be analysed conjunctionally with past energy record.

4. Literature analysis

This section will analyse and present the chosen literature in further detail conjunctionally with the concept of DT presented previously, to understand the current state-of-the-art application and challenges of applying DT for the context of DR. To enable DR in building energy management, the DT applied should be more than just a digital model and have a maturity of over level 3. As DR is highly time-sensitive, at level 3, the DT will provide a model with a real-time update on the information required, such as the current energy use and energy prices, where the real-time information captured could be further processed to provide timely DR strategies for the end-users.

Figure 2 provided an overview of the maturity level of the DT applied in 34 of the analysed studies. Level 3 DT accounted for the highest proportion, with 47% of the studies analysed. These studies all have elements that could provide a real-time or near-real-time update of data on the DT model. However, they do not allow bidirectional information flow, such as the ability to control the physical asset from the digital asset. 32% of the studies applied a DT of level 4 maturity. For example, the model developed by Behl and Mangharam (2016) allows for the automatic synthesis of DR strategies, in the case study in Benguerir, Morocco (Rochd et al., 2021), the user was allowed to configure the system based on their preference via a live app. 12% of the studies were reported as a level 2 DT. These studies are often a work in progress. For example, the model built by Agostinelli et al.(2022) has implemented BIM and Geographic Information System (GIS) data in the model but has yet to connect the physical asset to the virtual one with sensors or IoT. However, they have discussed the potential of utilising a more elaborated DT in the future. Only 3 of the papers analysed have an automated DT of level 5 (Agostinelli et al., 2021) (Chandra et al., 2020) (Amato et al., 2021) and will be analysed in later sections. The lack of level 5 DT used in DR could be because DR is often related to flexible loads such as home appliances, which rely on manual control, and occupant willingness and preference. Based on the definition of DT by Sharma et al. (2022), only maturity levels 4 and 5 are counted as “real” DT. The relatively low proportion of the studies in level 4 to 5 maturity implies much potential in upgrading a level 3 model to a “real” DT.

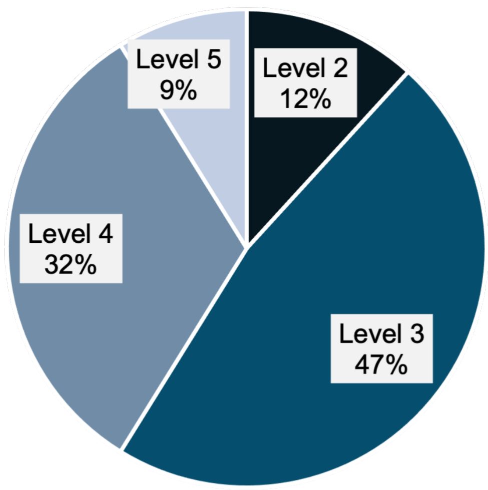

Figure 2 DT maturity level of the model applied in work analysed.

Figure 3 shows the relationship between the maturity level of the DT model used in each study and the year of publication of the literature. There is a clear trend of increasing focus on DT in the context of DR from 2019 to 2023. This review paper was reviewed in 2024 Q1, therefore, only a limited number of publications from 2024 is included. Regarding the maturity level of the

DT models, level 3 DT accounted for the most significant proportion of the work done between 2021 and 2023. The number of level 4 DTs has also slightly increased in recent years.

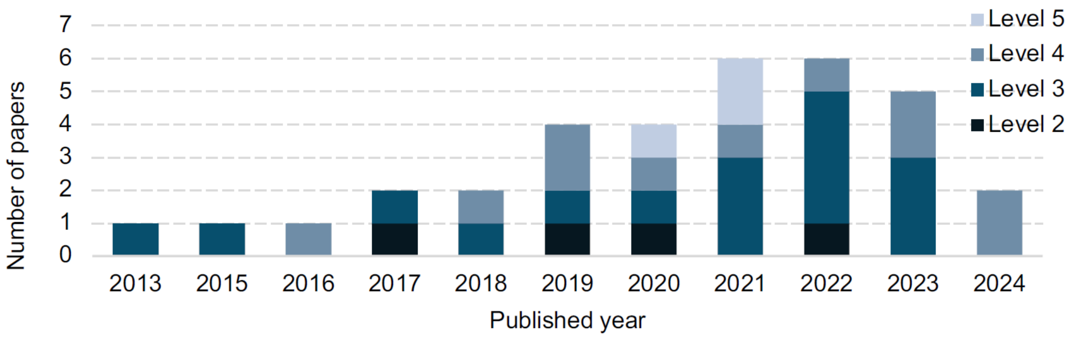

Figure 3 DT maturity level of the model in work analysed and their year of publication.

4.1 DT Framework development for DR

20 studies were analysed in further detail due to their relevance to DT and DR. They were grouped based on their main methodology into three groups, ones on presenting a new framework, ones on case study application, and ones on developing enabling technology for DT integration. Tables 3 and Table 4 provided an overview of the literature that focused on framework development. 13 studies were chosen as they provided an innovative framework involving the topic.

In Table 3, most of the studies analysed targeted the data/model integration layer of the DT. From the system architecture defined by Lu et al. (2020), the data/ model integration layer is the layer that focuses on data analysis, processing, and visualisation. In the context of DR, this layer conducts load forecasting and synthesises decision-making schemes for DR. The only two exceptions are Pasini (2018) and Amato et al. (2021), where Pasini (2018) worked on the transmission layer and digital modelling layer by focusing on building the DT model with existing BIM and connecting the DT with IoT. While the work done by Amato et al. (2021) emphasised on the digital modelling layer by integrating a Multi-Agent-System (MAS) in the DT model.

All the literature has proposed a framework with a DT maturity level of over level 4, with the exception of Abdelrahman and Miller (2022), which is level 3. Level 4 indicated that most studies have proposed a DT with bi-directional communication and interaction. Not only is the DT system enriched with real-time data, but the physical system can also be controlled via its digital counterpart. At maturity of level 5, the framework proposed by Chandra et al. (2020) with the use of energy nodes, a programmable representation of the electrical resources and interactions, was able to act DR decisions based on the electrical price and the building manager's preference and achieve cost savings of up to 62%. Amato (et al., 2021) also proposed a DT framework with level 5 maturity, where the MAS will execute control to minimise power consumption while maintaining occupant comfort. The studies analysed here are tested via simulation (Behl and Mangharam, 2016) (Bu and Yu, 2013) (Amato et al., 2021) (Song et al., 2022), small-scale controlled implementation (Abdelrahman and Miller, 2022) (Chou and Truong, 2019) or testbeds (Chandra et al., 2020) (Chen et al., 2021). Although all show positive results, they lack further testing of the proposed framework on larger-scale case studies. This is likely due to the complexity of conducting an elaborated case study and the constraints on resource availability.

Table 3 Overview of articles that targeted providing a new DT framework

Reference	Objective	Role of DT	Data Source
Behl and Mangharam (2016)	To provide a DR recommender system using the regression tree algorithm for the building's facilities manager that allows for closed-loop DR strategy synthesis and load forecasting.	Allows for real-time control synthesising	Historical weather and power data
Bu and Yu (2013)	Provide a decision-making scheme for optimal energy pricing using a four-stage Stackelberg game involving both retailer and customer for DSM.	Providing real-time bidirectional communications between retailers and customers	Advanced metering infrastructure
Chandra et al. (2020)	Creating a transactive energy-based energy management system with energy nodes for a scalable control strategy for DR	Allows for coordination of controls	Testbed with emulators
Amato et al. (2021)	DSM system for minimising power consumption and maximising human comfort using Multi-Agent System (MAS)	To be used as an autonomous network	Sensors
Abdelrahman and Miller (2022)	Using spatial proximity through applying BIM, GNN and wearable technology to identify occupants' thermal preferences.	Real-time visualisation	BIM, Smart watch

Chen et al. (2021)	Non-intrusively identify electrical appliances using fog-cloud computing and provide bi-directional information exchange interface between energy demand and supply sides.	Allows user intervention via a clean interface	Smart meter, IoT
Chou and Truong (2019)	Developing a web-based energy management system that allows load monitoring, forecasting, and automatic warnings for end users via a web interface and email.	Provide real-time information	Smart meters
Pasini (2018)	Provide real-time building insight through apps and websites to user to improve their awareness.	Connect information of different systems, allows user interaction	BIM, IoT
Song et al. (2022)	To provide a DT-based data-model fusion dispatch strategy for building energy flexibility that is capable of parameter fault tolerance and privacy protection by integrating data-driven methods with model-driven methods.	Simulation and testing, real-time update, privacy protection.	Meteonorm, TRNSYS

Table 4 also listed the literature that focused on proposing a new framework. However, the main focus of the literature was on proposing new demand response algorithms, DT was used as a medium for simulation to test out different algorithms for optimising DR schedule. Li and Xu (2024) applied Improved Whale Optimisation Algorithm (IWOA) and Long-Short Term Memory (LSTM) to simulate the DT of 10 different case studies. Zhou et al. (2023) applied Q-value enabled reinforcement learning on the DT of 5 case studies. Dellaly et al. (2023) specified the platform used for the DT simulation, a commercial microgrid platform SMARTNESS. They stated that the platform would provide a reliable framework to validate the proposed algorithms and allow for comparisons between simulated and experimental results. All other studies, although did not provide extensive detail on the DT simulation, they recognised that adopting DT for simulation allows for accurate real-time data collection and analysis, scenario testing, and energy simulations, which is highly beneficial in the application of DR. It is also worth noting that all literature analysed here were published more recently, between 2023 to 2024.

Table 4 Overview of articles that applied DT for simulation.

References	**Objectives**	**Roles of DT**	**Data source**
Li and Xu (2024)	To optimise the scheduling of household devices using the Improved Whale Optimisation	Simulation and testing of different DR algorithm	Historic data

	Algorithm (IWOA) and Long-Short Term Memory (LSTM) model.		
Zhou et al. (2023)	Applying Q-value enabled reinforcement learning method to optimise home appliance scheduling based on user preferences.	Simulation and testing	Historic data
Zhao and Zhang (2024)	Applying the Multi-Microgrid (MMG) architecture in renewable energy resources (RERs), with the integration of Covariance Matrix Adaptation algorithm and LSTM for precise forecasting and management of energy sources and storages.	Simulation and testing, real-time decision-making, personalised insight and interface	Historic data
Dellaly et al. (2023)	To develop an optimised energy management system that manages the injection of energy from photovoltaic (PV) systems into the distribution grid.	Simulation and testing	SMARTNESS platform

4.2 Case studies of DT in DR

Table 5 lists the literature overview that focuses more on the case study applications. Overall, fewer studies applied case studies, as the application is usually considered the next step in the research after developing the framework. Moreover, it is often resource-intensive to complete. The main trend for the application of DT in this domain is its application in the energy management system. Rochd et al. (2021) applied a home energy managing system (HEMS) in a case study in Morocco, where a level 4 DT was applied in conjunction with AI for multi-objective optimisation. The main role of the level 4 DT was to allow real-time bidirectional information exchange between systems and to provide a user interface for better control. Agostinelli et al. (2021) applied a level 5 DT in their energy management system of a residential district in Rome, Italy. Compared to the study done by Rochd et al. (2021), the level 5 DT by Agostinelli et al. allows automatic control by the digital model based on the optimised energy schedule produced by the model using ML methods. Furthermore, the level 5 DT was enriched with BIM and GIS data for near real-time building simulation, which enables a more detailed investigation towards the buildings' behaviours. The live app developed by Banfi et al. (2022) allowed users to visualise real-time building performance. However, the user could not control the system via the app; hence, the DT applied in Banfi et al.'s study is only at the maturity of level 3.

Agostinelli et al. (2021) highlighted that applying DT-based real-time monitoring can bridge the gap between the projected energy performance of the buildings and the actual building performance. By combining historical and live data, and coupling it with AI algorithms, the DT system can produce a more accurate consumption projection and provide a more tailored application and response for DR. The typical limitations identified by the analysed literature are the cost and complexity of implementing the system. As an elaborated DT is often associated with highly complex models and large sets of data; moreover, implementing a large number of sensors and their maintenance is costly. Agostinelli et al. (2021) also noted the difficulties in identifying the individual energy source due to the large number of sensors applied.

Table 5 Overview of articles that focused on DT applications in DR

Reference	Objective	Role of DT	Data source	Limitations
Agostinelli et al. (2021)	Using DT and ML for energy management optimisation and automation of a residential district in Rome to reach zero energy building requirements.	Investigate building behaviours	BIM, BEM, GIS, IoT, Sensors	Complex to identify individual energy source, i.e appliances
Banfi et al. (2022)	Applying a scan to BIM to BEM method for energy-efficient building envelope retrofit and developing a live app for monitoring the DT.	Real-time visualisation and life cycle management	BIM, IoT, Sensors	Cost of sensor maintenance
Abrol et al. (2018)	Developing a data-enabled energy-saving model to align the occupant's thermal preference with the apartment's unregulated temperature.	Real-time monitoring of thermal preference	Sensors	Work depended highly on assumptions
Rochd et al. (2021)	Proposing a HEMS with AI-based multi-objective optimisation methods for demand side and supply side management in a case study in Morocco	Real-time two-way information communications, provide human-machine interface	IoT	Implementation cost, complex model

4.3 Tools development for DT in DR

In addition, several tools have been developed that allow for better application of DT in DR. As summarised in Table 6, the tools developed by Chen and Yan (2018) and Chen et al. (2019)

focused on allowing the information transfer from sensors and IoT to be more efficient using machine learning methods. HyTube, the tool developed by Chen and Yan (2018) is a middleware layer between the data and management layer and the physical devices. It provides added data security and coordinates the otherwise heterogenous appliances, which were two of the main limitations in the application of DT as identified by Chen and Yan (2018). The smart power meter created by Chen et al. (2019) also overcomes the limitation of coordination between heterogenous devices by identifying them non-intrusively using the Artificial Neural Network. The DR-Adviser developed by Behl and Mangharam (2016) is a recommender system that uses the regression trees algorithm for DR strategy synthesis for building facility managers.

Table 6 Tools developed for DT implementation in DR

Reference	Tool developed	Function
Chen and Yan (2018)	HyTube	Provide a middleware layer to unify logic and control of heterogenous physical devices in building energy system.
Behl and Mangharam (2016)	DR-Adviser	Conduct load forecasting and automatically synthesise DR strategies
Chen et al. (2019)	Smart power meter	Based on the Arduino micro-controller unit, the smart meter can non-intrusively identify electrical appliances.

5. Discussion

This section will explore further the findings presented in the previous sections, providing a detailed analysis of the current applications, identifying existing challenges, and proposing directions for future research.

Recently, there has been a drastic increase in the number of studies utilising DT and similar concepts in the application of DR. DT proven to be beneficial in the application of DR, as DR is highly time-sensitive, for adopting shedding and shifting events, simpler approaches might not provide ideal performance. Moreover, DR is often associated with adopting renewable generation, which requires more advanced forecasting models and decision support tools to implement short-term control strategies (Zhao and Zhang, 2024).

Although the definition of DT varies, this review mainly utilised the maturity level defined by Evans et al., (2019), where six different levels (from 0 to 5) are used to describe the level of integration between the physical and digital systems. The use of a quantitative description allows for a better comparison between the DT of different studies. The above analysis also shows the potential of future studies to be conducted on utilising or upgrading the DT to a maturity level of 4 or over, as most of the current studies only applied a DT framework with a maturity level of 3. The high complexity of DT with maturity over level 4 is one of the main obstacles slowing the pace of progressing the DT model further, a possible research direction is to develop tools or methods that will assist the integration of DT. For example, adopting methods to increase the scalability and portability of frameworks across buildings to allow for more seamless application. In addition, most work in this area is still exploratory, focusing on framework development and has yet to be experimented on in more comprehensive experiments or case studies. Further testing would be beneficial for identifying the advantages and disadvantages of employing DT for DR on a larger scale, taking into account user behaviour and willingness, as well as how the users engage with such technologies.

Addressing the research questions set forth at the beginning of this study, DT primarily serves as an enabling tool for DR due to its capacity for real-time information exchange and clear visualisation. For instance, in a home energy management system (Rochd et al., 2021), DT could act as the system controller, providing human-machine interface, and clear visualisation, allowing the implementation of DR to be more user-friendly for stakeholders with limited knowledge such as the consumers. However, including a more elaborated DT model in a DR system increased the complexity of the modelling process compared to a more traditional DR system (Agostinelli et al., 2021). Moreover, the implementation cost, namely the maintenance of the sensor network that is required for a DT, could be substantial (Rochd et al., 2021).

As seen in the recent increase in the number of studies that used DT as a medium for simulation to test out different DR scenarios and algorithms, it is evident that simulation conducted on a DT can provide valuable and accurate insight in terms of DR. DT with the characteristic of being real-time and accurate, could allow for accurate simulation, and enable validation between simulated and experimental data (Dellaly et al., 2023). However, most of the analysed literature, although recognising the significance of using DT for simulation, they only provided simulation data and minimal detail on the DT model itself. Future studies could benefit from providing more detailed information on the DT model applied, enhancing the transparency and reproducibility of their applications.

6. Conclusions

This review explored the state-of-the-art research conducted on DT in the context of DR. To be applied in DR, the DT used should be more than just a digital model and have a maturity of over level 3, which will enable bidirectional information exchange. A total of 34 articles were analysed and presented in this paper. 47% of the analysed studies utilised a DT with a maturity of level 3, where real-time data was integrated into the model but did not allow for bidirectional information flow. 20 of the 34 articles were analysed further and grouped based on their methodology. The primary trend in the use of DT in the domain of DR is to conduct monitoring and simulation, such as energy load forecasting, and to provide decision-making aid, such as producing DR strategies. Applying DT allows for a much clearer visualisation of the model, thus providing a human-machine interface and improving the user experience of the system. Another recent trend is to use the DT of different buildings to conduct simulation and testing of DR algorithms. This gained popularity as it leverages the characteristics of DT to accurately represent the physical asset, hence allowing accurate testing.

Overall, the dramatic increase in the number of studies recently shows significant potential for further research in this domain. It is important to explore areas that could further enhance DT's functionality and integration. Such as the incorporation of knowledge graphs and portable analytics to improve the connectivity and scalability of DT systems. Future work could benefit from focusing on the examination of these developments. The main takeaway from this paper is the clear visualisation and real-time data exchange facilitated by DT significantly enhances the implementation of DR. Furthermore, future research should aim to bridge the gap between theoretical frameworks and their practical application, emphasising on conducting experiments and applying case studies to validate the advantages and address the challenges of employing DT in larger-scale DR implementations.

References

Abdelrahman MM and Miller C (2022). Targeting occupant feedback using digital twins: Adaptive spatial-temporal thermal preference sampling to optimise personal comfort models. Building and Environment, 218: 13.

Abrol S, Mehmani A, Kerman M, Meinrenken C and Culligan P, (2018). Data-Enabled Building Energy Savings (D-E BES). In Proceedings of the IEEE, 106(4): 661-679.

Agostinelli S, Cumo F, Guidi G and Tomazzoli C, (2021). Cyber-Physical Systems Improving Building Energy Management: Digital Twin and Artificial Intelligence. Energies, 14(8): 25.

Agostinelli S, Cumo F, Nezhad MM, Orsini G and Piras G, (2022). Renewable Energy System Controlled by Open-Source Tools and Digital Twin Model: Zero Energy Port Area in Italy. Energies, 15(5): 24.

Asadinejad A and Tomsovic (2017). Optimal use of incentive and price based demand response to reduce costs and price volatility. Electric Power Systems Research, 144: 215-223.

Aksanli B and Rosing TS (2020). Human Behavior Aware Energy Management in Residential Cyber-Physical Systems. IEEE Transactions on Emerging Topics in Computing, 8(1): 45-57.

Ali SS and Choi BJ (2020). State-of-the-Art Artificial Intelligence Techniques for Distributed Smart Grids: A Review. Electronics, 9(6): 25.

Antonopoulos I, Robu V, Couraud B, Kirli D, Norbu S, Kiprakis A, Flynn D, Elizondo-Gonzalez S and Wattam S, (2020). Artificial intelligence and machine learning approaches to energy demand-side response: A systematic review. Renewable & Sustainable Energy Reviews, 130: 35.

Amato A, Quarto A, Lecce V, (2021). An application of cyber-physical system and multi-agent technology to demand-side management systems. Pattern Recognition Letters, 141: 23-31.

Austin M, Delgoshaei P, Coelho M and Heidarinejad M, (2020). Architecting smart city digital twins: Combined semantic model and machine learning approach. Journal of Management in Engineering, 36(4).

Banfi F, Brumana R, Salvalai G and Previtali M, (2022). Digital Twin and Cloud BIM-XR Platform Development: From Scan-to-BIM-to-DT Process to a 4D Multi-User Live App to Improve Building Comfort, Efficiency and Costs, Energies, 15(12): 26.

Behl M, Jain A and Mangharam R, (2016). Data-Driven Modeling, Control and Tools for Cyber-Physical Energy Systems. In ACM/IEEE 7th International Conference on Cyber-Physical Systems (ICCPS), Vienna, Austria.

BMJ, (2021) PRISMA 2020 explanation and elaboration: updated guidance and exemplars for reporting systematic reviews.372:n160. See doi: 10.1136/bmj.n160 (Accessed 27/04/2024)

Bolton A, Butler L, Dabson I, et al. (2018) Gemini principles, Centre for Digital Built Britain, See https://www.cdbb.cam.ac.uk/system/files/documents/TheGeminiPrinciples.pdf (Accessed 09/04/2024).

Bu SR and Yu FR, (2013). A Game-Theoretical Scheme in the Smart Grid With Demand-Side Management: Towards a Smart Cyber-Physical Power Infrastructure. IEEE Transactions on Emerging Topics in Computing, 1(1): 22-32.

Campos-Ferreira A, Lozoya-Santos JJ, Vargas-Martínez A, Mendoza R, Morales-Menéndez R, (2019), Digital Twin Applications: A review. In Memorias del Congreso Nacional de Control Automático; Asociación de México de Control Automático, Puebla, Mexico, pp. 606–611.

Chandra R, Krishnanand KR, Thong H, Goh E, Panda SK and Spanos CJ, (2020). Demonstration of Transactive Control of Commercial Buildings as Energy Nodes. In 46th Annual Conference of the IEEE-Industrial-Electronics-Society (IECON), Singapore.

Chen C and Yan J, (2018). HyTube: A Novel Middleware Layer for Smart Building Systems. In 16th IEEE Int Conf on Dependable, Autonom and Secure Comp/16th IEEE Int Conf on Pervas Intelligence and Comp/4th IEEE Int Conf on Big Data Intelligence and Comp/3rd IEEE Cyber Sci and Technol Congress, Athens, Greece.

Chen YY, Chen MH, Chang CM, Chang FS and Lin YH, (2021). A Smart Home Energy Management System Using Two-Stage Non-Intrusive Appliance Load Monitoring over Fog-Cloud Analytics Based on Tridium's Niagara Framework for Residential Demand-Side Management. Sensors, 21(8): 25.

Chen YY, Lin YH, Kung CC, Chung MH. and Yen IH, (2019). Design and Implementation of Cloud Analytics-Assisted Smart Power Meters Considering Advanced Artificial Intelligence as Edge Analytics in Demand-Side Management for Smart Homes. Sensors, 19(9): 26.

Chou JS and Truong NS, (2019). Cloud forecasting system for monitoring and alerting of energy use by home appliances. Applied Energy, 249: 166-177.

Dellaly M, Skander-Mustapha S and Slama-Belkhodja I, (2023) Optimisation of a residential community's curtailed PV power to meet distribution grid load profile requirements, Renewable Energy, 218: 119342.

Djebali S, Guerard G, Taleb I, (2024). Survey and insights on digital twins design and smart grid's applications. Future Generation Computer Systems, 153: 234-248.

Evans S, Savian C, Burns A and Cooper C, (2019), Digital Twins for the Built Environment: An Introduction to the Opportunities, Benefits, Challenges and Risks. Built Environmental News, The IET, See https://www.theiet.org/impact-society/factfiles/built-environment-factfiles/digital-twins-for-the-built-environment/ (Accessed 09/04/2024).

Gong K, et al. (2022). Comprehensive review of modeling, structure, and integration techniques of smart buildings in the cyber-physical-social system. Frontiers in Energy, 16: 74-94.

Li W and Xu X, (2024), A hybrid evolutionary and machine learning approach for smart building: Sustainable building energy management design, Sustainable Energy Technologies and Assessments, 65: 103709.

Lu QC, Parlikad AK, Woodall P, Ranasinghe GD, Xie X, Liang Z, Konstantinou E, Heaton J and Schooling J, (2020). Developing a Digital Twin at Building and City Levels: Case Study of West Cambridge Campus. Journal of Management in Engineering, 36(3): 19.

Onile AE, Machlev R, Petlenkov E, Levron Y and Belikov J, (2021). Uses of the digital twins concept for energy services, intelligent recommendation systems, and demand side management: A review. Energy Reports, 7: 997-1015.

Pasini D (2018). Connecting BIM and IoT for addressing user awareness toward energy savings. Journal of Structural Integrity and Maintenance, 3(4): 243-253.

Rochd A, Benazzouz A, Abdelmoula IA., Raihani A, Ghennioui A, Naimi Z and Ikkan B, (2021). Design and implementation of an AI-based & IoT-enabled Home Energy Management System: A case study in Benguerir – Morocco. Energy Reports, 7: 699-719.

Sharma A, Kosasih E, Zhang J, Brintrup A and Calinescu A, (2022) Digital Twins: State of the art theory and practice, challenges, and open research questions, Journal of Industrial Information Integration, 30: 100383.

Song Y, Xia M, Chen Q and Chen F, (2023). A data-model fusion dispatch strategy for the building energy flexibility based on the digital twin, Applied Energy, 332: 120496.

Zhang Z, Lv L, (2022). Application status and prospects of digital twin technology in distribution grid, Energy Reports, 8: 14170-14182

Zhao X and Zhang Y, (2024). Integrated management of urban resources toward Net-Zero smart cities considering renewable energies uncertainty and modeling in Digital Twin, Sustainable Energy Technologies and Assessments, 64: 103656.

Zhou J, Yang M, Zhan Y and Xu L, (2023). Digital twin application for reinforcement learnin based optimal scheduling and reliability management enhancement of systems, Solar Energy, 252: 29-38.