Review of Digital Twins enabled applications for demand response

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Abstract. Digital Twins (DT), as one of the emerging trends in digitalisation, has attracted a large amount of research in the past few years. Recent research suggests that DT has the potential to provide more accurate models and better predictions for various energy-related applications. In the context of Demand Response (DR), the use of DT allows for real-time two-way communication between various physical and digital systems with the potential to improve energy efficiency in DR applications. This review focuses on exploring the concept of DT, namely its current applications in demand response. To investigate how the current research was conducted, comparisons were done on the methodology used, the framework and tools applied, and the benefits and drawbacks of applying DT for demand response. It was identified that most work in this area is still exploratory and presented high potential in further studies, and experimenting with case studies on DT with higher integration levels in the DR domain.

1. Introduction

Digitalisation has been among the priorities and has seen increasing investment in the past years, mainly due to its capability to bridge between different energy sectors, as well as allowing integrations and smooth communications across systems. 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. DT has seen surging applications in the built environment, healthcare, logistic, manufacturing and automotive industry. Although the universal definition for DT is yet to be agreed, the Centre for Digital Built Britain 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 the implementation of real-time monitoring of the physical building and the synchronisation of the associated events data (Austin et al.,2020). As DT is a relatively new terminology, the work conducted on similar system before the term was introduced may be referred synonymously. For example, cyber-physical-system (CPS) shares a lot of similarity with DT in terms of their core attributes, namely having a connected physical counterpart to the digital model.

The current energy crisis has led to soaring energy prices. This has attracted more attention to the urgency of efficient building energy management. Demand response (DR) is a measure to reduce energy consumption or improve energy consumption efficiency from the consumer end, through controlling and scheduling the energy consumption pattern of the consumer. This is achieved through shifting or reducing their energy usage during the peak energy consumption period (Ali and Choi,2020). There are commonly two DR schemes used, priced-based and incentive-based schemes. In price-based schemes, the price of electricity fluctuates during the day based on the demand to motivate consumer to use electricity when the price is lower. Incentive-based schemes usually involve having a contractual agreement between the end-user and service provider to reduce their energy consumption (Antonopoulos et al., 2020).

DR is a highly time sensitive energy management measure that requires end-users' active participation. The use of DT allows real-time two-way communication between various physical and digital systems, and therefore provides a more detailed and accurate representation of the building, grid, and occupant model. In the past few years, there have been numerous reviews analysing the application of DT published. Botin-Sanabria et el. (2022) conducted a comprehensive literature review on the challenges and application of the DT technology in domains such as smart cities, logistics, medicine and automotive. They analysed the current enabling technologies and tools for the application of DT and studied the present applications of DT in terms of the integrity level, the technology readiness level (TRL), the societal readiness level (SRL) and the maturity level. The main challenges identified from their research are the concerns related to data, such as privacy and large-scale acquisition, the lack of standards for DT, cost, and difficulties relating to the communication network. The review done by Onile ei al. (2021) focused on the use the DT in energy services on demand side management (DSM) specifically recommender systems. They noted the small number of publications associating DT with energy services such as energy conservation and recommendation systems, and this was the only review paper found focused on DT with DSM. Onile et al. (2021) concluded that data-driven twin technologies have the ability to determine the energy behaviors of consumer and hence to be applied in DSM.

The lack of reviews for DT in the domain of DR led to this research. The scope of this work is to conduct a systematic literature review of recent research on DT and similar modelling system within the context of DR applications. The follow research questions are proposed:

- What is the state-of-the-art research and application of DT in DR?
- What is the future possible work to be conducted in this domain?

This paper is structured as follow. Section 2 presents the methodology of the conducted systematic literature review. Section 3 will investigate the definition of DT and the definition used in this review. Section 4 will present the literature review conducted. Lastly, Section 5 will conclude the research findings from the review.

2. Methodology

A systematic literature review was adopted in this study to answer the proposed research questions.

The method used for the systematic review is as follows. First, through the iterative search of various combinations of keywords, 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, BIM and 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. 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’ ‘infrastructure’ OR ‘construction’ OR ‘facility’
Demand response	‘demand side management’ OR ‘demand response’ OR ‘energy flexibility’ OR ‘recommender system’ OR ‘decision support system’ OR ‘energy management’ OR ‘energy storage’ OR ‘building to grid’ OR ‘microgrid’

Then the search was conducted on Web of Science and Scopus data bases, including journal papers and conference papers from after 2010 to 2023. After removing duplicates there are 4006 papers found in total. The articles found were then screened and further selected based on their title and abstract, 82 were finally selected for full-text review. According on the relevance of the literature to the research question by using keywords check box, and the quality of the paper, a rating system of 1 to 5 stars was given to each article. In the end, a total of 27 pieces of literature were covered in this review.

3. DT from definitions to different maturity levels

DT, as a newly emerging concept in the built environment, has not been a unified definition that has been accepted widely across the industry. The Centre for Digital Built Britain (CDBB) defined DT as an effective functioning and trustworthy digital model that serves a clear purpose using the Gemini principles (Bolton et al., 2018). CDBB also emphasise that a DT is an accurate digital representation of physical assets, processes, or systems to the extent of detail that is appropriate to its purpose. This is a generic definition that would fit well for all studies in the DT domain despite the type of application and provides a good basis for the operation definition to be applied in this research.

To explore the definition of DT in further detail, 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. 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. Moreover, Evans et al. (2019) defined the maturity levels for DT on a scale of 0 to 5, as shown in Table 2, 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 lies. The concept of the maturity level provides a more quantitative measurement for the level of implementation of DT. 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 asset and virtual model, whereas digital shadow has a unidirectional information flow and DT has a bidirectional information flow. In the author’s opinion, maturity level and integration level are the two most important scales that distinguish the existing DT definitions and applications.

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

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

4. Literature analysis and discussion

This section will analyse the chosen literature in further detail to answer the proposed research questions. 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 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 1 provided an overview of the maturity level of the DT applied in 26 of the analysed studies, where a case study utilising DT has been presented. The full list of references for the literature included in this figure can be found at https://github.com/yuanxie12/EG-ICE2023-Reference.git. Level 3 DT accounted for the highest proportion with 50% of the studies analysed. These studies all have elements that could provide real-time or near real-time update of data to the DT model. However, they do not allow bidirectional information flow, such as the ability to control the physical asset from the digital asset. 23% 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, and in the case study in Benguerir Morocco (Rochd et al., 2021), the user is allowed to configure the system based on their preference via a live app. 15% 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) but yet to connect the physical asset to the virtual one. However, they have discussed the potential of utilising a more elaborated DT in the future. Only 3 of the papers analysed had an automated DT of level 5 (Agostinelli et al., 2021) (Chandra et al., 2020) (Amato et al., 2021) and will be analysed later in this section. The lack of level 5 DT used in DR could be because of 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 is counted as "real" DT. The relatively low proportion of the studies in level 4 to 5 maturity implies a lot of potential in upgrading a level 3 model to a "real" DT.

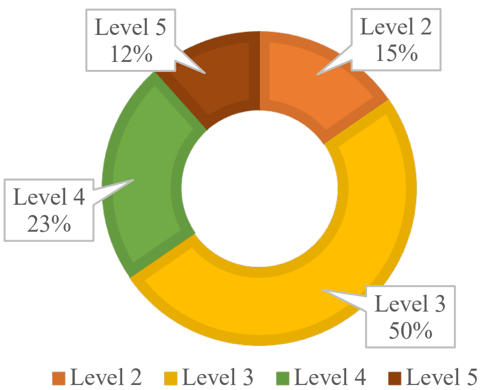

Figure 1: DT maturity level of the model applied in work analysed.

12 studies were analysed in further detail due to their relevance to DT and DR. They were grouped based on their main methodology into two groups, ones which focus on presenting a new framework and ones which focus on application. Table 3 provided the overview of the literature that focused on framework development. 8 studies were chosen as they provided an innovative framework using DT for DR or DSM. Most of the studies analysed targeted on the data/model integration layer of the DT, where they conducted data analysis and data processing such as load forecasting and synthesise decision making scheme 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 with BIM and connecting it with IoT. While the work done by Amato et al. (2021) emphasised on the digital modelling layer through integrating a Multi-Agent-System (MAS) in the model. All the literature has proposed a framework with DT maturity level of over level 4, with the exception of Abdelrahman and Miller (2022) which is level 3. 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 achieved 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 automatically to minimise power consumption while maintaining occupant comfort, the simulation results showed 35% saving in energy.

The studies analysed here are tested via simulation (Behl and Mangharam, 2016) (Bu and Yu, 2013) (Amato et al., 2021), small scale controlled implementation (Abdelrahman and Miller, 2022) (Chou and Truong, 2019) or testbeds (Chandra et al., 2020) (Chen et al., 2021). Although all showing positive results, they all 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 from resources availability.

Table 3: Overview of articles that targeted on providing new DT framework

Reference	Objective	Role of DT	Data Source
Behl and Mangharam (2016)	To provide a DR recommender system using regression tree algorithm for 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 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 occupant's thermal preference.	Real-time visualisation	BIM, Smart watch
Chen et al. (2021)	Non-intrusively identify electrical appliances using fog-cloud computing, and provide bi-	Allows user intervention via a clear interface	Smart meter, IoT

	directional information exchange interface between energy demand and supply sides.		
Chou and Truong (2019)	Developing a web-based energy management system that allows load monitoring, forecasting and automatic warning for the end users via web interface and email.	Provide real-time information	Smart meters
Pasini (2018)	Provide real-time building insight through apps and website to user to improve their awareness.	Connect information of different system, allows user interaction	BIM, IoT

Table 4 listed the overview of the literature that focused more on the application and case study of using DT for DR. Overall, there are less studies that focused more on the application than on the framework, as the application is usually considered as 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 used was to allow real-time bidirectional information exchange between systems, and improves user interface for better control. Agostinelli et al. (2021) applied a level 5 DT in their energy management system. Comparing 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 DT was enriched with BIM and GIS data which enable more detail investigation towards the buildings' behaviours. The live app developed by Banfi et al. (2022) allows user to visualise real-time building performance. However, the user could not control the system via the app, hence, the DT applied is only at maturity of level 3. The common 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 model and large sets of data, moreover implementing large number of sensors and its 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 4: 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 thermal preference of occupant with unregulated temperature of the apartment.	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	Real-time two-way information communications	IoT	Implementation cost, complex model

	demand side and supply side management in a case study in Morocco	between HEMS and grid, provide human-machine interface		

In addition, there has been several tools developed that allows for better application of DT in DR. As summarised in Table 5, 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 by 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 coordinate the otherwise heterogenous appliances, which was one of the main limitation 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 Artificial Neural Network. The DR-Adviser developed by Behl and Mangharam (2016) is a recommender system that used regression trees algorithm for DR strategy synthesis for building facility manager.

Table 5: Tools developed for DT implementation in DR

Reference	Tool developed	Function
Chen and Yan (2018)	HyTube	Provide a middlerware 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.

As analysed above, the main role of DT applied in the above studies is as an enabling tool for DR. This is due to the nature of DT of providing real-time information exchange and clear visualisation. In a home energy management system, DT could act as the controller of the system and allows for the implementation of DR to be more straightforward and user friendly. However, the inclusion of a more elaborated DT model in a DR system increased the complexity of the modelling process comparing to a more traditional DR system. Moreover, the implementation cost namely the maintenance of the sensors network could be substantial.

The above analysis also shows that the potential of future study to be conducted on utilising or upgrading the DT to a maturity level of over 4, as most of the current study only applied DT framework with maturity level of 3. The high complexity of DT with maturity over level 4 is one of the main obstacle 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. In addition, most work in this area is still exploratory which focused on framework development and yet to be experimented on more comprehensive case study. Further testing would be beneficial for identifying the advantages and disadvantages of employing DT for DR on larger scale, and taking into accounts user behaviour and willingness.

5. Conclusion

This review explored the state-of-the-art research conducted on DT in 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, which will enable bidirectional information exchange. A total of 27 articles were analysed and presented in this paper. 50% of the analysed studies utilised a DT with a maturity of level 3, where real-time data was integrated to the model, but does not allow for bidirectional information flow. 12 of the 27 articles were analysed further, they were grouped based on their methodology. The main trend in the use of DT in the domain of DR is to conduct energy load forecasting and producing DR strategies. By applying DT, it allows for a much clearer visualisation of the model, thus improving the user experience of the system.

The main limitations identified are the high complexity of implementing a full-scale DT with high maturity level and the associated high cost in sensor network maintenance. Overall, there were not a lot of studies conducted in this specific research area to-date. Hence, there is a large potential for further research in the future. In particular, upgrading the DT to level 4 maturity and above, developing tools to assist the integration of DT, and applying the framework proposed in the literature to real-life case studies.

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