DEVELOPING A DYNAMIC DIGITAL TWIN AT A BUILDING LEVEL: USING CAMBRIDGE CAMPUS AS CASE STUDY

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ABSTRACT A Digital Twin (DT) refers to a digital replica of physical assets, processes and systems. DTs integrate artificial intelligence, machine learning and data analytics to create dynamic digital models that are able to learn and update the status of the physical counterpart from multiple sources. A DT, if equipped with appropriate algorithms will represent and predict future condition and performance of their physical counterparts. Current developments related to DTs are still at an early stage with respect to buildings and other infrastructure assets. Most of these developments focus on the architectural and engineering/construction point of view. Less attention has been paid to the operation & maintenance (O&M) phase, where the value potential is immense. A systematic and clear architecture verified with practical use cases for constructing a DT is the foremost step for effective operation and maintenance of assets. This paper presents a system architecture for developing dynamic DTs in building levels for integrating heterogeneous data sources, support intelligent data query, and provide smarter decision-making processes. This will further bridge the gaps between human relationships with buildings/regions via a more intelligent, visual and sustainable channels. This architecture is brought to life through the development of a dynamic DT demonstrator of the West Cambridge site of the University of Cambridge. Specifically, this demonstrator integrates an as-is multi-layered IFC Building Information Model (BIM), building management system data, space management data, real-time Internet of Things (IoT)-based sensor data, asset registry data, and an asset tagging platform. The demonstrator also includes two applications: (1) improving asset maintenance and asset tracking using Augmented Reality (AR); and (2) equipment failure prediction. The long-term goals of this demonstrator are also discussed in this paper.

Notation

DT: Digital Twin

IoT: Internet of Things

BIM: Building Information Model

1. Introduction

This paper aims at (1) a comprehensive literature review from the perspective of data management; the identification and discussion of current limitations and research gaps in developing a dynamic DT in a building level; (2) a system architecture development of constructing dynamic DTs; (3) a pilot project at west Cambridge site based on proposed system architecture. The scope includes the specific needs and potentials of dynamic DTs development. The results of this research are useful for industry professionals, DT developers and asset management relevant researchers involved in the implementation of DTs.

Computerisation and digitisation are emerging to have a wide impact on the way the lifecycle of physical/engineering assets is managed (Pärn et al., 2017). For instance, NIC predicted that artificial intelligence (AI) could add 10% to the UK economy by 2030 (NIC, 2017). In addition, improved data sharing could result in lower consumer bills, reducing impact on the natural environment and realizing smart management in Architecture/Engineering/Construction (AEC) and Facilities Management field (AEC/FM) (NIC, 2017).

The O&M phase for building and civil infrastructure assets cover more than 50 years of the total time span (NRC, 1998). Achieving comfortable living environment and smart building management is a complex issue in the O&M phase. Comprehensive information needs to be recorded (e.g., historical O&M records, performances of facilities, accurate locations etc.) and multiple stakeholders would be involved (e.g., facility manager, site worker etc.). The process of asset management in O&M phases is required to keep the integrity, validity and interoperability (Wetzel and Thabet, 2015). Consequently, an effective and intelligent asset management system is needed to maintain dynamic information, support various activities and contribute to a comfortable environment (Lu et al., 2018). Various tools and systems have been implemented to enhance O&M management, such as Computerized Maintenance Management Systems (CMMS), Computer-Aided Facility Management (CAFM) systems, Building Automation Systems (BAS), and Integrated Workplace Management Systems (IWMS) (Sapp, 2015). For instance, CMMS is a computerized system for O&M management, which can record daily work orders, historically records, service requests and maintenance information. But it still requires significant effort and time for facilities management (FM) professionals to extract the diverse O&M information they need (e.g., data within CMMS, specifications, 3D models) (Wetzel and Thabet, 2015). Thus, there is still a lack of an integrated system that could manage information distributed in different databases and support various activities in O&M phases.

Building Information Model (BIM), as a digital representation of a building or civil infrastructure asset, can be extended to form the basis for a database of all assets and facilitate the exchange of information in a unified and digital manner (Eastman et al., 2011). Moreover, in the O&M phase, BIM can be used as an information source and a repository at the same time supporting various activities in existing buildings and infrastructure (Volk et al., 2014). BIM has been successfully adopted in the design and construction phases. However, BIM still has limited adoption within asset management (Lu et al., 2018; Volk et al., 2014). The research related to BIM and asset management is still at its infancy, but rapidly growing (Pishdad-Bozorgi et al., 2018). Moreover, in daily O&M management, BIM is not enough for complex situations and comprehensive data management.

The development of Level 3 BIM Strategy, which is known as "Digital Built Britain" (DBB), will further accelerate benefits and development of BIM and other digital technologies in the asset management sector based on the momentum created by Level 2 BIM (Shayesteh, 2015). Furthermore, data for public good (NIC, 2017) states that: "The UK needs a digital framework for data on infrastructure to harness the benefits from sharing better quality information about its infrastructure; how it is used, maintained and planned."

Hence, the digital twin (DT) is widely promoted. DT is a digital model, which is a dynamic representation of an asset and mimics its real-world behaviours (CDBB, 2018; NIC, 2017). DT is built on data. However, in DTs' research, a clear-defined and well-organised system architecture is still needed to supervise their current implementations, identify the gaps and provide roadmaps for future development. Moreover, without such a system architecture, they are susceptible to omit some possible improvement and key limitations.

Thus, a well-designed framework can benefit for better understanding the performance data and realising the true value of data in DTs. Hence, in order to maximize the value of data, present DT development processes and further evaluate the value and challenges of DTs, this study firstly presents a system architecture for dynamic DTs at the building level. Moreover, this architecture is brought to life through the development of a dynamic DT demonstrator in Cambridge, U.K..

2. Literature Review

There are some research aiming at improving efficiency of O&M management based on partial DT concepts. However, majority of current works concentrate on specific implementations or limited data resources, such as providing software architecture, or improving real-time emergency response (shown as Table 1). They lacked a comprehensive overview and a system architecture (i.e., DTs) to guide for further development and complementary.

Table 1 Brief summary of research using partial DT concepts [a]

Author/year	Brief introduction
Shen et al., (2012)	Presenting a conceptual framework of the proposed agent-based service-oriented integration approach for facility lifecycle information integration
Dibley et al., (2012)	Presenting an intelligent multi-agent software framework (OntoFM) supporting real time building monitoring
Lee et al., (2013)	Presenting intelligent urban facilities management for real-time emergency response
Ko et al., (2013)	Developing a web-based RFID FM system for enhancing facility management efficiency
Lin et al., (2014)	Proposing a mobile automated BIM-based facility management (BIMFM) system for FM staff in the O&M phase
Motamedi et al., (2015)	Providing a knowledge-assisted BIM-based visual analytics approach for failure root-cause detection in FM
Kang and Hong, (2015)	Proposing a software architecture for the effective integration of BIM into a GIS-based FM system
Róka-Madarász et al., (2016)	Elaborating a methodology to gathering building O&M costs data
Shalabi et al., (2016)	Proposing an automated process that responds to alarms by retrieving alarms reported by FM systems for corrective maintenance
Peng et al., (2017)	Proposing a BIM-based Data Mining approach for extracting meaningful patterns and detecting improper records
Arslan et al., (2017)	Develop a proactive safety facility management system
Suprabhas et al., (2017)	Developing an application that integrates sensor data and reports the data via the virtual model of the building.
Hu et al., (2018)	Developing a cross-platform Mechanical, Electrical and Plumbing (MEP) management system

[a] GIS: geographic information system; RFID: radio frequency identification devices

DT is built on data. Recognising the importance of data for the UK economy, the UK National Infrastructure Commission published a report "Data for the Public Good" that sets out a series of recommendations for HM Government stating, *"...high quality, standardised data on all our infrastructure assets, along with the ability to share this securely, will enable the UK's infrastructure to be viewed as an interdependent,* *dynamic system*". This review would mainly be conducted from the perspective of data management and highlight the challenges and requirements of DT development in building levels.

2.1 Data integration in DTs

To realise a DT poses various data management challenges; especially related to how to integrate data from autonomous, disparate and heterogeneous sources. This is exemplified in the DT produced in this study which integrates data from sources such as real-time sensors, building management systems, cloud services, and asset management systems etc.

From a technical point of view, there are many technologies available to support the integration of data, from Extract Transform and Load (ETL) technologies that support the transfer of data be-tween systems (Vassiliadis, 2009) (Woodall et al., 2016), to Service-oriented Architectures that can expose data as a service (Budgen et al., 2007), to data virtualisation, to data warehouses and data lakes (Beyer et al., 2017).

2.2 Heterogeneity in source systems

The vital data needed as input for monitoring and prediction algorithms often reside in a large variety of systems with different software platforms and database systems. One key problem that arises because of this is the lack of globally unique identifier for data records in different systems. This makes it difficult to know, for example, whether a data record about a machine in one system relates to the same data record about the same machine in another system or not; this problem is termed: entity linking, record linkage, entity resolution, data matching, and data deduplication (Talburt, 2011). Also, there is the important problem of how to reconcile the differences in the semantics and syntax of data. For instance, the definition of a hot water boiler in one data source may include the external pipework and in another system it may not; the area of Master Data Management (MDM) is a topic that deals with these issues to advise how to reach a consensus on the definitions of data and manage its changes and evolution over time (Loshin, 2009; Otto, 2012; Otto et al., 2012).

2.3 Data synchronisation in DTs

A key problem in a DT is when to synchronise copies of data in order to provide up-to-date data in the DT. The problem is non-trivial because a trade-off exists between synchronisation costs and quality (staleness) of the data (Qu and Jiang, 2018). Synchronisation costs include the cost of resources used, such as Information Technology (IT) staff and computing resources etc. Further-more, to avoid disruptions to systems during business hours, organisations often resort to batch synchronisation of data, which is attempted out of business ours (such as overnight) (Woodall et al., 2016). However, for DTs with a requirement to monitor engineering assets in real-time, a continuous stream of data will be needed, which shifts the trade-off towards high synchronisation costs.

2.4 Data Quality in DTs

Data quality is defined as fitness for use (Wang and Strong, 1996), which captures the dual concepts of how the data is to be used and whether it meets the requirements of that use. The use of the data in the DTs must support various applications at once, such as enabling maintenance decisions and maintenance predictions. However, in a DT the data can degrade causing it to be not fit for use for various reasons, including:

a). the quality of the data extraction process from the data sources;

b). the inherent quality of the data in the underlying (internal/external) data sources;

c). quality loss due to abstraction required by the integration of data;

d). differences in the quality requirements from different data sources (repurposing).

Data quality can be reduced when extracting data from source systems if, for example, the query to extract the data is incorrectly formulated and gathers the incorrect records, it may also be reduced if the transformations on the data (per-formed in ETL workflow) are incorrect.

DTs could utilise publicly available online data in order to enhance their predictions, such as using weather forecasts etc. However, the quality of online data can be questionable, and the use of this type of data could demand a different notion of data quality compared to traditional database systems (Lukyanenko et al., 2014).

Data quality loss can also occur when it is necessary to abstract certain details from multiple concepts. For example, imagine integrating the temperature of a radiator, temperature of a sump, temperature of combustion chamber into an overall measure of engine temperature; to do so results in a contextual loss of the actual location of the measurement.

Finally, there are many different applications of the data from DTs such as from Security and Health Management to Energy management. Each of these applications will have their own data quality (fitness for use) requirements which need to be catered for. This is problematic when data comes from different systems because the source system may have a different intended use of the data which does not match the requirements of the DT development.

3. System Architecture Establishment of Dynamic DT at the Building Level

With the basis of comprehensive analysis in the literature review from the perspective of data (e.g., data integration, sources heterogeneity, data synchronisation and data quality), this study proposed the hierarchical architecture at the building level (Fig.1). This proposed dynamic DT architecture aims at integrating heterogeneous assets and data sources with their applications, supporting intelligent asset management, providing effective O&M management, and further bridge the gap between human relationships with buildings/cities via more intelligent, visual and sustainable channels.

This architecture comprises of five layers, namely data acquisition layer, transmission layer, digital modelling and data complementary layer, data/model integration layer and application layer (see Figure 1).

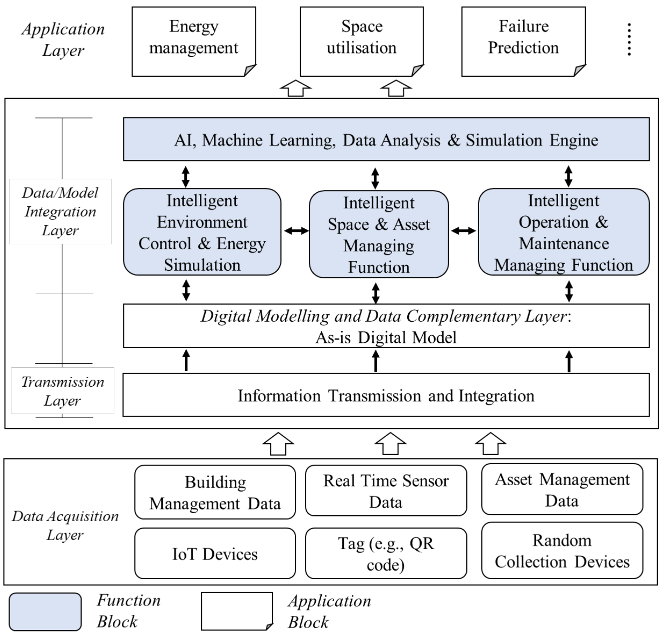

Figure 1 The system architecture of dynamic DT development in a building level

• Data acquisition layer is the foundation of each DT and collecting needed data. Due to technological advances, contactless data acquisition (e.g., RFID, QR codes, image-based techniques), distributed sensor systems, wireless communication, mobile access (e.g., WiFi environment) etc are available in markets currently. Based on different functions requirements of daily building management, techniques and systems should be connected with their physical assets and designed based on well-organised DT architecture, which is presented in Fig.1 and designed for buildings.

• Transmission layer mainly aims at transforming collected data to the upper layers. Data would be collected from physical devices, which are attached to physical assets/spaces of a building or surrounding environment. Various communication technologies can be used in this layer, such as 5G, low-power wide area networks (LP-WAN). Among all available technologies, Wi-Fi is the well-known wireless local area network (WLAN) technology and widely used one.

• Digital modelling and data complementary layer presents the digital model (e.g., BIM) and supplements complementary information (e.g., backgrounds of the target building) that support for upper layers and connect the bottom layers. Different types of digital models/model can be used for different purposes in DTs. For instance, energy model can be used for energy simulation and agent-based model would model scenarios and support decision. When a DT at building levels is designed, a pre-defined modelling processes and types are required to be defined and complementary data would be confirmed for further applications.

• Data/model integration layer is the kernel in this architecture, including data and model storing, analysing, integrating, processing, and AI-supported decision-making functions etc. (Glaessgen and Stargel, 2012). In this architecture, real-time data analysis and processing functions would update as-is conditions building assets or environments (including work orders, up-to-date maintenance information, status). Visualised data/model managing frameworks can achieve dynamic and effective data management. Furthermore, intelligent functions (e.g., AI, machine learning modules) provide operating advanced decision-making management (e.g., energy usage control, space utilization and workplace design).

• The application layer is the top and implementation layer of the dynamic DT architecture that interacts with facility mangers and provides services for users.

4. Dynamic DT Demonstrator Development based on the Proposed System Architecture

4.1 General Introduction

The case study of developing a dynamic DT in a building level was conducted at west Cambridge site and used Institute for Manufacturing (IfM) as the target area. This research is led by the asset management group at IfM and started in September 2017. The IfM building is a three-story building (i.e., IfM building) at the west Cambridge site and includes study, office, research and laboratory spaces, which covers over 40000-square-foot (Fig.2). This dynamic DT demonstrator in Cambridge is developed based on the proposed system architecture in Section 3.

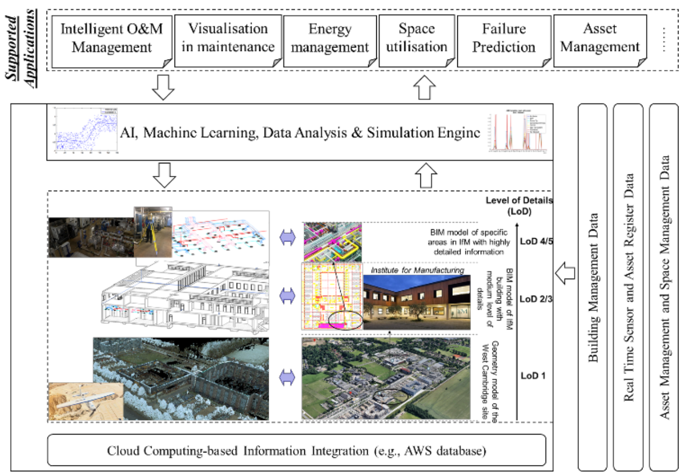

Figure 2 The dynamic DT development at Cambridge campus

4.2 Data Acquisition Layer and Transmission layer

Data acquisition from environments and physical assets is a fundamental requirement of the proposed system architecture of the dynamic DT. This presents several challenges for developing a data acquisition system: it needs to support data up-loads from the sensors that are deployed at dis-tributed locations since the assets are dispersed, and it needs to be scalable to support a large number of assets in building levels. In this work, these challenges are overcome by developing an IoT-enabled wireless sensor network (WSN) for data acquisition.

WSN refers to a collection of distributed and dedicated sensors for monitoring and recording conditions of environments and equipment (Lewis, 2004). The sensors in WSNs are called nodes and they measure environmental conditions such as indoor temperature and relative air humidity, and equipment conditions such as component vibration, surface temperature and speed of the rotating parts. In addition to the sensor nodes, WSNs consist of gateway nodes that act as the bridge be-tween the local sensors and the remote applications such as cloud-hosted databases and online web pages that visualise data. In recent years, WSNs gained attention due to the emergence of IoT and proliferation in Micro-Electro-Mechanical Systems (MEMS) technologies (Yick et al., 2008). These technologies allowed WSNs to be smarter by utilising computing capabilities yet cheaper and smaller (Yick et al., 2008). In this section, a discussion on the IoT-enabled WSN developed for the proposed system architecture of the dynamic DT is provided. Firstly, the IoT devices used as the nodes in the WSN are introduced and secondly a discussion on the overall WSN is provided.

The IoT sensors used in this work are the Monnit wireless sensors (Monnit, 2018a). A Monnit sensor consists of two 1.5V AA-sized batteries and according to Monnit, it is capable of an approximate lifetime of two years at one-minute heartbeat setting (i.e. data sensing and the transmission interval of one minute). The sensors and gateways communicate over the radio frequency (RF). The RF antenna in the sensors acts as the transmitter and the receiver, and it forwards the measured da-ta into the gateways and receives commands from the gateways respectively. These sensors are capable of 250 – 300 feet non-line-of-sight (partially obstructed path for radio transmission) RF range (Monnit, 2018b). The wireless communication capability of these sensors over RF is suitable for the distributed nature of the DT system architecture as RF is a low-cost communication medium (Lanzisera et al., 2011), and it supports the required range to connect the distributed set of sensors with the gateways. In this work, a wide range of sensors is used for capturing data from the locations and equipment in the IfM building. Table 1 shows the types of sensors used in the WSN deployed at the IfM building and their functions.

Monnit ethernet gateways (Monnit, 2018c) are used for the gateway nodes in the WSN. These devices are AC powered and consist of RF antennas that allow the communication with sensors. More-over, gateway devices consist of ethernet ports which allow them to communicate with the remote applications over the internet. According to Monnit, a single Monnit gateway can support up to 100 sensors, hence provides better scalability for a large number of assets in building levels.

Figure 3 shows the schematic of the WSN developed for data acquisition from environments and equipment. The nodes in the WSN are grouped into different clusters depending on the distance be-tween sensors and gateways. This allows robust connection between sensor nodes and gateway nodes as sensors can connect with the closest gateways which increase the RF signal strength be-tween the two devices. During the initialisation phase of the WSN, the gateways are pointed to a virtual server (i.e. connected with the IP addressed of a virtual server) created by the Sensor Manager software. Sensor Manager is a custom-developed .NET software which is hosted on a Windows server and integrated with the Monnit Mine API. The Monnit Mine API is an interface that allows custom-developed applications to retrieve data from the Monnit gateways. Once the gateways are pointed to the server hosted by the Sensor Manager, the sensors are registered with the gateways by sending a command to the gateways over the in-ternet using the HyperText Transfer Protocol (HTTP). This command contains the unique device identifiers (UDIDs) of the sensors a gateway needs to be connected with. After the initialisation phase, the sensor nodes are capable of monitoring environmental and equipment conditions, and up-load data over RF to the gateway nodes. Upon receiving the data, gateway nodes upload data into the Sensor Manager over the internet. Finally, the Sensor Manager stores data in a cloud database. In this WSN developed for the dynamic DT, the whole process of sensing condition data to storing data in the cloud database occurs every minute to facilitate timeliness of the dynamic DT.

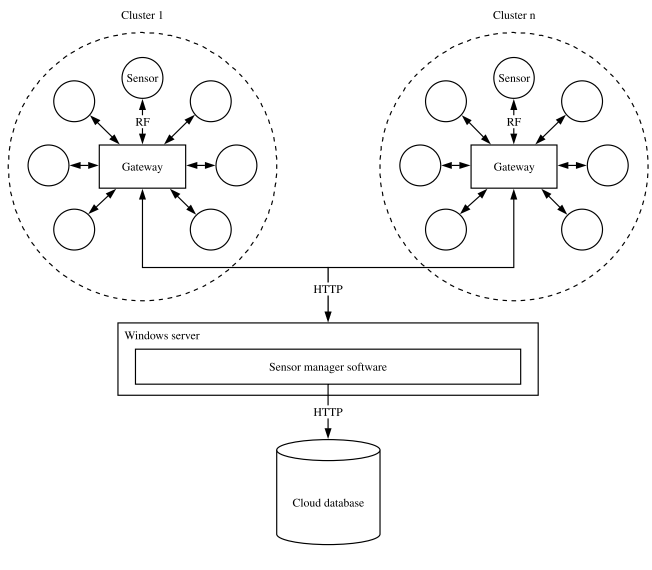

Figure 3 Schematic of the WSN for data acquisition from the assets

Table 1. Types of sensors used in the WSN deployed at the IfM building

Sensor type	Locations	Function
Temperature	Lecture theatres, seminar rooms, meeting rooms and plantroom	Measures indoor room temperature.
Humidity	Lecture theatres, seminar rooms, meeting rooms and plantroom	Measures relative air humidity.
Motion detection	Lecture theatres, seminar rooms and meeting rooms	Detects motion (e.g. detects whether anyone is present in the room).
Light meter	Lecture theatres and seminar rooms	Tracks light level in the environment.
Open/ closed	Meeting rooms	Detects whether a door or a window is opened or closed.
Carbon monoxide	Surrounding of the biomass boiler	Measures carbon monoxide gas level in the air.
Vibration count	Surface of the milling machines, lathes, pumps and robotic arms	Measures the number of vibrations of a component above a predefined threshold.
AC current meter	Lathes and robotic arms	Measures amp hours, maximum RMS current, minimum RMS current and average RMS current used by the equipment.

4.3 Digital Modelling and Data Complementary Layer

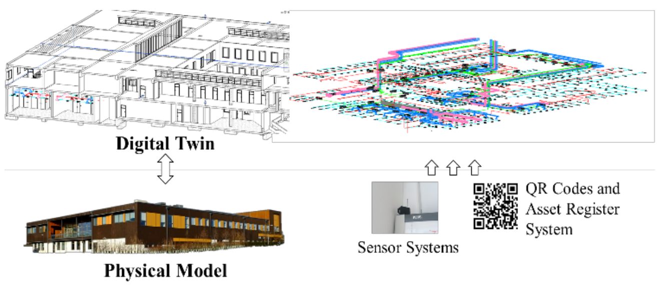

Figure 4 The development of digital models

High detailed BIM model is developed as the centralized digital model in this DT demonstrator and meets the information requirements of DTs (shown as Figure 4): including architecture, structure and mechanical, electricidal and pumping (MEP) components, and a context capture model of specific areas in IfM with highly detailed information (i.e., plant room). This layer aimed to establish a visualised digital model-based platform to link between upper and bottom layers.

4.4 Data/model Integration Layer and Application Layer

Based on the proposed system architecture, the developed DT is integrated with the data acquired from Building Management System (BMS), asset management system (AMS) (Planet system used in Cambridge), space management system (SMS) (MiCAD system used in Cambridge), and 'real-time' sensor dataset. The 'real-time' sensor datasets are integrated in a cloud-based computing platform (using AWS in this project). The BMS, AMS and SMS are all computer-aided control systems installed in buildings and they control the mechanical and electrical systems (e.g. power systems, heat ventilation and air conditioning (HVAC) systems and security systems), provide services of assets and manage space utilisation separately for various buildings in Cambridge site (see Figure 5). In this DT development, two main proposed applications were designed, including as-is conditions monitoring and future performance prediction (shown in Figure 6).

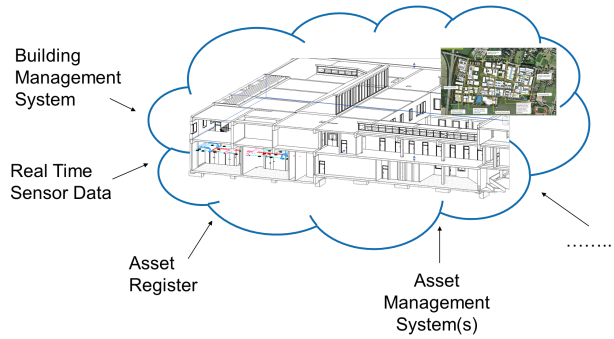

Figure 5 The data resources integration of the developed dynamic DT

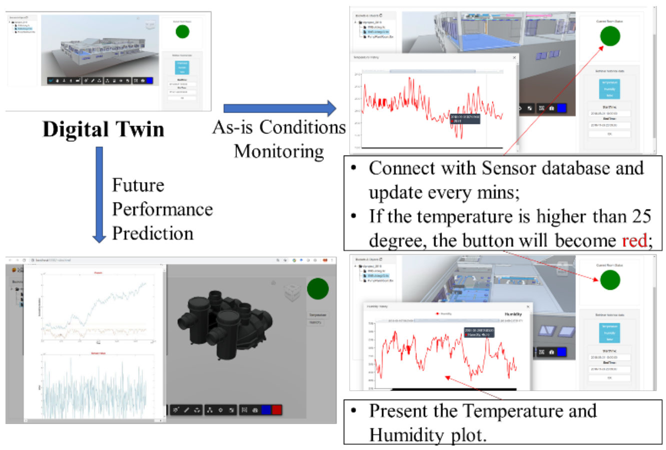

Figure 6 Proposed applications

In the as-is asset management monitoring function, temperature monitoring functions are designed to keep working environments comfort. In the predictive maintenance function, the health of assets is monitored and analysed in the real-time to forecast the remaining useful life of the asset and in turn to enable effective maintenance planning (Camci, 2015).

5. Discussion

Stating by Gemini principles (CDBB, 2018), national DTs should be purposeful, trustworthy and functional (CDBB, 2018). Basic elements are descripted as following:

Purpose (DTs must have clear purpose):

• Public good – The DTs must be used to deliver genuine public good in perpetuity;

• Value creation – The DTs must facilitate value creation and performance improvement;

• Insight – The DTs must provide additional insight into the built environment or surroundings.

Trust (DTs must be trustworthy):

• Security – The DTs must enable security and be secure itself;

• Openness – The DTs should be open (e.g., open data schema implemented);

• Quality – The DT must be built on data of an appropriate quality.

Function (DTs must be valid and workable):

• Federation – The DTs must be based on the secure interoperability of data;

• Curation – The DTs must be clearly owned, governed and regulated;

• Evolution – The NDT must be able to adapt, develop and extend as technology advances.

According to research project results and DT principles, successful development of DT in building levels can be summarised:

1) a clear objective of DT construction, such as the applications would be achieved based on DT (insight) and a clear definition of DT constitutes following this architecture (value creation);

2) a well-designed and practical process of collecting, updating, transferring and integrating data and digital model throughout the building life cycle (federation). For instance, the data structure design should consider data integration, heterogeneity in source systems and data synchronization.

3) a well-executed and standardised interoperability procedure and data compatibility plan and further possible evolution proposals (curation and evolution). More application, such as space management, would be extended based on DT.

4) a valid quality and security control strategy for developing DTs (security, openness and quality). For instance, the WSN is designed for data acquisition from the assets assist in controlling data quality and security features of a DT.

This research examined a real-world dynamic DT development using the IfM building in Cambridge site, to integrate various data resources, to develop digital models, to test proposed system architecture, to provide possible applications, and to summarise key items learned for developing dynamic DTs in building levels.

The long-term goals of this demonstrator are to: (1) demonstrate the impact of digital modelling and analysis of infrastructure performance and use on organisational productivity; (2) provide the foundation for integrating city-scale data to optimise city services such as power, waste, transport and understand the impact on wider social and economic outcomes; (3) establish a 'research capability platform' for researchers to understand and address the major challenges in implementing digital technologies at scale; and (4) foster a research community interested in developing novel applications to improve the management and use of infrastructure.

6. Conclusion

With the extensive attention to implementations of DTs in the AEC/FM areas and the expectations to take all the advantages of DTs and digital techniques, this study provided a comprehensive review and analysis from the perspective of data management. In order to present the insight into the field of DTs development in the AEC/FM areas, this study further presented a system architecture for dynamic DTs construction and provided possibilities to achieve this goal. Following the proposed architecture, the IfM building is chosen as a case study. Detailed current practices and lessons learned from this research have been discussed and analysed. Furthermore, it is also clear that more efforts should be made from the five proposed layers based on the proposed perspective system architecture. Specifically, the AI-supported decision-making functions and data analysis functions would highly improve the intelligence and integration of the whole dynamic DT system in the data/model integration layer. Moreover, the effective and efficient communication and interaction between people and DTs will be our future research targets. Moreover, how the performance of the asset changed with the use of this dynamic DT will be evaluated in the future study.

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