Understanding design change propagation in complex engineering systems using a digital twin and design structure matrix

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ABSTRACT

Purpose

As the engineering design process becomes increasingly complex, multidisciplinary teams need to work together, integrating diverse expertise across a range of disciplinary models. Where changes arise, these design teams often find it difficult to handle these design changes due to the complexity and interdependencies inherent in engineering systems. This paper aims to develop an innovative approach to clarifying system interdependencies and predicting the design change propagation at the asset level in complex engineering systems based on the digital-twin-driven design structure matrix (DSM).

Design/methodology/approach

The paper first defines the digital-twin-driven DSM in terms of elements and interdependencies, where we have defined three types of interdependency, namely, geospatial, physical and logical at the asset level. The digital twin model was then used to generate the large-scale DSMs of complex engineering systems. The cluster analysis was further conducted based on the improved Idicula-Gutierrez-Thebeau Algorithm (IGTA-Plus) to decompose such DSMs into modules for the convenience and efficiency of predicting design change propagation. Finally, a design change propagation prediction method based on the digital-twin-driven DSM has been developed by integrating the change prediction method (CPM), a load-capacity model and fuzzy linguistics. A section of an infrastructure mega-project in London was selected as a case study to illustrate and validate the developed approach.

Findings

The digital-twin-driven DSM has been formally defined by the spatial algebra and Industry Foundation Classes (IFC) schema. Based on the definitions, an innovative approach has been further developed to (1) automatically generate a digital-twin-driven DSM through the use of IFC files, (2) to decompose these large-scale DSMs into modules through the use of IGTA-Plus, and (3) predict the design change propagation by integrating a digital-twin-driven DSM, CPM, a load-capacity model and fuzzy linguistics. From the case study, the results showed that the developed approach can help designers to predict and manage design changes quantitatively and conveniently.

Originality/value

This research contributes to a new perspective of the DSM and digital twin for design change management and can be beneficial to assist designers in making reasonable decisions when changing the designs of complex engineering systems.

Keywords: Digital twin; Design structure matrix; Design change propagation

1. Introduction

Through a series of infrastructure projects and programmes including those at Heathrow, London, the 2012 Olympics, Crossrail, Tideway and High-Speed 2 (HS2), the UK is developing significant expertise in the delivery of major infrastructure projects (Whyte, 2019; Davies, 2017). To address the challenges of infrastructure delivery, multidisciplinary teams work together, integrating diverse expertise across disciplines. One challenge that arises is that design teams find it difficult to understand the impacts of late design changes in such complex engineering systems (e.g. infrastructures), where changes in one sub-system may have implications for other systems (Whyte et al., 2016). While there is ongoing interest in systems integration in large projects, there is a need to articulate the complexity of and interdependencies found in such systems to understand the design change propagation and its impacts.

Previous efforts have been made to identify system interdependencies and trace design changes of complex infrastructures. Eusgeld et al. (2011) proposed a 'system-of-systems' approach to identify and analyse interdependencies between industrial control systems (ICS). Goldbeck et al. (2019) developed a new, effect-based classification of interdependencies between infrastructure systems. The Design Structure Matrix (DSM) is a matrix showing interdependencies between components in the system (Browning, 2001). With the increasing complexity of infrastructures, it has become used as a simple, compact and visual representation of a complex system. It has been adopted widely to model and analyse the product decomposition and interdependencies (Pimmler and Eppinger, 1994), to show data interdependencies in the multidisciplinary design process (Lambe and Martins, 2012), to formulate the interdependencies between drawings of physical components at the lowest level of abstraction in construction design (Senthilkumar and Varghese, 2009), and to predict and manage design changes in complex engineering systems (Clarkson et al., 2004; Fu et al., 2012).

While data consistency and quality have traditionally been relatively poor, such complex engineering systems are becoming rich sources of data deriving from multidisciplinary models and systems (Whyte et al., 2016), raising new opportunities to understand the interdependencies and model design change propagation in the design of new infrastructures. However, current DSM methods are inefficient in handling design changes with a large number of elements and the complex interdependencies of increasingly integrated and expanded complex engineering systems. There is a need to develop a new method applicable to complex engineering systems which can not only generate the large-scale DSMs conveniently but analyse the design change propagation risk reliably.

The development of digital technologies, especially Building Information Modelling (BIM) and digital twin techniques, provides a way to transfer complex engineering systems into the digital built environment, which enables the identification of complex building components and interdependencies digitally and automatically. The IFC functioning as a standard representation of BIM knowledge for interoperability further opens the possibility to integrate DSM with digital data for more convenient identification of system interdependencies and more effective design change management. Inspired by the interoperability of the IFC schema, Pektas (2010) proposed the complementary integration of IFC process modelling (e.g. IDEF0) and a parameter-based DSM in modelling the collaborative building design process. Jacob and Varghese (2011) proposed a logic of integration of BIM and DSM to improve construction design processes through the definition of new classes 'IfcDSM' and 'IfcConnectsByInformation'. Based on that, Jacob and Varghese (2012) made further efforts to handle design process complexity, derived from the increased sophistication of product models through an integrating process model (e.g. IFC process model and DSM) with a product model (i.e. IFC product model). However, these efforts were mainly premised on the hypothesis of potential IFC extensions (e.g. IfcDSM) and were limited to activity-/parameter-based DSM. Gopsill et al. (2016) succeeded in automatically generating a component-based DSM by monitoring the design changes in the digital models representing products. Saoud et al. (2017) proposed the integration of a parameter-based DSM with BIM to predict change propagation of design parameters within the BIM model. Although these efforts have succeeded in generating component-based or design parameter-based DSMs for predicting design change propagation, the work of Gopsill et al. (2016) is found to be inadequate for clarifying and classifying different kinds of interdependencies between elements in a DSM, and the work of Saoud et al. (2017) only focused on the spatial and analytical interdependencies for predicting and visualising design change propagation. There is still a need to develop an approach for predicting design change propagation based on a digital-twin-driven DSM with comprehensive system interdependencies identified.

This research aims to develop an innovative approach to clarifying system interdependencies to predict change propagation in complex engineering systems at the asset level based on the digital-twin-driven DSM. Drawing on the literature review, this research first defined the digital-twin-driven DSM in terms of elements and interdependencies. The IFC files from a digital twin model were then used to generate the large-scale DSMs of complex engineering systems. Cluster analysis was further conducted based on the IGTA-Plus to decompose such DSMs into modules for the convenience and efficiency of predicting design change propagation. Finally, a design change propagation prediction method based on the digital-twin-driven DSM was developed by integrating the CPM, a load-capacity model and fuzzy linguistics. A tunnel section of an infrastructure mega-project in London was selected as a case study to illustrate and validate the developed approach.

The structure of the paper is organised as follows: We define the key concepts and clarify their relationships in section 2; The research methodology is set out in section 3; The development and modularity of digital-twin-driven DSM are introduced in section 4; Section 5 develops the design change propagation prediction method based on a digital-twin-driven DSM; Section 6 introduces the implementation of the developed approach in a case study; Section 7 is the discussion and conclusions are in section 8.

2. Background

2.1 System interdependencies in complex engineering systems

Complex engineering systems are characterised by having a large number of dimensions, non-linear models, strong interactions, unknown or inherently random plant parameters and time delays in the dynamical structure (Jamshidi, 1996; Eusgeld et al., 2011). Many modern engineering projects are large complex engineering systems within dynamic environments, which usually comprise a large number of interacting sub-systems for components, processes, activities, stakeholders, resources and information (Abdoli and Kara, 2020; Zhu and Mostafavi, 2017). As shown in Table 1, these complex engineering systems can be divided into four levels based on the unified classification from Uniclass, namely, the system-of-systems, system, sub-system and asset levels (Pimmler and Eppinger, 1994; Senthilkumar and Varghese, 2009; Chou and Tseng, 2010; Eusgeld et al., 2011; Delany, 2019).

The design of such complex engineering systems is very challenging due to complex system interdependencies among or within systems and with external environments (Li, 2018). These system interdependencies can be defined as bi-directional or uni-directional relationships at different levels where the output of one item is essential to the input of another (Rinaldi et al., 2001; Zimmerman, 2001). For example, interdependency exists between a water pumping station and an electricity substation providing electricity for it (Holden et al., 2013). Another kind of system interdependency also exists between the water pumping station and a sewer tunnel which transports the sewage from the pumping station (Whyte et al., 2019).

Table 1 Decomposition of complex engineering systems

Level	Sub-level	Definition	Example	References

System-of-systems		Assembly of multiple, heterogeneous, distributed, occasionally independently operating systems embedded in networks at multiple levels	• National infrastructure scheme • Smart city • Community • Space exploration etc.	Zhang and Peeta, 2011; Eusgeld et al., 2011; Chen and Whyte, 2020.
System		Assembly of physical sub-systems for high-level functions	• Transportation engineering system: Airport, railway etc. • Water engineering system: sewer etc.	Pimmler and Eppinger, 1994; Rinaldi et al., 2001; Senthilkumar and Varghese, 2009; Chou and Tseng, 2010; Eusgeld et al., 2011.
Sub-system		Geographically distinct entity created to meet specific high-level functions for the users of the system.	• Terminal building or station in transportation engineering system • Pumping station, tank and tunnel section etc. in water engineering system	Pimmler and Eppinger, 1994; Eusgeld et al., 2011; Heracleous et al., 2017; Chen and Whyte, 2020.
Asset	Section	Physical entity created to meet specific functions for the system.	• Architecture • Structure • MEP • HVAC etc.	Senthilkumar and Varghese, 2009; Chou and Tseng, 2010.
	Component	Physical entity with specific functions in each section.	• Duct • Beam • Column • Foundation pile etc.	Pimmler and Eppinger, 1994; Senthilkumar and Varghese, 2009; Chou and Tseng, 2010; Saoud et al., 2017; Chen and Whyte, 2020.

Infrastructure projects are complex engineering systems in which large sets of components are brought together and interact with one another. Each component of infrastructure constitutes a small part of the intricate web that forms the overall infrastructure (Rinaldi et al., 2001). This complexity exhibited by infrastructure as a whole is beyond the simple aggregation of its components and should be investigated by clarifying the system interdependencies of infrastructures (Chen et al., 2020). For instance, Rinaldi et al. (2001) identified four types of system interdependency between infrastructure systems, including physical, cyber, geographic and logical. Mendonça and Wallace (2006) focused on service and space connections and also defined four categories of system interdependency, namely input, shared, exclusive-or, and co-location. Eusgeld et al. (2011) extended the aforementioned insights and looked at different system interdependencies in more detail, where nine types of system interdependency have been identified, including input, mutual, co-located, shared, exclusive-or, physical, cyber, geographic, and logical. Most of the previous works focused on the system or sub-system levels while the system interdependencies at the asset level were rarely explored which, however, are significant for the delivery and service provision of infrastructures (Table 2). Although Saoud et al. (2017) identified spatial and analytical interdependencies at the asset level, it is still necessary to identify the system interdependencies at the asset level more comprehensively and systematically.

Table 2 System interdependencies identified in previous works

Level	Identified system interdependencies	References
System	Four types of interdependency, including physical, cyber, geographic, and logical.	Rinaldi et al., 2001
	Two types of interdependency, including functional and spatial.	Zimmerman, 2001
	Four interdependent conditions defined, including input, shared, exclusive-or, and colocation.	Mendonça and Wallace, 2006
	Five types of interdependency, including physical, informational, geospatial, procedural and societal.	Dudenhoeffer et al., 2007
	Four types of interdependency, including functional, physical, budgetary, market and economic.	Zhang and Peeta, 2011
	Two categories of interdependency, including location-specific (physical), and functional.	Utne et al., 2011
System & sub-system	Nine categories of interdependency, including input, mutual, co-located, shared, exclusive-or, physical, cyber, geographic, and logical.	Eusgeld et al., 2011
	Two kinds of interdependency defined, including internal and external, where the external interdependencies were further represented by physical, cyber, geographic, and logical.	Heracleous et al., 2017
	Four types of interdependency, including stochastic failure propagation, logic, asset utilisation, and resource input.	Goldbeck et al., 2019
Asset	Two kinds of interdependency defined with BIM, including spatial and analytical interdependencies.	Saoud et al., 2017

Within the context of the above complex system interdependencies, different approaches have been proposed to represent and visualise system interdependencies. Utne et al. (2011) adopted the cascade diagram to show interdependencies between critical infrastructures, which was useful to quantify the system interdependencies but ignored the bidirectional ones and did not leverage the network and spatial characteristics of infrastructures (Zhang and Peeta, 2011).

To address this limitation, many efforts have been made based on network-based approaches. For instance, Jeong et al. (2006) developed a network-based model to show interdependencies at the sub-system level in water systems, which were composed of a plant, transmission pipelines, storage stations, and distribution lines. Wang et al. (2012) developed a network-based model for representing and analysing topological interdependencies between power and water systems. Based on these, Zhang and Peeta (2011) developed a multilayer infrastructure network framework to model infrastructure interdependencies, where individual infrastructure systems were represented as network layers and system interdependencies were represented as links within and across network layers. Using this framework, Holden et al. (2013) and Goldbeck et al. (2019) proposed a network flow model for interdependent infrastructures, which consisted of a set of directed edges representing interdependencies and vertices indicating general multi-functional infrastructure systems or sub-systems. Eusgeld et al. (2011) adopted a "system-of-systems" architecture to describe the interdependencies between the supervisory control and data acquisition (SCADA) and the system under control (SuC) including the electric power supply system and the gas supply system. However, the granularity of these network-based models was not suitable to describe system interdependencies at an asset level, nor sufficiently efficient to perform functional analysis (Eusgeld et al., 2011; Heracleous et al., 2017).

Some software has also been developed and applied to the identification and visualisation of system interdependencies at the asset level, such as Solibri, BIM 360 and Navisworks, which is convenient for analysing spatial interdependencies through clash detection and is becoming popular among designers due to the straightforward 3D visualisation. However, they are not capable of the holistic "what-if" analysis of design changes (Zhang and Peeta, 2011). The matrix structure has been further employed by Mendonça and Wallace (2006) and Saoud et al. (2017) to create "what-if" scenarios for interdependency analysis, raising new opportunities to improve the performance of the software by combining it with the matrix structure.

2.2 Design change propagation via system interdependencies

Change is common in project delivery processes, with design changes arising to improve the performance of projects or to address newly emerged requirements (Eckert et al., 2004). Yet it is costly, with changes and rework activities having a significant impact on the project delivery schedule, cost and quality (Ma et al., 2017). It is, thus, necessary to manage design changes properly. The system interdependencies in complex engineering systems have a major impact on design change management, where changes to one part of such systems may induce a change to another part via system interdependencies. The greater the interdependencies between parts, the larger the chance that a change to one part spreads to others. A change, thus, rarely occurs alone, and multiple changes can have interacting effects on other elements of the system (Eckert et al., 2004). Understanding how and why changes propagate during the design process is critical for the design change management of complex engineering systems (Giffin et al., 2009; Pasqual and de Weck, 2012).

In this research, the design change propagation is defined as a process "by which a change to one part or element of an existing system or product configuration or design results in one or more additional changes to the system, when those changes would not have otherwise been required" (Giffin et al., 2009). Change propagation occurs due to the interdependencies between the sub-systems or assets of complex engineering systems (Pasqual and de Weck, 2012). Eckert et al. (2004) distinguished between two types of design change with change propagation behaviour taken into account, namely, initiated change and emergent change. The initiated change usually arises from new requirements and needs, while the emergent change is unintended and occurs when some aspects of the system design require changing because of errors or undesirable emergent system properties, often due to an earlier initiated change. Based on that, the authors further provided the basic framework for classifying change propagation effects within a certain time frame, including ripple, blossom and avalanche, where the former two are predictable and can be contained within the expected duration while the last one is unpredictable and can become completely out of control (Eckert et al., 2004; Li et al., 2020).

To mitigate small changes propagating and becoming an undesirable avalanche of changes, multiple methods of predicting the design change propagation risk have been developed, which assess the risk in terms of propagation probability and the impact of change for each component. For instance, Isaac and Navon (2013) developed a graph-based model to detect the impact of a proposed design change, and they also adopted a clustering algorithm to identify directly affected components and a path-search algorithm to identify the indirect impact on the project. Lee and Hong (2017) developed a Bayesian approach to change propagation analysis. Lee et al. (2010) used the analytic network process (ANP) to measure the relative importance of parts and modules in a modular product in terms of design change impacts and propagation. Kocar and Akgunduz (2010) employed sequential pattern mining techniques to process captured engineering change history for a virtual engineering change management solution. However, these approaches cannot accommodate feedback and iterations that are commonly extant in the design of complex engineering systems. Recent studies pay more attention to network-based methods because complex engineering systems are more readily modelled as networks (Pasqual and de Weck, 2012; Li et al., 2020). For instance, Fu et al. (2012) established a network-based model to predict the risk of change propagation and thereby optimise module organisation. Li et al. (2020) proposed multilayer networks with a product layer and an organisation layer to reveal the law of design change risk propagation and mitigate the disruptive design change risk. The network-based methods can effectively represent and analyse the interdependencies in and between different elements in complex engineering systems, which have been thus applied to this research to predict and analyse the design change propagation risk.

2.3 A design structure matrix for design change propagation

The DSM has been the most widely adopted network-based method and provides a simple, compact, and visual representation of complex engineering systems that is effective in addressing decomposition and integration problems, and managing iterative tasks (e.g. design process). A DSM is a square matrix (N^2) with identical row and column labels, where an off-diagonal mark ('cross' in Figure 1) signifies the dependency of one element on another. Reading across a row indicates input sources while reading down a column reveals sinking outputs. In Figure 1, element B provides something to or is related to element E, and it depends on something from or relates to element A (Browning, 2001).

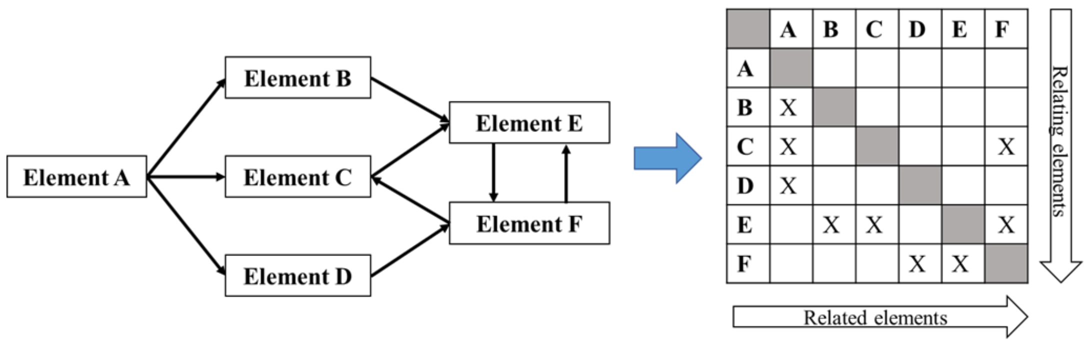

Figure 1. Related elements and the representation of interdependencies in DSM

There are four main categories of DSM in applications (Browning, 1999, 2001). These are (1) Component-based or an architecture DSM, which is used for modelling system architectures based on components and/or sub-systems and their relationships; (2) Team-based or organisation DSM, which is used for modelling organisation structures based on people and/or groups and their interactions; (3) Activity-based or schedule DSM, which is used for modelling processes and activity networks based on activities and their information flow and other dependencies; and (4) Parameter-based or low-level schedule DSM: which is used for modelling low-level relationships between design decisions and parameters, systems of equations, subroutine parameter exchanges etc. (Table 3).

The use of DSM in analysing and managing project designs has been increasing, especially in the design change management of complex engineering systems, where the development of such DSM is based on either knowledge-driven methods, data-driven methods, or digitally-driven methods (Table 3).

The majority of DSM-related studies are based the knowledge-driven methods, which leveraged expert opinions from design documents and interviews when identifying the system elements and interdependencies. For example, Clarkson et al. (2004) developed the CPM-based DSM which estimated the combined risk of change propagation by quantifying both the likelihood and impact of design changes by interviewing designers. Li et al. (2020) mapped the complex product development projects into multilayer DSMs with product layers and organisation layers based on multilayer network theory and built the model of design change risk propagation based on DSM and load-capacity model. Although the knowledge-driven methods are flexible to generate DSMs for different purposes, they are labour intensive and time-consuming when dealing with a large-scale DSM. For instance, it took five months to construct the 462^2 NASA pathfinder DSM (Brady, 2002).

Data-driven methods made use of historical design record to identify co-changing relationships and probability. For example, Giffin et al. (2009) used data mining to process 41,500 change requests for constructing a change network. Similarly, Gopsill et al. (2016) developed an automatic generation method for DSM by monitoring the design changes in the digital models representing the product. These methods are efficient in generating DSMs from large datasets, but they are lacking in a systematic view of system elements and interdependencies.

Digitally-driven methods have been proposed recently to make full use of digital information (e.g. BIM and IFC files) from complex engineering systems. Jacob and Varghese (2011) defined a new IFC class 'IfcDSM' and proposed to generate a DSM using object parameters and relationships from IFC model files. They further proposed a DSM-based framework to integrate the information from the product, design process, and design teams by using IFC files and manually pre-defined rules (Jacob and Varghese, 2012, 2018). Saoud et al. (2017) integrated a parameter-based DSM with BIM to predict the change propagation of design parameters. These pioneering works are time-saving and can clarify system elements and interdependencies, but they only focused on design sequences or specific spatial and analytical interdependencies, lacking a comprehensive understanding of such elements and interdependencies at different levels.

These DSM-based methods are inefficient to handle a large number of complex elements and interdependencies for increasingly integrated and expanded complex engineering systems. There is a need to develop a new DSM-based method that can both automatically generate a DSM comprehensively and systematically and conveniently analyse design change propagation risk for complex engineering systems.

Table 3. Example of DSM in design change management of complex engineering systems

DSM Types	References	Elements of DSM	Interdependencies of DSM	Data Collection
Component-based	Brady, 2002	Technologies	Technology interface	Knowledge-driven
	Clarkson et al., 2004	Product sub-systems	Design change propagation risk	Knowledge-driven
	Senthilkumar and Varghese, 2009	Drawings	Design issues of drawings	Knowledge-driven
	Giffin et al., 2009	Design areas	Design change propagation	Data-driven
	Fu et al., 2012	Product architectural components	Design change propagation risk	Knowledge-driven
	Jacob and Varghese, 2012	Building components	Spatial dependencies	Digitally-driven
	Colombo et al., 2015	Product architectural components	Component interfaces	Data-driven
	Gopsill et al., 2016	Digital models (e.g. CAD, CFD, FEA[1])	Component dependencies across models	Data-driven
	Li et al., 2020	Product architectural components	Inter-component interfaces	Knowledge-driven
Team-based	Senthilkumar and	Design teams	Design interfaces between	Knowledge-

	Varghese, 2009		teams	driven
	Li et al., 2020	Design teams	Inter-team iterations	Knowledge-driven
Activity-based	Austin et al., 2000	Design activities	Design information dependencies	Knowledge-driven
	Jacob and Varghese, 2012	Design activities	Design sequence	Digitally-driven
	Prasad and Jacob, 2018	Design activities	Design information dependencies	Knowledge-driven
Parameter-based	Pektaş and Pultar, 2006	Design parameters and requirements	Design information flows	Knowledge-driven
	Pektas, 2010	Design parameters	Design information flows	Knowledge-driven
	Jacob and Varghese, 2011	Design parameters	Spatial dependencies	Digitally-driven
	Saoud et al., 2017	Design parameters (geometry, position, specification)	Spatial and analytical dependencies (in, inter, self, join, host, s.host, s.sys[2])	Digitally-driven/Knowledge-driven
Hybrid	Jacob and Varghese, 2018	Building components, work sets, design teams	Spatial, temporal and organisational dependencies	Digitally-driven/Knowledge-driven

Note: [1]CAD: Computer-aided design; CFD: Computational fluid dynamics; FEA: Finite element analysis.
[2]in: elements belong to; inter: intersection between; self: relation within the same item; join: elements are connected to each other; host: being the host element; s.host: two elements have the same host element; s.sys: elements are defined in one system.

2.4 Digital twin and IFC for system interdependencies

As the wave of digitalisation is already here, infrastructures are becoming increasingly cyber-physically integrated, being rich sources of data from multidisciplinary models and systems for understanding complex interdependencies and design change propagation in complex engineering systems (Whyte et al., 2016). At the heart of digitalisation, the digital twin was first proposed by Michael Grieves in 2002 as the virtual representation of current physical products (Tchana et al., 2019). Then the digital twin in infrastructure was further clarified as: "realistic digital representations of physical things. They unlock value by enabling improved insights that support better decisions, leading to better outcomes in the physical world" (Bolton et al. 2018). While the shift from computer-aided design (CAD) to Building Information Modelling (BIM) involved the addition of semantic information of infrastructure assets as well as geometry, the shift to a digital twin requires the use of a broader range of sources of data, which may involve geometries, asset information and associated time series data on processes. Such data may be generated through the activities of professionals, in production and operation, and through a range of sensing devices (including photographs, laser scans, and embedded sensors).

Currently, attention is being drawn to the use of flows of such digital information to identify specific system interdependencies of infrastructures for better decisions, outcomes and performance, which are mainly based on IFC. As a comprehensive international standard for information interoperability, IFC is developed and managed by building SMART. It is a set of definitions describing the consistent data representation of building components for storing and exchanging building information over the whole life cycle (Zhang and Issa, 2013). The IFC entities represent not only geometric information (e.g., geometry representation and spatial topology) but also semantic properties, processes and relationships (e.g., materials, fabrication, and ontology), thereby endowing the IFC entities with intelligence. Based on the IFC schema, most current efforts have concentrated on developing semantic object-oriented information models for clarifying specific system interdependencies of assets. For instance, Dibley et al. (2012) captured the interdependencies of building and sensors by developing an ontology framework. Zhang and Issa (2013) modelled and extracted the logical interdependencies of building elements with a web ontology language (OWL) based on IFC specifications. Terkaj and Šojić (2015) also defined the interdependencies between non-abstract subtypes of IfcObject and IfcTypeObject using ifcOWL. However, these works are unable to interpret the geometric information including spatial objects and interdependencies that are implicitly or explicitly contained in the digital models. To fill this gap, Borrmann and Rank (2009) developed concepts and techniques for topological operators for spatial topological analysis based on an octree-based algorithm. They further developed a boundary representation based method for processing spatial topologies (Daum and Borrmann, 2014).

These efforts are beneficial in identifying and extracting specific system interdependencies, but they cannot support the development of DSM with complex and multiple system interdependencies for design change management of infrastructures. A new digital-twin-driven method is, thus, needed to be developed for automatic DSM generation and analysis using the IFC schema, wherein both the geometry information and the objectified relationships can be used for both spatial and non-spatial interdependencies' identification of infrastructure assets.

3. Research Methodology

This research developed a new digital-twin-driven method for understanding design change propagation in complex engineering systems at the asset level by integrating IFC and DSM. The innovative digital-twin-driven DSM and associated design change propagation prediction method will be developed and validated based on three interconnected steps, namely, (1) the development of DSM at the asset level, (2) design change propagation based on DSM and fuzzy linguistics, and (3) a case study for validation (Figure 2).

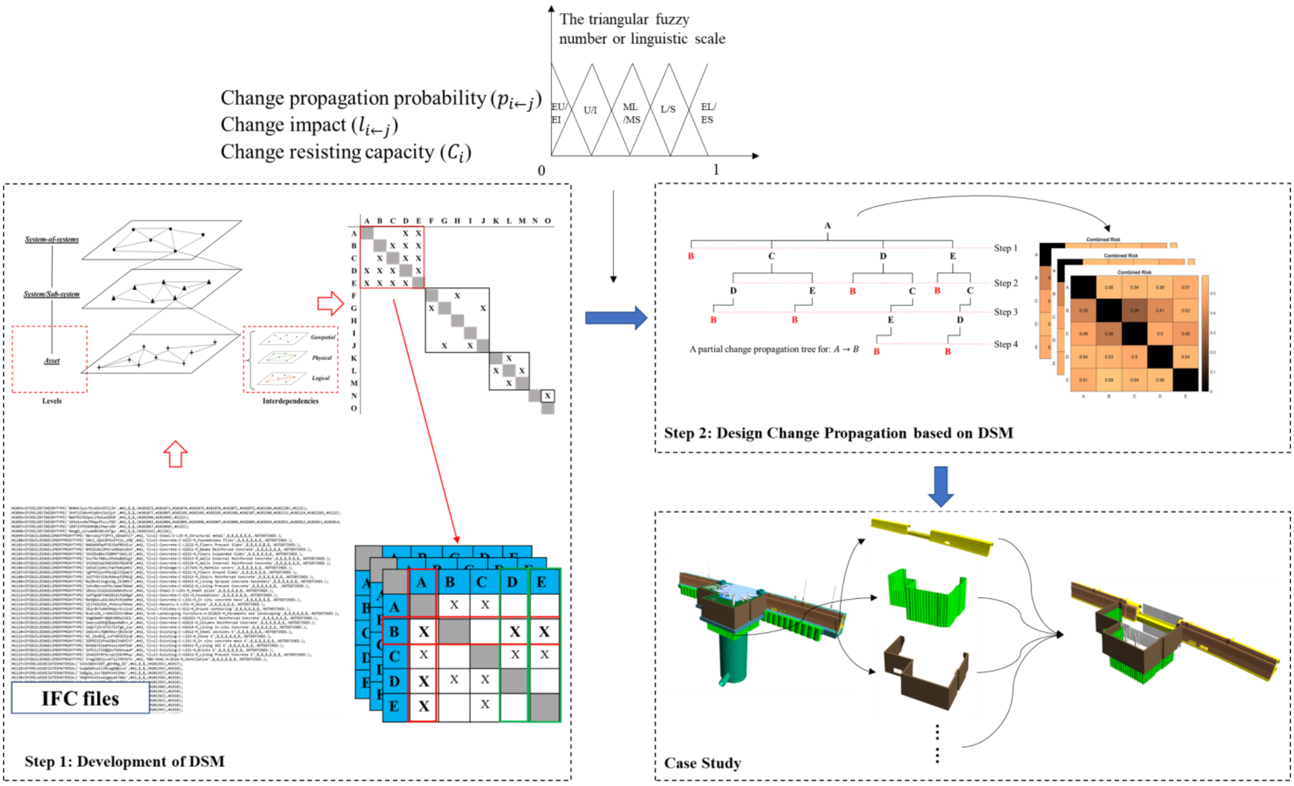

Figure 2. Research structure of design change propagation using DSM

The critical interdependencies of DSM at the asset level have first been proposed and defined according to the IFC schema for design change management of complex engineering systems. In total, three types of interdependency have been formally defined. The 9-Intersection Model (9-IM) based on spatial algebra was used in this research to formally define the spatial topological interdependencies contained in the digital twin model, which is useful when defining spatial topological interdependencies in a BIM environment, including cases of solid-to-solid relationships (Borrmann and Rank, 2009; Daum and Borrmann, 2014). The IfcRelationship entity and its subtypes were also adopted in this research to handle non-spatial interdependencies between assets, which were the abstract generalisation of all objectified relationships in IFC and can be sufficient for defining most semantic interdependencies in practice (buildingSMART, 2019).

These three types of system interdependency at the asset level were further examined through focus group meetings and a workshop. The monthly focus group meetings were held between the research team and key stakeholders from the industry partner (i.e. the infrastructure mega-project) from December 2018 to June 2019 at Imperial College London. Each meeting lasted for around 1 hour and focused on defining, identifying and qualifying the critical interdependencies emerging in complex engineering systems. One workshop with the wider community involved input from academia and project managers and data scientists from the major infrastructure project and was held on 2nd July

2019 at Imperial College London. It lasted for around four hours and mainly focused on evaluating, modifying and verifying the findings.

Based on the developed digital-twin-driven DSM, the IGTA-Plus with suppressing multi-cluster allocation (SMA) was then used to break up the large-scale DSMs into smaller sub-DSMs, i.e. modules (Borjesson and Hölttä-Otto, 2012). The IGTA-Plus with SMA improvement was adopted in this research due to its sound extension to IGTA and widely validated usefulness in the past decade (Thebeau, 2001; Borjesson and Hölttä-Otto, 2012; Borjesson and Sellgren, 2013). This cluster analysis was concerned with the grouping of elements into homogeneous modules based on their interdependencies, which will maximise interactions within the modules while minimising the interactions between modules (Michelena and Papalambros, 1995). Designers can, thus, focus only on corresponding modules and changes within modules, simplifying the design architecture significantly and improving the efficiency of computational procedures.

A novel hybrid approach has been further developed to predict design change propagation within modules of complex engineering systems by integrating fuzzy linguistics, CPM and the load-capacity model (Clarkson et al., 2004; Chen and Pan, 2016; Li et al., 2020). The risk-capacity model is one of the most popular models to deal with the risk of change propagation in complex project networks, which contains two elements: risk load and risk resisting capacity (Li et al., 2020). When risk loads of elements surpass their capacities, these elements will trigger the potential change in neighbouring elements. However, such a model only focuses on the adjacent elements for the direct risk of change propagation while ignoring the indirect risk. In this research, the CPM (Clarkson et al., 2004) was thus integrated into the load-capacity model for calculating the combined risk of change propagation from both direct and indirect elements. Fuzzy linguistics (Chen and Pan, 2016) was also adopted to deal with uncertainty and minimise bias when collecting subjective data for qualifying the design change propagation risks in focus group meetings. This novel hybrid approach first computed the risk load of design change propagation for each element based on CPM, where the fuzzy linguistic scales were used to estimate the change propagation probability ($p_{i \leftarrow j}$) and change impact ($l_{i \leftarrow j}$). It then identified the critical design change paths in DSM based on the load-capacity model. The results were finally visualised in a digital-twin-driven DSM for better understanding (as shown in Figure 2).

A tunnel section of a major infrastructure project in London was selected as a case study to validate this developed approach for design change propagation using digital-twin-driven DSM (Figure 2). A tunnel section of the infrastructure mega-project was chosen with the following considerations in mind: (1) the project is representative by its complexity, importance and size. It involves a major ongoing intervention in London, developing an infrastructure that crosses or impinges on a range of existing infrastructures; (2) there has been intensive use of digital modelling in this project, with operational models driving design decisions, as well as an emergent set of increasingly sophisticated modelling practices developing over time (Whyte et al., 2019); and (3) the tunnel section is a sub-system level model where the volume of data is appropriate to conduct analyses at the asset level. The digital twin model and drawings of the tunnel section were collected from the project management team, and the parameters related to design change parameters were collected from experts during focus group meetings and examined at the workshop. These parameters included (1) change propagation probability ($p_{i \leftarrow j}$), (2) change impact ($l_{i \leftarrow j}$), and (3) change resisting capacity (C_i).

4. Development and Modularity of Digital-twin-driven DSM

Based on the IFC files converted from digital models, the geometric and semantic information can be extracted for defining and identifying the elements and system interdependencies, which can finally generate the required DSMs at the asset level.

The elements have been defined as the assets of infrastructures in this research, which can be directly identified through mining the IFC files or using BIM Views engine in BIMserver. For example, the assets 'Civil Concrete: C-G215-M Foundations Piles' with different globally unique identifiers can be identified directly in the definition of IfcBuildingElementProxy (Figure 3).

```
#101355=IFCBUILDINGELEMENTPROXY('2bjawV7EowwjO2vqt2$xzh',#42,'Civil-Steel--C-L35-M Structural metal','1,PW_WORKDIR:dms06592\\100-DW-CVL-PWR1X-363760.dgn,Defa
#101356=IFCBUILDINGELEMENTPROXY('1Jzfx_e9jHTY_A$E26KkLK',#42,'Civil-Concrete--C-G215-M_Foundations Piles','1,PW_WORKDIR:dms06592\\100-DW-CVL-PWR1X-363760.dgn
#101357=IFCBUILDINGELEMENTPROXY('18RzZXPucFSwvwBXwQNuNS',#42,'Civil-Concrete--C-G215-M_Foundations Piles','1,PW_WORKDIR:dms06592\\100-DW-CVL-PWR1X-363760.dgn
#101358=IFCBUILDINGELEMENTPROXY('3cIRy8KBb0I_Z6vu_wjlPI',#42,'Civil-Concrete--C-G215-M_Foundations Piles','1,PW_WORKDIR:dms06592\\100-DW-CVL-PWR1X-363760.dgn
```

Figure 3. Example of identifying DSM elements in IFC file

The system interdependencies are classified based on the work of Rinaldi et al. (2001), where three types of interdependency have been defined, including geospatial, physical and logical interdependencies (Table 4). The cyber interdependencies are ignored here because the behaviours of information exchange are beyond the scope of this research, which focuses instead on the design of infrastructures from the perspective of civil engineering.

Table 4. Definitions of interdependencies for digital-twin-driven DSM at the asset level

Interdependency types	Sub-types	Definitions	Demonstrations in digital twins	References
Geospatial		The physical adjacency or topological relationship between assets.	Disjoint, Inside, Equal, Touch, Contain, Overlap, Cover, CoveredBy	Borrmann and Rank, 2009; buildingSMART, 2019
Physical		An objectified relationship between a material definition and elements or element types to which this material definition applies	IfcRelAssociatesMaterial	Rinaldi et al., 2001; Borrmann et al., 2015; buildingSMART, 2019; Goldbeck et al., 2019

Logical	**Grouping**	The state of each asset depends on the state of the other via a functional mechanism, or that is neither a physical nor a geospatial connection.	IfcRelAssignsToGroup[1]	Rinaldi et al., 2001; buildingSMART, 2019; Goldbeck et al., 2019
	Resource sharing		IfcRelAssignsToResource[2]	

Note: [1]An objectified relationship assigning object definitions (IfcObject) to a group (IfcGroup).
[2]An objectified relationship assigning objects (IfcObject), acting as a resource usage or consumption, to a resource (IfcResource).

Geospatial interdependencies occur when an environmental event can create state changes in entities, which is usually identified as physical adjacency or a topological relationship between assets. The 9-IM has been adopted in this research to define the geospatial interdependencies. The 9-IM calculus is extended from 4-IM and based on the mathematical theories of algebraic topology and set topology (Egenhofer and Franzosa, 1991). The geospatial interdependencies can, thus, be defined by the intersection of the interior, exterior and boundary of two operands, where an intersection can yield an empty $\emptyset$ or a non-empty set $\neg\emptyset$ in a 3×3 matrix to represent eight solid-solid relations in a digital twin environment, as shown in eq. (1) (Daum and Borrmann, 2014):

$$I = \begin{pmatrix} A^{\circ} \cap B^{\circ} & A^{\circ} \cap \partial B & A^{\circ} \cap B^{-} \\ \partial A \cap B^{\circ} & \partial A \cap \partial B & \partial A \cap B^{-} \\ A^{-} \cap B^{\circ} & A^{-} \cap \partial B & A^{-} \cap B^{-} \end{pmatrix} \tag{1}$$

where A° and B° are the interiors; ∂A and ∂B are the boundaries; A^{-} and B^{-} are the exteriors of the solids A and B respectively. These eight geospatial interdependencies include Disjoint, Inside, Equal, Touching, Containing, Overlapping, Covering, and CoveredBy (Table 5).

Table 5. Definitions of the geospatial interdependencies by the 9-IM

$A^{\circ} \cap B^{\circ}$	$A^{\circ} \cap \partial B$	$A^{\circ} \cap B^{-}$	$\partial A \cap B^{\circ}$	$\partial A \cap \partial B$	$\partial A \cap B^{-}$	$A^{-} \cap B^{\circ}$	$A^{-} \cap \partial B$	$A^{-} \cap B^{-}$	
$\emptyset$	$\emptyset$	$\neg\emptyset$	$\emptyset$	$\emptyset$	$\neg\emptyset$	$\neg\emptyset$	$\neg\emptyset$	$\neg\emptyset$	Disjoint
$\neg\emptyset$	$\neg\emptyset$	$\neg\emptyset$	$\emptyset$	$\emptyset$	$\neg\emptyset$	$\emptyset$	$\emptyset$	$\neg\emptyset$	Inside/ Contain
$\neg\emptyset$	$\emptyset$	$\emptyset$	$\emptyset$	$\neg\emptyset$	$\emptyset$	$\emptyset$	$\emptyset$	$\neg\emptyset$	Equal
$\emptyset$	$\emptyset$	$\neg\emptyset$	$\emptyset$	$\neg\emptyset$	$\neg\emptyset$	$\neg\emptyset$	$\neg\emptyset$	$\neg\emptyset$	Touch
$\neg\emptyset$	$\neg\emptyset$	$\neg\emptyset$	$\neg\emptyset$	$\neg\emptyset$	$\neg\emptyset$	$\neg\emptyset$	$\neg\emptyset$	$\neg\emptyset$	Overlap
$\neg\emptyset$	$\neg\emptyset$	$\neg\emptyset$	$\emptyset$	$\neg\emptyset$	$\neg\emptyset$	$\emptyset$	$\emptyset$	$\neg\emptyset$	Cover/ CoveredBy

The physical interdependencies represent the relationships between elements via material, which can be identified from IFC files using IfcRelAssociatesMaterial (Rinaldi et al., 2001). For example, the IfcRelAssociatesMaterial denotes that the physical interdependencies occur between elements #101355 and #101853 sharing the same type of material #1917 'C-L35-M_Structural metal', where the material change of one element will affect usage of the material in the other element (Figure 4).

```
#1127=IFCRELASSOCIATESMATERIAL('3iVxS$dnJIBT_gOr0Xg_6Z',#42,$,$,(#101355),#1917)
#1625=IFCRELASSOCIATESMATERIAL('3xg7M2j7qiQTZjCUpgqD7H',#42,$,$,(#101853),#1917)
#1917=IFCMATERIAL('C-L35-M_Structural metal')
```

Figure 4. Example of physical interdependencies in IFC file

The logical interdependencies represent the functional relationships, or not geospatial or physical connections (Rinaldi et al., 2001; Goldbeck et al., 2019). Two sub-types of logical interdependencies have been defined in this research, including grouping and resource sharing. The grouping interdependencies are essential in identifying the interactive elements (i.e. IfcObject) under a logical aggregation (i.e. IfcGroup), to provide specific functions, where the entity IfcRelAssignsToGroup can be adopted to extract such interdependencies. For example, the IfcRelAssignsToGroup assigns objects (i.e. IfcObject #575641, #575667 etc.) to a group (i.e. IfcGroup #1188039) for lighting, where the functional change in one object will affect the functions of other objects in this group. The resource sharing interdependencies define the logical relationships of objects (i.e. IfcObject) in resource (i.e. IfcResource) assignment, where the resources contain the costs, schedules, and other impacts from the use of a thing in a process except the materials. For example, the objects will interact logically if they share the budget, where the cost change in one object will affect the budget of other objects.

```
#1188039= IFCSYSTEM('2HvuEsbYzAmfY8Bnlmy9mE',#41,'lighting 7',$,'lighting');
#1188040= IFCRELSERVICESBUILDINGS('1K6wTyQ4fBhwqwB5ImS39_',#41,$,$,#1188039,(#115));
#1188043= IFCRELASSIGNSTOGROUP('1MGBN1dinDSRmoNWFAQRJM',#41,$,$,(#575641,#575667,#575843,
#575873,#576045,#1067665,#1067675,#1067688,#1067698,#1067710,#1067722,#1067738,#1067751),$,#1188039)
```

Figure 5. Example of logical interdependencies (Grouping) in IFC file

With the digital-twin-driven DSM developed, the IGTA-Plus is then adopted to decompose the large-scale DSMs into modular configurations, which will cluster a square matrix by moving elements from one cluster to another while minimising the interactions between modules and maximising the interactions within the modules.

To apply the IGTA-Plus, each element is initially and randomly placed in a module. Then the total coordination cost $TotalCost$ of DSM is calculated out as the criteria to determine whether the DSM is clustered optimally by (Thebeau, 2001):

$$TotalCost = ExtraClusterCost + IntraClusterCost \quad (3)$$

$$ExtraClusterCost = \sum_{i,k \notin Cluster_j} \big(DSM(i,k) + DSM(k,i)\big) \times DSMSize^{powcc} \quad (4)$$

$$IntraClusterCost = \sum_{j=1}^{n_{cluster}} \left(ClusterSize_j^{powcc} \sum_{i,k \in Cluster_j} \big(DSM(i,k) + DSM(k,i)\big)\right) \quad (5)$$

where j is the cluster (i.e. module) number; $IntraClusterCost$ is the cost of interdependencies within a module; $ExtraClusterCost$ is the cost of interdependencies outside any module;

$DSM(i,k)$ and $DSM(k,i)$ are the interdependencies between the ith and jth elements; $DSMSize$ is the number of elements in the DSM; $ClusterSize_j$ is the number of elements within jth module; $powcc$ is the penalty of the size of modules and $powcc = 1$ in most cases (Thebeau, 2001).

It will then select an element randomly from an existing module and determine whether there is another module with a better fit, where the degree of fit can be calculated out by the ClusterBid (Thebeau, 2001):

$$ClusterBid_j = \frac{inout_j^{powdep}}{ClusterSize_j^{powbid}} \tag{6}$$

where $inout$ is the sum of DSM interdependencies between the chosen element and every other in the jth module; $powdep$ is the exponential to emphasise interdependencies and $powdep = 4$ in most cases; $powbid$ is the exponential to penalise size of the jth module and $powbid = 1$ in most cases. The selected element will be moved to the module with the highest value of $ClusterBid_j$. When two or more modules have the same value of $ClusterBid_j$, the SWA feature will assign the selected element randomly to one of these modules (Borjesson and Hölttä-Otto, 2012). Finally, $Totalcost$ will be updated accordingly and the procedure will be repeated for a new randomly selected element until the value of $TotalCost$ cannot be made any lower.

5. Design Change Propagation Prediction based on DSM

Based on the developed DSM, the designers need only focus on the essential interdependencies within the clustered modules while ignoring the non-essential interdependencies outside the modules for high efficiency and acceptable accuracy in design change propagation prediction.

The design change propagation can be traced and predicted properly based on change propagation probability and change impact (Fu et al., 2012; Li et al., 2020). The change propagation probability measures the likelihood of a change of one element directly causing a change of others, and the change impact measures how significantly the impacted elements will change. Both can be measured using the 5-point triangular fuzzy linguistic scales (Table 6).

Table 6. Triangular fuzzy linguistic scales

Linguistic scale for change propagation probability	Linguistic scale for change impact	Triangular fuzzy numbers
Extremely unlikely (EU)	Extremely insignificant (EI)	(0, 0, 0.25)
Unlikely (U)	Insignificant (I)	(0, 0.25, 0.50)
Moderately likely (ML)	Moderately significant (MS)	(0.25, 0.50, 0.75)
Likely (L)	Significant (S)	(0.50, 0.75, 1)
Extremely likely (EL)	Extremely significant (ES)	(0.75, 1, 1)

The arithmetic of two triangular fuzzy numbers $\tilde{A}_1 = (l_1, m_1, u_1)$ and $\tilde{A}_2 = (l_2, m_2, u_2)$ are as follows (Chen and Pan, 2016):

$$\tilde{A}_1 + \tilde{A}_2 = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \tag{7}$$

$$\tilde{A}_1 - \tilde{A}_2 = (l_1 - u_2, m_1 - m_2, u_1 - l_2) \tag{8}$$

$$\tilde{A}_1 \times \tilde{A}_2 = (l_1 \times l_2, m_1 \times m_2, u_1 \times u_2)\ (l_i > 0, m_i > 0, u_i > 0) \tag{9}$$

$$\tilde{A}_1 / \tilde{A}_2 = (l_1/u_2, m_1/m_2, u_1/l_2)\ (l_i > 0, m_i > 0, u_i > 0) \tag{10}$$

According to the load-capacity model, each element in DSM for complex engineering systems embodies the maximum capacity to resist design change. When the risk load of design change propagation is higher, the elements will need to be paid more attention to for design changes. Specifically, the design of the element must be changed when the risk load exceeds the capacity:

$$s_{i\leftarrow j} = \begin{cases} 0, R_{i\leftarrow j} \le C_i \\ 1, R_{i\leftarrow j} > C_i \end{cases} \tag{11}$$

where $s_{i\leftarrow j}$ is the state of the ith element (e_i) when impacted by the jth element (e_j), $R_{i\leftarrow j}$ is the combined risk of change propagation from the jth to ith element, and C_i is the change resisting capacity of e_i.

The risk of change propagation can be defined as the product of change propagation probability ($\tilde{p}_{i\leftarrow j}$) and change impact ($\tilde{l}_{i\leftarrow j}$) using triangular fuzzy numbers (Fu et al., 2012; Li et al., 2020):

$$\tilde{r}_{i\leftarrow j} = \tilde{p}_{i\leftarrow j} \times \tilde{l}_{i\leftarrow j} \tag{12}$$

Where $\tilde{r}_{i\leftarrow j}$ is the risk of change propagation from e_j to e_i, and $\tilde{p}_{i\leftarrow j}$ and $\tilde{l}_{i\leftarrow j}$ are the probability and impact of change propagation from e_j to e_j, respectively.

A predictive model for design change propagation should include such risks from both direct and indirect elements (Clarkson et al., 2004; Fu et al., 2012). The combination of these risks can be estimated through $\cap$ (AND) and $\cup$ (OR) operators:

$$\tilde{p}_{i\leftarrow j} \cap \tilde{p}_{r\leftarrow s} = \tilde{p}_{i\leftarrow j} \times \tilde{p}_{r\leftarrow s} \tag{13}$$

$$\tilde{p}_{i\leftarrow j} \cup \tilde{p}_{r\leftarrow s} = \tilde{p}_{i\leftarrow j} + \tilde{p}_{r\leftarrow s} - \left(\tilde{p}_{i\leftarrow j} \times \tilde{p}_{r\leftarrow s}\right) = I - \left(I - \tilde{p}_{i\leftarrow j}\right) \times \left(I - \tilde{p}_{r\leftarrow s}\right) \tag{14}$$

where the risks of elements in the same branch (e.g., A-C-D-B in Figure 6) are combined by an 'AND' operator, while the risks of elements in different branches (e.g., C-D-B and D-B in Figure 6) are combined by an 'OR' operator. The combined risk of change propagation $R_{i\leftarrow j}$ can be calculated as the cumulative risk from both direct and indirect elements:

$$\tilde{r}_{i\leftarrow j}^{(m)} = \left(\tilde{p}_{i\leftarrow m-1} \times \tilde{p}_{m-1\leftarrow m-2} \times \cdots \times \tilde{p}_{2\leftarrow 1} \times \tilde{p}_{1\leftarrow j}\right) \times \tilde{l}_{i\leftarrow m-1} \tag{15}$$

$$R\left[\tilde{R}_{i\leftarrow j}\right]_{N\times N} = \left[\tilde{R}_{i\leftarrow j}\right]_{N\times N} = \left[\sum_{m-1}^{N} \tilde{r}_{i\leftarrow j}^{(m)}\right]_{N\times N} \tag{16}$$

where m indicates that a design change from e_j propagates to e_i after m transmission steps (Figure 6). When $m = 1$, $\tilde{r}_{i\leftarrow j}^{(1)}$ is the direct risk of change propagation. $\tilde{r}_{i\leftarrow j}^{(m)}$ is the indirect risk when $m \geq 1$. A practical limit of three or four steps is suggested for saving time with required accuracy, and the routes returning to previously visited elements can be ignored for clarity and simplification (Clarkson et al., 2004).

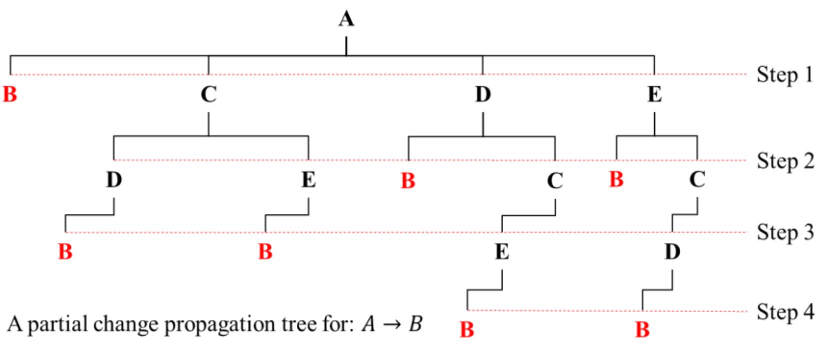

Figure 6. Design change propagation tree

When the risk is propagated to the element, its capacity of resisting change will decide whether this element needs to be changed or not. The capacity of ith element ($\tilde{C}_i$) shows the design flexibility and is related to the out-degree of the impacted element ($K_{i(out)}$) and the average impact of all probable change risks ($\bar{\tilde{L}}_i$) (Pasqual and de Weck, 2012; Zhang and Yang, 2013; Li et al., 2020):

$$C\left[\tilde{C}_i\right]_N = \left[\tilde{C}_i\right]_N = \left[\alpha K_{i(out)}^{\beta} \bar{\tilde{L}}_i\right]_N \tag{17}$$

$$\bar{\tilde{L}}_i = \sum_{j=1}^{M} \tilde{R}_{i\leftarrow j} / M \tag{18}$$

where α and β are adjustable parameters and $\alpha, \beta > 0$. $K_{i(out)}$ represents the out-degree of the element e_i, and $\bar{\tilde{L}}_i$ shows the average impact when upstream elements propagate change risks to the element e_i. In this research, we fix $\alpha = 0.1, \beta = 1$ (Li et al., 2020).

After determining the risk load and resisting capacity, the triangular fuzzy numbers need to be de-fuzzified into crisp numbers for comparison in eq. (11) and visualisation in DSM:

$$x_{defuzzified} = [(u_i - l_i) + (m_i - l_i)]/3 + l_i \tag{19}$$

6. Case Study

A tunnel section of a major infrastructure project in London was selected as a case study to validate this developed approach for design change propagation using a digital-twin-driven DSM (Figure 7). This ongoing project is delivering a 25 km super sewer under the Thames that will prevent the tens of millions of tonnes of pollution from entering the River Thames every year. This complex and important infrastructure mega-project is being built across 24 construction sites/sections, spanning from Acton in West London to Beckton in the East and will be completed in 2025.

With the digital model and drawings of this case project, the digital-twin-driven large-scale DSMs at the asset level can be established based on IFC files and further clustered into modules using IGTA-Plus. This research focused on just one of these modules in this case study to demonstrate and validate the developed approach due to the limited data access and data confidentiality. However, it can be representative to fully examine the usefulness in practice through generating the digital-twin-driven DSM and predicting the design change propagation.

Based on IFC files of the tunnel section, the digital-twin-driven DSMs have been developed and clustered, where the geospatial and physical interdependencies have been identified automatically while the logical interdependencies were not defined in these IFC files (Figure 7). The five elements have been clustered into one module in the geospatial DSM.

With this module of DSM generated (Figure 8(1)), the change propagation probability ($\tilde{p}_{i\leftarrow j}$) and change impact ($\tilde{l}_{i\leftarrow j}$) were estimated using triangular fuzzy linguistic scales (Figure 8(2)), where such parameters were defined according to the literature review and authors' project experience in this research for demonstration purpose only (Li et al., 2020). Then using eq. (12–16) and eq. (19), the combined risks of design change propagation were predicted and visualised in DSM (Figure 8(4)). Finally, by comparing the change-resisting capacity (eq. (17–18)) and combined risk, the design change propagation can be predicted and visualised (Figure 8(6)). For example, when the element A is changed, the combined risks of downstream elements B, C, D, E exceed the change-resisting capacities and such elements must be changed accordingly.

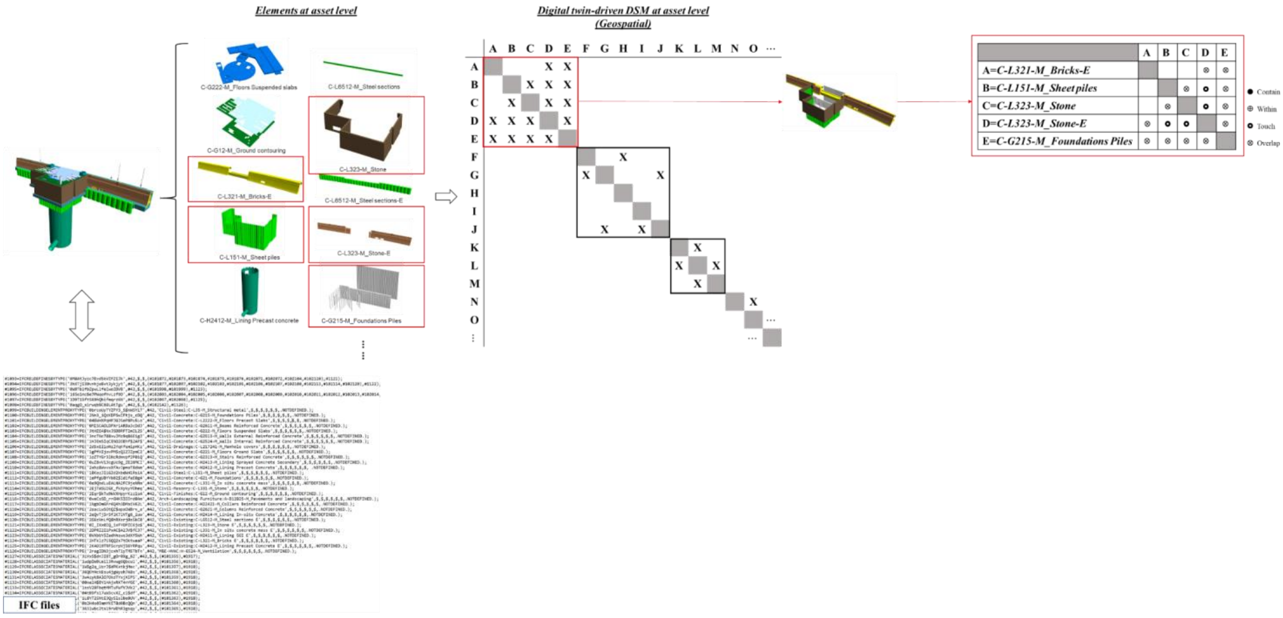

Figure 7. Generating digital-twin-driven DSM for tunnel section at the asset level

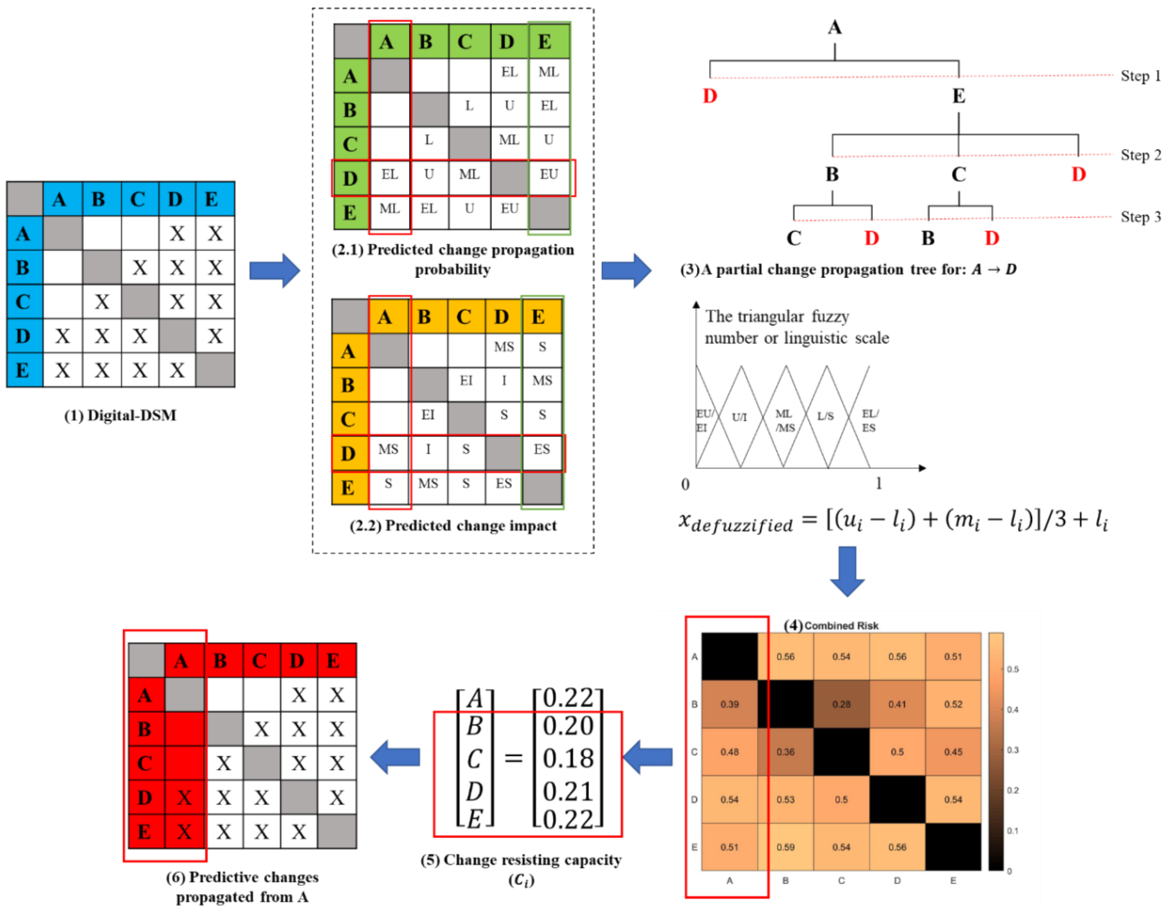

Figure 8. Design change propagation prediction based on a digital-twin-driven DSM

7. Discussion

This research contributes to the literature on the design change propagation of complex engineering systems by developing a digital solution based on digital-twin-driven DSM. Compared to previous methods, this developed approach can (1) comprehensively clarify the system interdependencies of infrastructures at the asset level; (2) generate and modularise the DSM in a more convenient way through digital information and clustering analysis; and (3) provide a more reliable prediction of design change propagation.

First, this research has extended the definitions of system interdependencies to the asset level of infrastructures. Three types of system interdependency have been formally defined for infrastructures at the asset level, including geospatial, physical and logical interdependencies (Table 4). Unlike previous works (e.g. Jacob and Varghese, 2011, 2012; Saoud et al., 2017) which focused on limited interdependencies (e.g. design sequence, spatial and analytical interdependencies), this approach provided a more comprehensive insight into the complexity of infrastructures by defining three types of system interdependency at the asset level, including geospatial, physical, and logical interdependencies. These formally defined interdependencies can cover most interactions between infrastructure assets.

It further identified the demonstrations of these defined interdependencies in digital twins, where the 9-IM based on spatial algebra has been adopted to define eight geospatial interdependencies and the entity IfcRelationship and its subtypes, IfcRelAssociatesMaterial, IfcRelAssignsToGroup and IfcRelAssignsToResource, which were adopted to handle physical and logical interdependencies, respectively (Table 4). Based on these definitions and digital information, the DSMs at the asset level have been developed automatically and conveniently for infrastructures by mining the IFC files or using the BIM Views engine in the BIMserver. This digitally-driven method of generating DSMs can be more time-saving and efficient than previous knowledge-driven methods (e.g. Clarkson et al., 2004; Li et al., 2020) when dealing with complex engineering systems with thousands of elements. The generated DSMs are usually large-scale due to the complexity of infrastructures. The clustering analysis has been further conducted to modularise large-scale DSMs using IGTA-Plus, which is helpful for designers to focus on design changes and estimate the strengths of interdependencies (i.e. change propagation probability and impact) within decomposed small-scale modules.

Finally, the newly developed change propagation prediction method improved the robustness of traditional CPM by integrating CPM with a load-capacity model. This method considered both the combined risk load and resisting capacity to judge whether the design changes can be propagated, which is more reliable than the CPM propagating the changes all the time (Clarkson et al., 2004; Fu et al., 2012; Zhang and Yang et al., 2013; Li et al., 2020). The fuzzy linguistics has also been integrated into the prediction method to deal with the uncertainty and reduce the bias when estimating the strengths of interdependencies, thereby improving the reliability of collected data and results.

8. Conclusions

Design change can introduce uncertainty and complexity into the design of complex engineering systems, where tracking and predicting such change propagation is significant for project delivery with high quality and data consistency. This research developed a new approach for predicting design change propagation of complex engineering systems based on the use of a digital twin and DSM. It first defined the digital-twin-driven DSM in terms of elements and interdependencies at the asset level, providing both a theoretical understanding and a practical approach for integrating the digital twin with a DSM. A clustering analysis based on IGTA-Plus was then conducted to decompose the large-scale DSMs into modules for the convenience and efficiency of predicting design change propagation. Then the design change propagation prediction method has been developed through integrating CPM, load-capacity model and fuzzy linguistics. A case study of the tunnel section of an infrastructure mega-project in London finally illustrated how the digital-twin-driven DSM at the asset level helped to predict design change propagation in infrastructures.

This research makes a theoretical contribution to the body of knowledge by defining the system interdependencies of a digital-twin-driven DSM at the asset level. It provides the first step towards next-generation complex engineering systems by demonstrating the feasibility of using a digital twin to generate new insights on systems relationships and interdependencies. The developed approach also makes a practical contribution to generating a digital-twin-driven DSM and the attendant design change management of complex engineering systems. Using spatial algebra and IFC schema, large-scale DSMs can be generated from IFC files automatically and conveniently. The integration of digitally-driven DSM and design change propagation analytics can further enable decision-makers to rapidly understand interdependencies and design change propagation within modules and across their boundaries in complex engineering systems.

Some limitations also need to be addressed in future research. First, the interdependencies defined based on the IFC schema (Table 4) are limited. Second, the size of DSM generated in the case study is limited by data access and confidentiality. Third, although the size of clustered modules is small, it is still time-consuming for experts to estimate the interdependency strengths. Future research should be conducted to address these limitations through (1) generalising the definition of digital-twin-driven DSM not only based on IFC but considering the behaviour data from the digital twin; (2) validating and tailoring the developed approach by generating and analysing large-scale DSMs with rich data from more case studies and feedback in the industry; and (3) integrating machine learning techniques to provide risk estimations based on past project experience.

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