Digital Twin Smart Cities for Disaster Risk Management

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It is widely accepted that digital and intelligence technologies can help solve key aspects of disaster risk management such as disaster prevention and mitigation, and rescue and recovery. Digital Twin (DT) is one of the most promising technologies for multi-stage management which offers significant potential to advance disaster resilience. Smart Cities (SCs) use pervasive information and communications technology to monitor activities in the city. With increasingly large applications of DTs combined with big data generated from sensors in a SC, it is possible to create Digital Twin Smart Cities (DTSCs).

digital twins | disaster risk management | preparedness | smart cities | resilience | natural hazards | vulnerability

1. Introduction

A disaster is a ‘serious disruption of the functioning of a community or a society at any scale due to hazardous events interacting with conditions of exposure, vulnerability and capacity, leading to one or more of the following: human, material, economic and environmental losses and impacts’ [1]. Natural hazard-induced disasters can have a life-altering influence on the individuals and families fortunate enough to survive them [2]. Despite the ingenuity, the effect of natural hazard-induced disasters can be felt at the community, city, and state level, or can even impact an entire country [3]. Over the last decade, a series of such events have caused economic losses in the tens of billions of pounds. Examples include hurricane Ida (United States) in 2021, the North American windstorm (United States, Mexico and Canada) in 2021, China floods (China) in 2020, cyclone Amphan (Eastern South Asia) in 2020, and hurricanes Harvey and Maria (United States) in 2017. In 2020 alone, direct economic losses and damages from natural hazard-induced disaster events were estimated at GBP 205 billion. Comparatively, this was well below the record-breaking highs of GBP 425 billion in losses in 2011 and GBP 370 billion in 2017 [4]. Recent storms Dudley and Eunice, which hit the UK in February 2022, are predicted to cost between GBP 2.5 billion and GBP 3.7 billion [5]. Over the last two decades, there have been over 7000 disaster events globally, claiming over 1.23 million lives (averaging over 60,000 lives per year) and affecting more than 4 billion people (many on multiple occasions) [6]. Additionally, disasters led to approximately GBP 2.26 trillion in economic losses worldwide [6]. These numbers present major demands for improving existing disaster risk management systems, including disaster response and recovery on a continuous basis [7], and there are many difficulties inherent in achieving these aims.

Such devastating and increasing social and economic impacts caused by disasters worldwide have necessitated the authorities to improve how they seek to mitigate, prepare for, respond to, and recover from disasters as a key priority at international, national, and local levels [8]. These collective efforts resulted in the establishment of emergency and disaster management systems such as the Federal Emergency Management Agency (FEMA) (United States), the Ministry of Emergency Management of China, and the United Nations Office for Disaster Risk Reduction (UNDRR) [9]. However, these systems lack technical interoperability, functional integration, and resource sharing, which currently remain obstacles to effective disaster management [10].

The increasing trend in the use of digitalisation may open new avenues to more network-centric and data-centric disaster risk management. The Coronavirus (COVID-19) pandemic is a living example which demonstrated how technology can offer substantial improvements to disaster responses in many forms; for example, improved testing and disease detection [11], improved policy and decision-making [12], improved training and education, and to efficiently manage imposed work and social distancing [13]. The role of technology in optimising risk reduction, mitigation, preparedness, response, and recovery is paramount from both an operational and strategic viewpoint, and digital innovations associated with Industry 4.0 have become key tools to use therein [14]. Hence, digital transformation and technologies have now become essential choices for disaster risk management. Among these technologies, the advent of Digital Twin (DT) and Smart City (SC) applications have emerged, presenting new opportunities for leveraging digitalisation to better manage disaster risk management.

The Digital Twin (DT) is one of the most beneficial technologies for better managing complex environments and facilitating connectivity through a variety of self-operative functionalities [15]. Digital Twin is a digital replica of a real-world asset or operation and differs from traditional Computer-Aided Design (CAD) and is based on massive, cumulative, real-world, real-time data measurements in multiple dimensions [16][17][18]. DTs evolve along with the physical asset or operation during their whole life cycle, enabling real-time bidirectional mappings between the virtual and physical assets or operations [19]. The term Smart City (SC) is rather ambiguous as the precise content, features, and nature of SCs tend to vary from country to country, depending on geographical conditions, ecosystems, and resource availability [20][21][22]. Broadly, though, a Smart City (SC) can be defined as an integrated living solution that perceptively and efficiently connects many life aspects such as power, transportation, and buildings to improve the quality of life for its citizens. A SC also looks to the future, emphasising the importance of resource and application sustainability for future generations [21][23]. Whilst there is some debate as to whether a SC is being used as a tool for smart public administration or a marketing tool [24], there is wider acceptance of the benefits associated with the concept. A Digital Twin Smart City (DTSC) combines these two components to provide functionalities that can synthesise the unique characteristics and constraints of a community during a disaster event and predict the evolution of a community during the aftermath of a disaster, enabling better disaster risk management [25].

2. Concepts and Evolution of Digital Twin, Smart City and Disaster Risk Management

2.1. Digital Twin (DT)

A digital twin (DT) is a digital counterpart of a real-world physical asset, and it is a model with a time dimension for all its attributes. Hence, it incorporates the changes over time in the same model while representing different virtual instances at a given point in time. A DT differs from traditional Computer-Aided Design (CAD) and is based on massive, cumulative, real-time, real-world data measurements in multiple dimensions [16][17][18][26]. DTs evolve along with the physical asset during their whole life cycle, enabling real-time bidirectional mappings between the physical and virtual assets [19]. A DT uses the information of a digital model across the entire life cycle of an infrastructure, and its concept dates back to Dr Grieves' presentation at the University of Michigan to the industry in 2002 [27]. Industry experts predict that the DT market will reach USD 48.2 billion by 2026 [28][29]. The dynamic nature of maintenance, along with the growing application of digital twin systems to tackle the aftereffects of the COVID-19 pandemic, are the primary drivers of the digital twin market's growth.

These DTs are of four levels: Digital Twin Prototype (DTP), Digital Twin Instance (DTI), and two types of Digital Twin Environments (DTEs) known as Adaptive DT and Intelligent DT. These DTs differ depending on their relationship with the physical asset's life cycle and their dependency on the DTs' operators. The following describes the four types of DTs as defined in literature [27][30][31][32][33][34][35][36][37].

- Level 1: Digital Twin Prototype (DTP)—design engineers produce a DTP that describes the prototypical artefact for a new asset [27]. Hence, the DTP exists before there is a physical asset. This model contains design attributes such as initial designs, analyses, and processes generated by project stakeholders. DTPs hold the end-user requirements and other data necessary to define the new asset's intended function [37]. Therefore, it supports decision-making at the concept design, preliminary design, and detailed design stages of the building/infrastructure [35]. The users exploit these attributes to assess technical risks and issues in upfront engineering and later twin its physical asset in the real world.

- Level 2: Digital Twin Instances (DTIs)—project stakeholders continuously produce individual virtual instances of the physical assets known as DTIs. These DTIs represent different virtual twin variants throughout the physical asset's life cycle once the asset has been built [27]. Hence, the DTI defines the physical asset's specific correspondences at any given point in time and uses it to explore the physical asset's behaviour under various what-if scenarios [35]. Data capturing sensors (i.e. laser scanners, drones, photogrammetry) often update the DTI during alternative instances [38]. Capturing the asset's actual conditions during different asset life cycle stages is beyond the scope of this text. Readers can refer to Kopsida and Brilakis [39] and Omar and Nehdi [40] for a detailed literature review of the available data-capturing solutions.

- Levels 3 and 4: Digital Twin Environment (DTEs)—Two types of DTEs exist, known as 'Adaptive DT' and 'Intelligent DT'. An Adaptive DT is a high-level DT that offers an adaptive user interface to the physical and virtual twins [35]. This user interface is sensitive to the preferences and priorities of the end-users by learning and prioritising the end-users' preferences for different instances [30][32] with supervised machine learning techniques [34]. Thus, facility managers and operators can leverage adaptive DTs for real-time planning and decision-making processes. An Intelligent DT is the most evolved version of a DT, developed with supervised and unsupervised machine learning techniques. An Intelligent DT can define assets and patterns encountered in the operational environment by itself [31] to update itself automatically; it provide benefits and abilities beyond the explicitly defined information in the existing DT versions. This DT has the highest autonomy level, allowing it to analyse more meticulous performance and maintain data from the physical asset.

The four core parts of a DT are (1) models, (2) data, (3) connections, and (4) services. As illustrated by Arup [41], physical and digital assets are interconnected in a digital twin ecosystem. The user interacts with the DT through applied intelligence, enabling the DT to perform minimal or no-human labour tasks. The digital thread in the middle connects the physical and digital assets and can be used for 3D simulations, Internet of Things (IoT) devices, networks, cloud computing, and Artificial Intelligence (AI).

2.2. Smart City (SC)

People's perceptions of SCs differ from technological perceptions. Although the SC phenomenon is widespread around the world, its definition remains elusive. Without a universally agreed definition, the SC sector is still in the 'I know it when I see it phase', which means that there is no agreed-upon definition for a SC and defining a standard global definition has proven difficult. These definitions, on the other hand, underline universal attributes and elements that may characterise SC perceptions.

For instance, some view SCs as enriching the quality of life for a certain city segment or citizens. Galán-García et al. [42] viewed the SC as a very broad concept, including social aspects that encompass physical infrastructure, human, and societal factors. This definition was emphasised further by Neirotti et al. [43] when they defined the SC as improving citizens' quality of life, with increasing importance on policymakers' agendas. They added policymakers to the definition of SCs as an additional component. In order to achieve an enhanced quality of life for a city and its people, SCs need to be utilised by information technology hardware, software, networks, and data on different services and regions. Different city components such as natural resources, infrastructures, power, transportation, education, healthcare, government, and public safety are all incorporated into these definitions. For instance, Su et al. [44] discuss the computational element of SCs and emphasise how future-oriented computing is critical to creating this SC. Their definition of a SC involves utilising future-oriented computing capabilities in all essential services such as healthcare, power grids, transportation, buildings, and utility lines, and forming the IoT through the internet. This definition was reinforced by Kitchin [45] who discusses how a city should monitor and integrate the status of all of its major infrastructures, including land and air transportation, communications, and utilities. Chourabi et al. [46] view a SC as a future paradigm of interconnected components. Their definition for a SC explains how different components such as economy, people, governance, mobility, environment, and living can be cooperated and assembled as a smart combination of endowments and activities of self-decisive, independent, and aware citizens. It is argued that this provides a more generic view that brings together all of the main aspects of a SC, making it one of the most comprehensive definitions of a SC [21].

These definitions conclude that a SC is a holistic dwelling that smartly and efficiently connects numerous life components such as power, transportation, and buildings to improve the quality of life for its residents. Furthermore, the definitions concentrate on the future by highlighting the importance of resources and application sustainability for future generations. The researchers observed these characteristics in every SC proposal, regardless of size, location, or available resources. It is evident that the wide landscape of SCs has eight main domains as summarised in Bellini et al. [47], that are widely used in the field of SCs such as governance, living and infrastructures, mobility and transportation, economy, industry and production, energy, environment, and healthcare. It should be noted that these eight domains are not essentially orthogonal, as they often intertwine in a variety of settings and applications.

One of the challenges of forming and sustaining a SC is the availability, size, and capabilities of such resources. Another challenge is the regulatory systems, which could have a significant impact on success. On top of that, there are technical issues that call for cutting-edge solutions. Technologies that are new and developing, on the other hand, can assist in transforming such challenges into opportunities.

2.3. Digital Twin Smart Cities (DTSC)s

Data obtained from smart city initiatives can be used to create digital twin cities [48]. The virtual version enables the simulation of spatiotemporal information in a city. A great deal of the recent advancements in global SCs has been made possible through integrating Information Communication Technology (ICT) systems into the city to make its digital replica [48][49]. A preliminary attempt to establish a DTSC was made in Singapore, also known as 'Virtual Singapore' [50]. However, this 'Virtual Singapore' had significant limitations, including the fact that the model has never been made accessible to the public, so citizens cannot engage with it or provide input, and it does not incorporate urban mobility data. A number of private companies, such as CityZenith (https://cityzenith.com/, accessed on 28 January 2023), Agency9, and SmarterBetterCities (https://www.smarterbettercities.ch/, accessed on 30 January 2023) have started to develop in the DTSC space [51]. The DTSC proposed by White et al. [52] relies on six distinct levels of data in the city. The first five levels contribute information about the city's geography, buildings, infrastructure, mobility, and IoT devices by stacking on top of each other. The smart city component gathers data from the city and sends them to the digital twin component. The data collected in the SC are used by the DT to run additional simulations on aspects such as transportation optimisation, building placement, and the design of renewable energy sources. Simulations thus play a crucial role in the implementation of DTSCs. This information is then transmitted back via the model's layers and applied in the physical world.

2.4. Disaster Risk Management

In some cultures, disasters have been viewed as an act of god, and disaster damages were considered as punishment for their misdoings [53][54][55]. This philosophy ignored natural global environmental change processes. Later, knowledge of the physical earth system directed the connection of disasters with natural hazards such as floods, earthquakes, and others [56]. People began to perceive the world more scientifically and rationally as economic growth and education progressed. Governments started to respond to disasters in a more logical and systematic manner [57]. Hazards, according to current knowledge, are not exceptional events, and many of them are centered on and reiterated in specific locations [58]. This has sparked a more philosophical debate about defining disasters as 'unnatural'. These natural hazards become disasters when humans fail to implement appropriate preventative and preparedness actions to mitigate their effects. According to this philosophy, disasters happen as a consequence of interactions between people and the environment [59]. This is particularly the case in urban flooding, where human-induced factors such as poor land-use planning, inadequate drainage systems, and poor flood risk management practices often contribute to fatalities and infrastructure damages [60].

The state of research in disaster management reflects that the disaster management approach should shift from reactive approaches to proactive approaches with more inter-sectoral risk management [61]. The 1990s were designated as the ‘International Decade for Natural Disaster Reduction’ by the United Nations General Assembly in 1987. The goal of these steps was to improve preparedness potentials, minimise the impacts of disasters, and develop appropriate regulations. In 1994, the United Nations’ Yokohama Strategy and Plan of Actions for a Safer World emphasised the importance of sustainable development in disaster reduction and prevention [62]. The World Conference on Disaster Reduction (WCDR) developed the Hyogo Framework for Action (HFA) in 2005, which called for strengthening nations’ and communities’ resilience to disasters. The HFA addressed issues such as community participation, capacity building, and early warning, as well as multi-hazard strategies to reduce deaths. The Sendai Framework for Disaster Risk Reduction (2015–30) was adopted at the United Nations’ third disaster risk reduction conference [61]. This framework advocated for a paradigm shift from disaster management to risk management.

The disaster management cycle is an indispensable tool in disaster management [63]. It is intended to guide nations in mitigating the effects of disasters and has been widely used in disaster management over the past three decades [64]. It is acknowledged that the terminology used for various stages of a disaster can be traced back to the 1930s, and also some experts used such terms in humanitarian action to better understand and improve the system [65]. Professionals from different disciplines and scientific upbringings are involved in disaster risk management. This has resulted in various viewpoints and model specifications of disaster management cycle theories [64]. This cycle illustrates how various stages of disaster management involve interconnected activities [66].

The stages of the disaster risk management cycle are three-fold: (a) pre-disaster (risk reduction), (b) during the disaster, and (c) post-disaster (recovery). Pre-disaster approaches commonly include prevention, mitigation, and preparedness, whilst response approaches include rescue and relief. Recovery and development are post-disaster activities [67]. Each of these activities contributes to the reduction in the risk of physical and human losses and enhances disaster response and recovery. Alexander [58] expanded on the disaster management cycle by categorising it into two stages: pre- and post-disaster. Preparedness and mitigation were classified as pre-disaster, while response and recovery were classified as post-disaster. Yet, there are advantages and disadvantages inherent to the disaster management cycle. Furthermore, there has been a critique of disaster management’s continuous cyclic nature. As a result, experts have differed on the effectiveness of the disaster management cycle [63][64]. The cycle has been modified to allow for better management in terms of time, resources, preferences, capacities or needs, and institutional transformations. Extreme events have been linked to climate change [68][69]. Recent research highlights the importance of incorporating disaster risk reduction and climate change adaptation [70][71][72]. Alternative solutions, such as panarchy [73][74], and resilience, have been proposed to explain effective disaster coping mechanisms [75]. Nonetheless, despite its shortcomings, the disaster risk management cycle continues to be used due to its convenient and robust nature [76].

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