2022 European Conference on Computing in Construction
Ixia, Rhodes, Greece
July 24-26, 2022

A KNOWLEDGE MANAGEMENT STRATEGY FOR URBAN DIGITAL TWINS

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Abstract

The idea of a Digital Twin [DT] has been gaining increasing attention in the field of urban management. Several case studies, pilot projects and proof-of-concepts are carried out to demonstrate the value of DTs which also generates 'DT knowledge' (i.e. know-how) about how DTs are developed. However, there appears to be no clear Knowledge Management [KM] strategy to guide proper capturing and retrieval of such DT knowledge by DT researchers and practitioners. This paper uses a Design Science Research [DSR] methodology to propose a codification KM strategy, built upon a novel Knowledge-based System for DT Design and knowledge Transfer [KB2DT] that facilitates capturing, sharing and reuse of DT knowledge. This strategy can help reproduce DT best practices and thus, support the thriving of DT market at a large scale.

Introduction

Recently, the concept of Digital Twin [DT] has pervaded the field of urban management, promising to deliver huge benefits pertaining to managing the urban eco-system comprising built assets, city infrastructure and natural environment (Al-Sehrawy & Kumar, 2021). With that said, the importance of Knowledge Management [KM] for DT researchers and practitioners within urban environment must not be underestimated. Alsehrawy et al. (2021) highlighted how crucial it is to capture, share and disseminate knowledge related to and created through various DT practices (i.e. know-how).

KM is widely recognized as strategies and processes used to capture, share, structure, maintain and reuse knowledge. (Lin ,2005; Tan et al., 2010; Al Sehrawy & Amoudi, 2020). In a general sense, Hansen et al. (1999) identified two types of KM strategies adopted by different organizations. First is the codification strategy, where computers with databases are used to stored codified knowledge that are made available for everyone else to retrieve and reuse. On the other hand, there is the personalization strategy, where computers are used not to store knowledge but merely to help establish "direct person-to-person" communication, since one can only acquire knowledge through direct contact with the person who created it.

However, the nascent discipline of digital twinning for urban management seems to lack a clear KM strategy. This has limited the DT practitioners' accessibility to currently available expertise and the legacy of know-how accumulated by virtue of DT projects, demonstrators and case studies already carried out across the global DT market, thus hindering the latter's development.

Therefore, this paper proposes a codification KM strategy that exploits IT to enable capturing, dissemination and reuse of existing DT (know-how) at a large scale and support the creation of new knowledge as well.

Methodology

The methodology adopted in this paper is Design Science Research [DSR] (Dresch et al., 2015). DSR has evolved to fill the gap in the traditional scientific approaches which are mainly exploratory, explanatory and descriptive yet not known for solving problems. However, DSR are concerned with producing solutions of relevance to real world problems and simultaneously contributing to knowledge. DSR includes the following five stages:

- Stage 1 – Awareness of problem: the problem DSR addressing has been highlighted by the researcher in the introduction of this study, that is, the lack of a clear KM strategy for DT practices for urban management.
- Stage 2 – Suggestion: the second step in DSR requires, first, to match the different aspects of the problem identified in stage 1 with a corresponding set of design requirements that an artifact must fulfil to solve the problem. Consequently, use creativity and abduction reasoning to suggest a conceptual proposal of an artifact that is potentially capable of fulfilling the set requirements and thus, solving the problem. This stage is detailed in the following section.
- Stage 3 – Development: once a tentative design of an artifact is proposed, the third stage of DSR, commences through constructing the artifact and all of its detailed components. The primary output of this step is a functional and ready-to-use artifact.
- Stage 4 – Evaluation: at this stage, the developed artifact is put to the test to assess whether it can perform in a manner that provides a satisfactory solution to the problem highlighted in the first stage. This is achieved by comparing the artifact evaluation results to the requirements recommended for the artifact to acquire in stage 2. In stage 4, three DT case studies were used as demonstrators of key parts of the artefacts.

- Stage 5 – Conclusion: in the final stage of DSR, research is concluded through highlighting its key results, contribution, limitations and opportunities for future studies.

Stage 2 – Suggestion

To tackle the problem above – the lack of a KM strategy for digital twinning for urban management – it is crucial to propose an artifact upon which the clear codification KM strategy can be founded. Such an artifact, hence, is supposed to enable capturing, storing, retrieving as well as creating DT knowledge (table 01). It is suggested that this artifact be a DT Knowledge-Based System [KBS] for the many significant benefits they provide in support of KM (Wiig, 1997).

Table 1: Types of knowledge relevant to KB2DT

Types of knowledge	Description	KB2DT system
Declarative	Knowledge about things and their properties (Genesereth & Nilsson, 1987)	DT features taxonomy (DTUCS Prong-C), DT uses taxonomy (DTUCS Prong-A), existing DT systems and their classification
Procedural	Knowledge about how to do something including rules, procedures, strategies, etc. (McNamara, 1994)	DT use case scenarios (DTUCS Prong-B) expressed via UML scenario diagrams
Heuristic	Expert knowledge based on previous experiences, such as best practices, guidelines, principles, etc. (Llorens et al, 2009)	KB2DT ontological knowledge base represented in XML and including DTUCS Prong-A, B and C and their relationships. Best practices are captured by the weighted interconnection between layers based on previous utilisations and users' feedback
Structural	Knowledge about relationships between concepts, such as 'is a', 'composed of', 'Part of', etc. (Jonassen, 2000)	Relationships between the different concepts of the KB2DT ontological knowledge base: 'Includes', 'Ensures' and 'Detailed by'

Artificial intelligence (AI) enables automatically reproducing the cognitive processes of human experts with tools such as knowledge-based systems, machine learning techniques, and optimization algorithms (Doukari & Greenwood, 2020). A knowledge-based system (KBS) is a tool designed and developed mainly for sharing and transferring knowledge (Hendriks, 1999; Oleshchuk & Fensli, 2011). This knowledge is acquired directly or indirectly from domain experts in different expertise areas. KBS provides aid and support to users lacking a specific know-how, and so substitutes for human experts (Ahmed et al., 2019). Its intelligence emerges from its ability to mimic the human decision process while reasoning and using domain specific knowledge (Mirmozaffari, 2019).

Starting from the mid-60s, where the first Knowledge-based systems were developed (Liao, 2005), they have evolved and been used, thanks to the advances of Information and Communications Technology (ICT) solutions, for different purposes and applied within several domain applications including construction-related applications such as: design optimization (Andersen et al., 2013; Chou & Thedja, 2016; Laptali & Bouchlaghem (1995), logistical problems (Zhang et al., 2002) and enrichment (Doukari & Greenwood, 2020; Lee et al., 2006) or validation of BIM models (Lee et al., 2016; Stuurstraat & Tolman, 1999; Motawa & Almarshad, 2013).

Design of innovative systems is a complex, time and cost consuming task. Setting the right specifications for the system is crucial to satisfy users' requirements and maximize the business value of the product (Ruhe et al., 2002). To develop a valuable and efficient system, developers must have sound knowledge of the domain and possess the relevant professional skills. Implementing a KM strategy supported by a KBS to help practitioners develop DTs will certainly contribute to reducing the complexity of this process and solving the related multi-constraints problem – time, cost, quality, resources, and users' requirements and satisfaction and coherence.

Figure 1 illustrates the Knowledge-based for DT Design and knowledge Transfer System [KB2DT]. It comprises a set of uses or functionalities that can possibly be the following two types of system users:

- DT Practitioners: KB2DT users who need to acquire the know-how elaborating how existing DTs were built; visualize and compare different existing DTs, design their own DTs; and share or transfer the know-how pertaining to their own DT projects, all in a standard common language.
- DT Expert: Who maintains KB2DT by updating it frequently and validating new DT knowledge shared by other DT practitioners. DT Expert needs to authenticate published knowledge in terms of semantic soundness, whereas the KB2DT system should be able to automatically integrate it and maintain the whole consistency of the knowledge

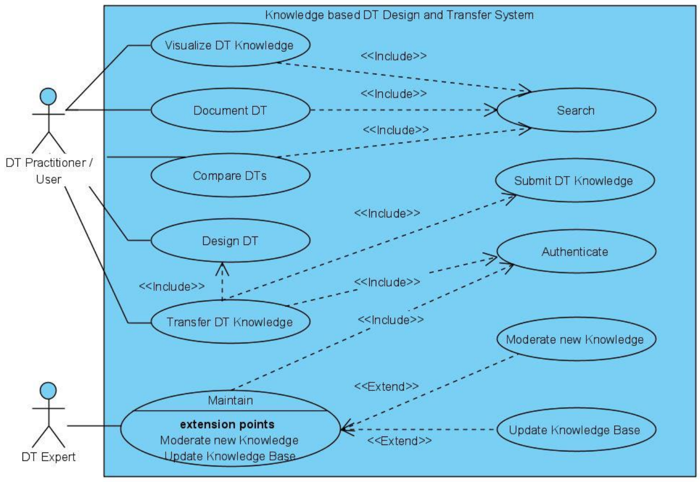

Figure 1: Knowledge-based for DT Design and knowledge Transfer System [KB2DT] use-cases diagram

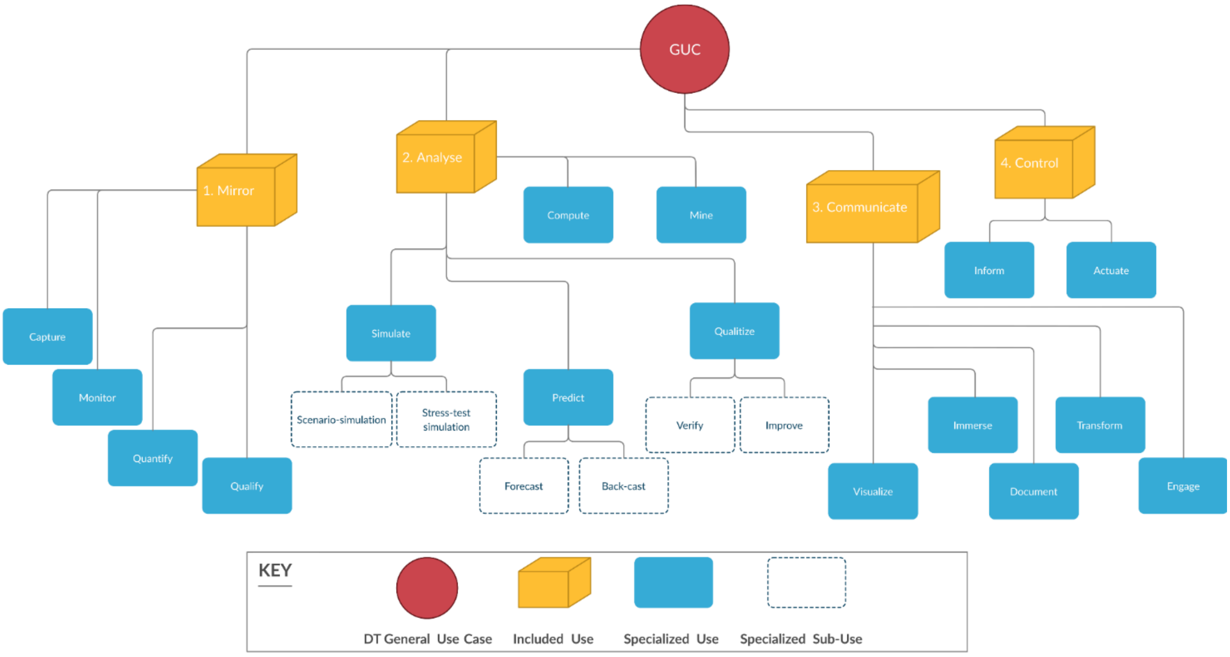

Figure 2: DTUCS Prong-A: DT Uses. (Alsehrawy et al., 2021)

Figure 3: DTUCS Prong-C (Alsehrawy et al., 2021)

base through algorithms and procedures combining logical reasoning operators (e.g. knowledge fusion and revision operators (Doukari et al., 2007)) and expert knowledge.

Stage 3 – Development

DTUCS – A standard common language

Before explaining the different parts of KB2DT, we shall first introduce the Digital Twin Uses Classification System [DTUCS] (Alsehrawy et al., 2021) selected to form the basis of KB2DT and its ontological knowledge base. In a nutshell it is the system that offers the standard common language for capturing, sharing and creating DT knowledge within KB2DT. It is made up of the following three Prongs:

Prong-A: comprises a taxonomy of all identified 'DT uses' (Fig.2), which are "the technical functions or actions executed" by a DT amongst a DT use case scenario. They are "the standard building blocks upon which a standard common language is founded".

Prong-B: enables modelling of a DT use case scenario [UCS], representing the DT delivery plan demonstrating how a particular DT has been developed, including implemented DT uses and DT-users interactions. This is done based on Unified Modelling Language (UML).

Prong C: a multi-dimensional classification framework (Fig.3) comprising at its center the purpose of the DT, also known as the General Use Case [GUC], surrounded by seven distinct dimensions representing the various DT features altered and refined as necessary to deliver the DT's GUC.

KB2DT System Architecture

KB2DT's system architecture, shown in figure 4, comprises typical core parts of KBSs. These include the following four main components:

(A) DT Ontological Knowledge Base: Where KB2DT stores the DT knowledge tied to all published DT Use Case Scenarios [UCSs], including (i) the DT uses implemented as per the standard terminology in DTUCS prong-A (Fig.2), (ii) the different DT-user interactions captured by DTUCS prong-B and (iii) the specifications or characteristics of the developed DTs as captured by DTUCS prong-C (Fig.3). This DT knowledge is stored in Extensible Markup Language [XML], which is a human

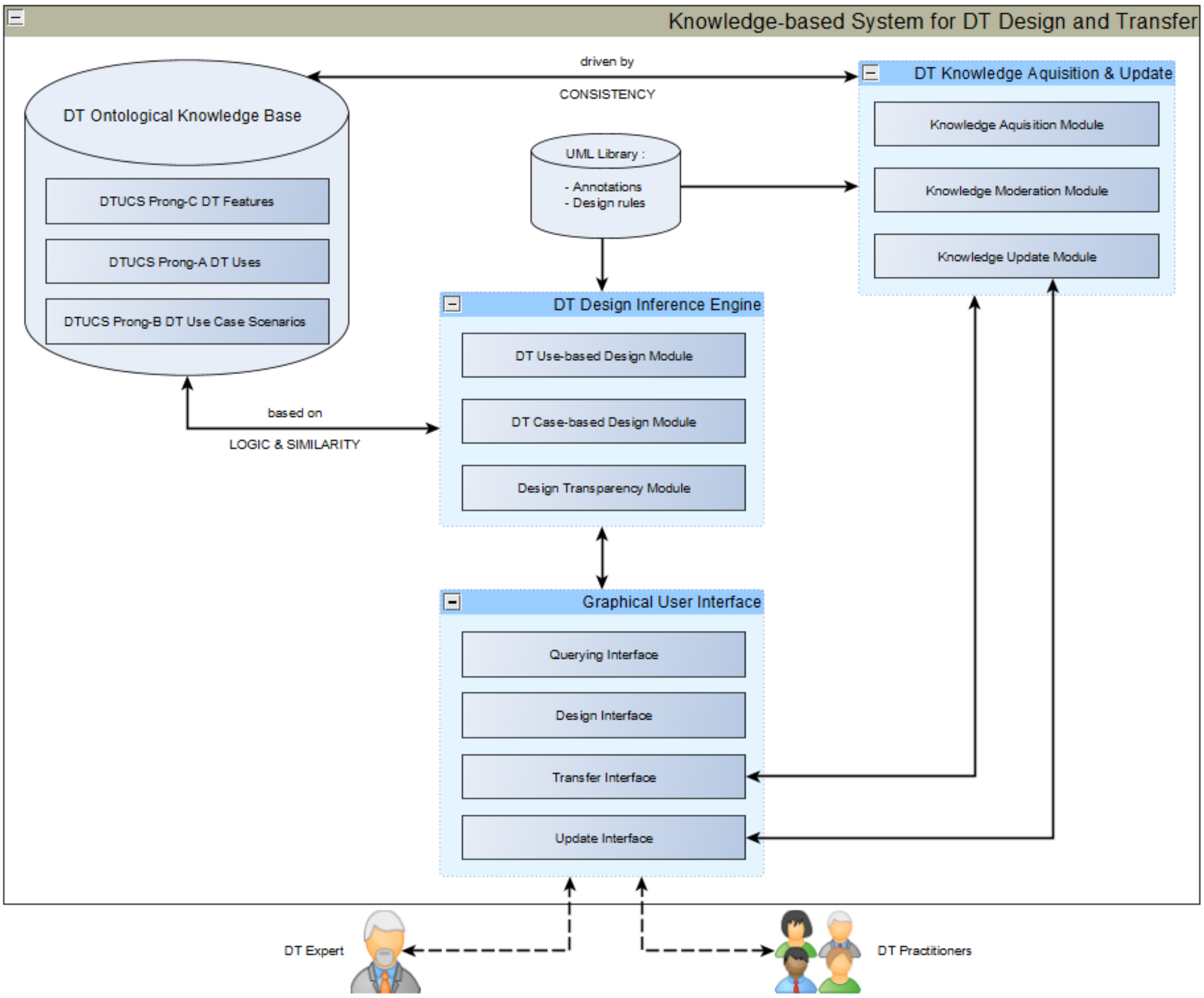

Figure 4: KB2DT System Architecture

and machine-readable format. As such, DT knowledge is represented independently from the context and the inference engine component, so as it can be transparent, sustainable and easily understood and extensible by the users. The Ontological Knowledge Base is further detailed in the following section.

(B) DT Design Inference Engine: To design a DT UCS, equivalent to a DT delivery plan, the DT Practitioner/user will initially provide input about the DT uses expected to be implemented or the features specified for the proposed DT. Accordingly, KB2DT will retrieve either or both of the following:

- based on “DT Uses Design” module, a set of existing DT UCSs including DT uses (Fig.2) similar to the ones suggested by the user.
- based on “DT Features Design” module, a set of existing DTs already characterized by DT features (Fig.3) similar to those specified by the user.

Results retrieved are ranked based on similarity measurement as well as weight which depends on previous utilizations and users’ feedback. When a user accepts reusing a suggested result, this will increment its weight and reinforces its future retrieval by the system. If the user does not accept any recommendation, they can still proceed with their own design from scratch, which will be integrated into the knowledge base upon experts review and validation in terms of semantic soundness.

Using users’ feedback and historical data tools props up KB2DT with additional learning capabilities and enhances its future recommendations. Several similarity measures were used in literature, like Vector space distance (Liao et al., 2000), taxonomy-tree measure (Camarillo et al., 2017) and k-Nearest-Neighbours algorithm (Adam & Aurich, 2013). Implementing an appropriate metric is fundamental to retrieve appropriate knowledge and make relevant recommendations (Zhu et al., 2015). KB2DT system implements the k-Nearest-Neighbours algorithm, since it has shown promising results and demonstrates applicability in many domains, especially in structured and well-classified knowledge bases (Burggräf et al., 2020).

The third module in the DT Design Inference Engine component is the “Design Transparency” module, which provides information about the inference and reasoning processes that have taken place to endow KB2DT with explainability and transparency necessary for justifying the recommendations provided for users.

(C) DT Knowledge Acquisition and Update: Allows DT experts and practitioners to enrich, extend and modify the knowledge base. Once new DT knowledge (i.e. a UCS) is submitted for publication, this component automatically checks the consistency of the whole knowledge base and notifies the DT expert, before integration, if any further action is required.

(D) Graphical User Interface: comprising four main functionalities or tabs, to support query, design, transfer and update of DT knowledge.

The “UML Library” is additional external and open resource component linked to the DT Design Inference Engine in order to provide the system with UML-based annotations and modeling rules required to model and document a UCS.

KB2DT Ontological Knowledge Base

The knowledge base is typically considered the most important component of any KBS, whereas creating it represents an essential step in developing a KBS (Hayes-

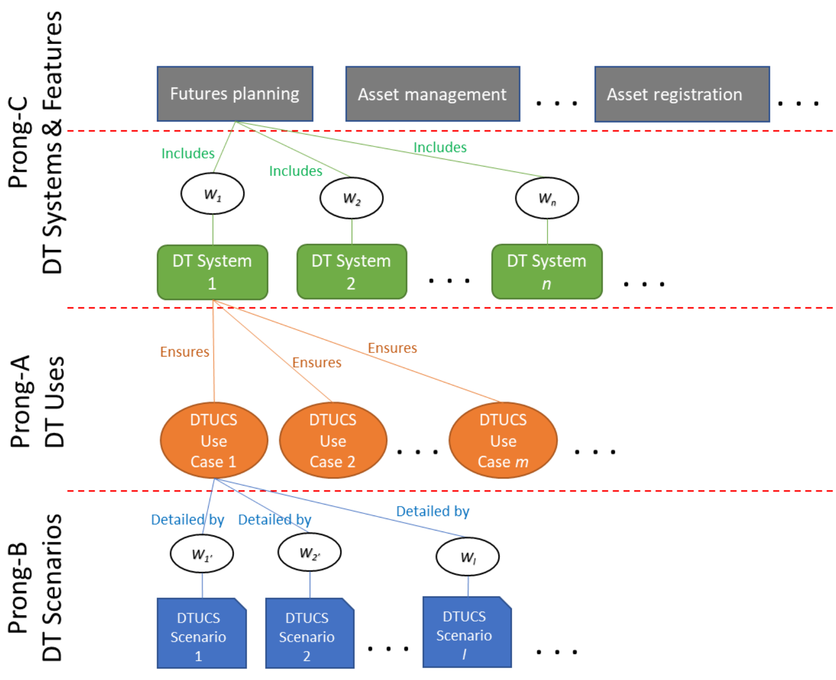

Figure 5: KB2DT Ontological Knowledge Base

Roth, 1984). In this paper, a simplified prototype version of KB2DT's knowledge base is presented. It is built to store and accumulate new DT related knowledge and case studies published and shared by DT practitioners. How to validate and verify a KBS's knowledge base and the way it operates remains a key issue in AI research domain (Yanase & Triantaphyllou, 2019). To mitigate this problem and enable transparent reasoning the KB2DT system is enhanced by integrating the Design Transparency module that will provide explanation about the inference and reasoning processes that have been taken.

In knowledge representation and reasoning, several representation formalisms and knowledge structures have been proposed and developed. Propositional logic formalism using "If-Then" rules is the most applied to represent knowledge bases. While "If-Then" logical rules are easy to implement, they are limited in terms of expressiveness when dealing with incomplete, fuzzy and uncertain knowledge (Doukari et al., 2007). For KB2DT, we propose an ontological representation of DT knowledge made of four layers, namely: DT Features, DTs, DT Uses and DT Use Case Scenarios [UCSs] (Fig.5). Our approach is based on the notion of 'program slicing' aiming at splitting systems and software in different subsystems each one responsible for specific computations and system behaviours (Weiser, 1982; 1984). System engineers intuitively break down complex systems into smaller coherent components and modules made of functions and subroutines with specific purposes. Figure 5 illustrates this rational by capturing and representing DT knowledge through four structured layers derived from DTUCS. Such a structure will help reduce DT design and development time, since nearly 80% of system design tasks seem to be repetitive (Skarka, 2007)

Stage 4 – Evaluation

Selection and analysis of DT case studies

The following three case studies were selected randomly from the case studies' repository in UK National Digital Twin Programme DT Hub in order to eliminate bias.

Case study 01 – City-scale Digital Twin Prototype for Cambridge

This DT (National Digital Twin programme, 2021a) focuses on "exploring behavioral insight for reducing car dependence by considering the socio-economic characteristics of various site users". A *[GUC]* suggested for this DT is "support city policy-making.", lying at the heart of 'futures planning' *area of application* and addressing the 'initiation' *lifecycle stage*.

It *captured* GIS model of road network within Cambridge while *monitoring* the Automated Number Plate Recognition (ANPR) sensor data and their respective travel direction, time of arrival and parking duration for one week in 2017, thus, producing a *dynamic* yet *offline* DT with a city *spatial scale* and individual vehicles *spatial resolution*. Based on such data, a rule-based algorithm is used to *document* distinct car user groups through a *computational* process.

While this DT is performing at a sub-system *level of federation*, involving only road networks, there is a plan to operate at a systems level through integrating multiple

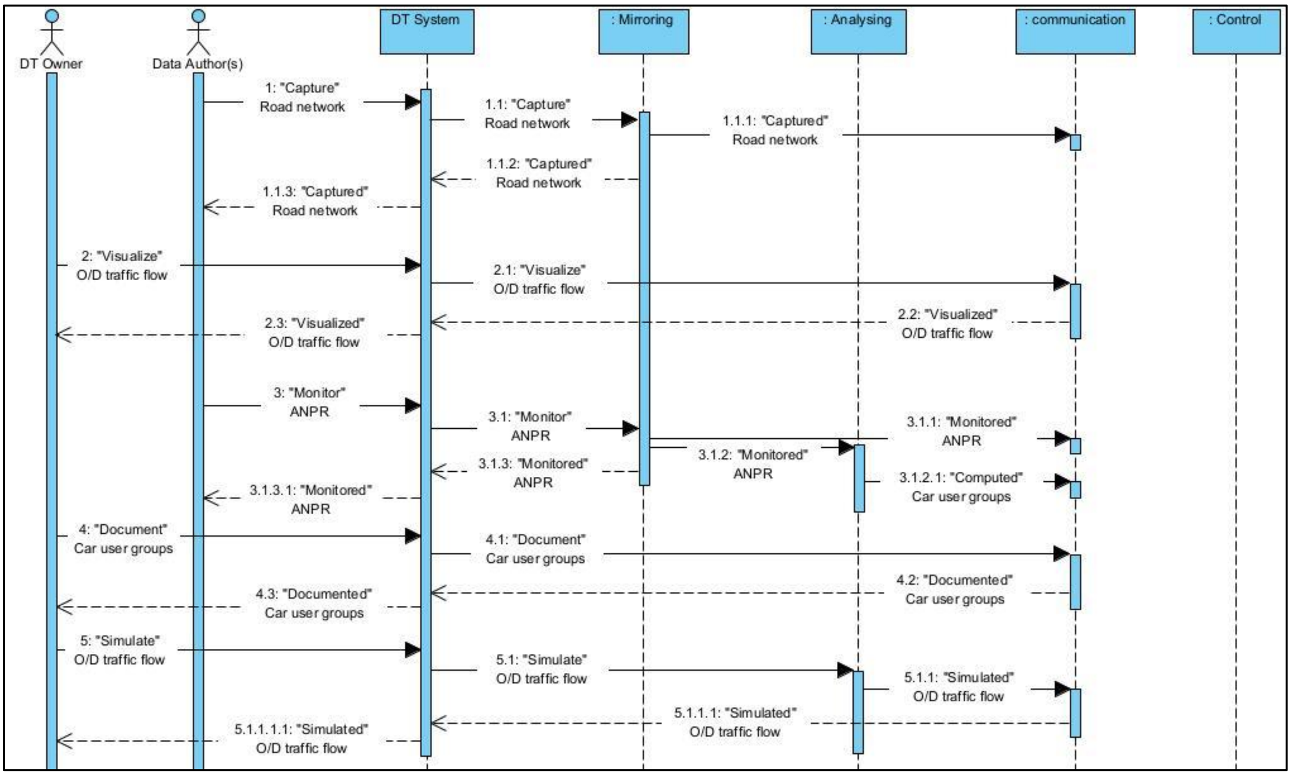

Figure 6: DT Case Study 01 Use Case Scenario

digital twins related to transportation infrastructure systems such as “roads, traffic signals, kerb side, bus/rail networks and legacy systems”.

The DT is utilized to run *scenario simulations*, through altering user-defined input like “future employment, housing growth and the associated spatial distribution” to explore what the outcomes might be against users’ expectations. This obviously indicates how the DT cuts through both urban layers of infrastructure assets, comprising road networks, and the socio-economic environment, including housing and employment related variables.

This DT is primarily built to *inform* policy making and “support human decisions … hence does not include algorithmic decision making” (i.e. *actuate*). The Origin-Destination flow data and simulation results are *visualized* over GIS platform for decision makers to have better understanding of road network dynamics. The developed prototype, however, does not support community *engagement*, whereas “the user interface … is oriented towards professionals in local authorities and academic users”. Nonetheless, it is pointed out that “extended user interface tailored according to different user backgrounds is to be explored”. Figure 6 shows this DT use case scenario modelled by KB2DT.

Case study 02 – Coventry University Digital Campus

The Digital Twin of Coventry University (National Digital Twin programme, 2021b) is built through digitising over 110 individual buildings constituting the main Coventry Campus. It is developed to “manage building information more efficiently, reduce operational costs and provide accurate building and asset data for all estates and university stakeholders”.

The DT *general use case [GUC]*, inferred from the documented purpose, can then be: ‘reduce operational cost’, which is most relevant to the *application area* of ‘resource management’ and the ‘operation and maintenance’ *lifecycle stage*.

The DT involved *capturing* BIM models of buildings at the Coventry Campus and *monitoring* energy data and air temperatures via sensors, thus, *mirroring* both built and natural *layers* of urban environment in a *dynamic online* manner. Moreover, various building systems like CAFM and BMS were integrated and linked to the Common Data Environment [CDE] as well, presenting a *system* level of *federation*. The DT, comprising a full campus, is spatially equivalent to a *neighborhood* scale yet provides a higher resolution at an *individual* building space or zone.

Through *visualizations* of different building graphical and non-graphical information, the DT *informed* decisions including “decisions on when to service assets, dates for planned preventive maintenance, information about energy consumption and reduction can be monitored, occupancy and space utilisation and access control management decisions”. Figure 7 shows this DT use case scenario modelled by KB2DT.

Case study 03 – Smart Energy Digital Twin for Bridgend County Borough Council (BCBC), Wales

This case includes a district heat network DT that “automates optimised plant, pipe sizing, and network routing based on peak load analysis using real property data in conjunction with established benchmarks” (National Digital Twin programme, 2021c). Thus, a suggested *[GUC]* for this DT is “Optimize heat network design”, which is relevant to ‘resource management’ *area of application.*

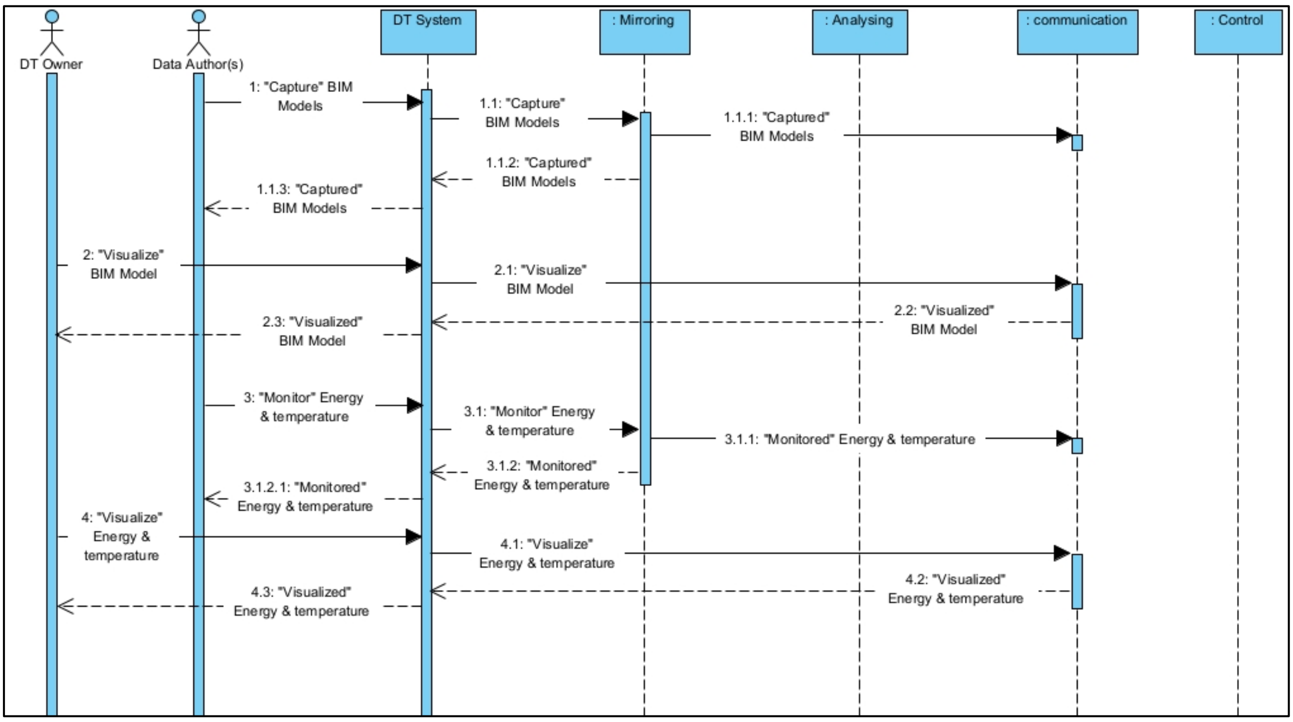

Figure 7: DT Case Study 02 Use Case Scenario

The DT is obviously serving the ‘design’ *lifecycle stage*. It *captured* GIS model of the district of interest and other unstructured data sets. Also, it *monitors* the heat energy loads at district households. It, therefore, *mirrors* aspects of two urban *layers* – built and socio-economic environments – in a *dynamic online* manner. Moreover, datasets relevant to various heat energy network components like pumps, piping and outlets at households were integrated, demonstrating a *system* level of *federation*.

The DT, involving a heat energy network spreading over a full district is spatially equivalent to a *neighborhood* scale yet provides a higher resolution at an *individual* network component and household.

Data *mirrored* are leveraged in different ways. They are used to *compute* heat pump sizing and *verify* produced network design based on “benchmarks”. Data were also exploited to *compute* fuel poverty indicators based on household income, household energy requirements and fuel price elements. Further, the DT can run *scenario-simulations* based on alternative input scenarios of energy usage profiles.

Communication with DT users is done through the *visualization* of dashboard infographics (e.g. digital representation of a smart energy network that is automatically generated, flow metrics, health energy profiles, quarterly heat energy requirements) to provide analytics and insights. Another form of *communication,* in pursuit of transparency and community buy-in, is the use of interactive 3D web mapping platform for community *engagement*. Furthermore, DT developers are planning to use Unreal Gaming Platform for *immersive* interactions.

The DT *informed* decisions including “decisions on when to service assets, dates for planned preventive maintenance, information about energy consumption and reduction can be monitored, occupancy and space utilisation and access control management decisions”. Figure 8 shows this DT use case scenario modelled by KB2DT.

Stage 5 – Conclusion

This paper has shed light on the need for shaping a Knowledge Management [KM] strategy for urban digital twinning. A codification KM strategy is promoted with a proposed Knowledge-based system (i.e. KB2DT) upon which the former is founded. The main purpose of KB2DT is to facilitate the capturing and sharing of DT practical knowledge (i.e. know-how) across DT market using the standard common language offered by DTUCS. Three case studies were used to theoretically demonstrate how KB2DT may support a codification KM strategy at a large scale. The attempt to capture the know-how from the textual documentation of each case study in a coded form

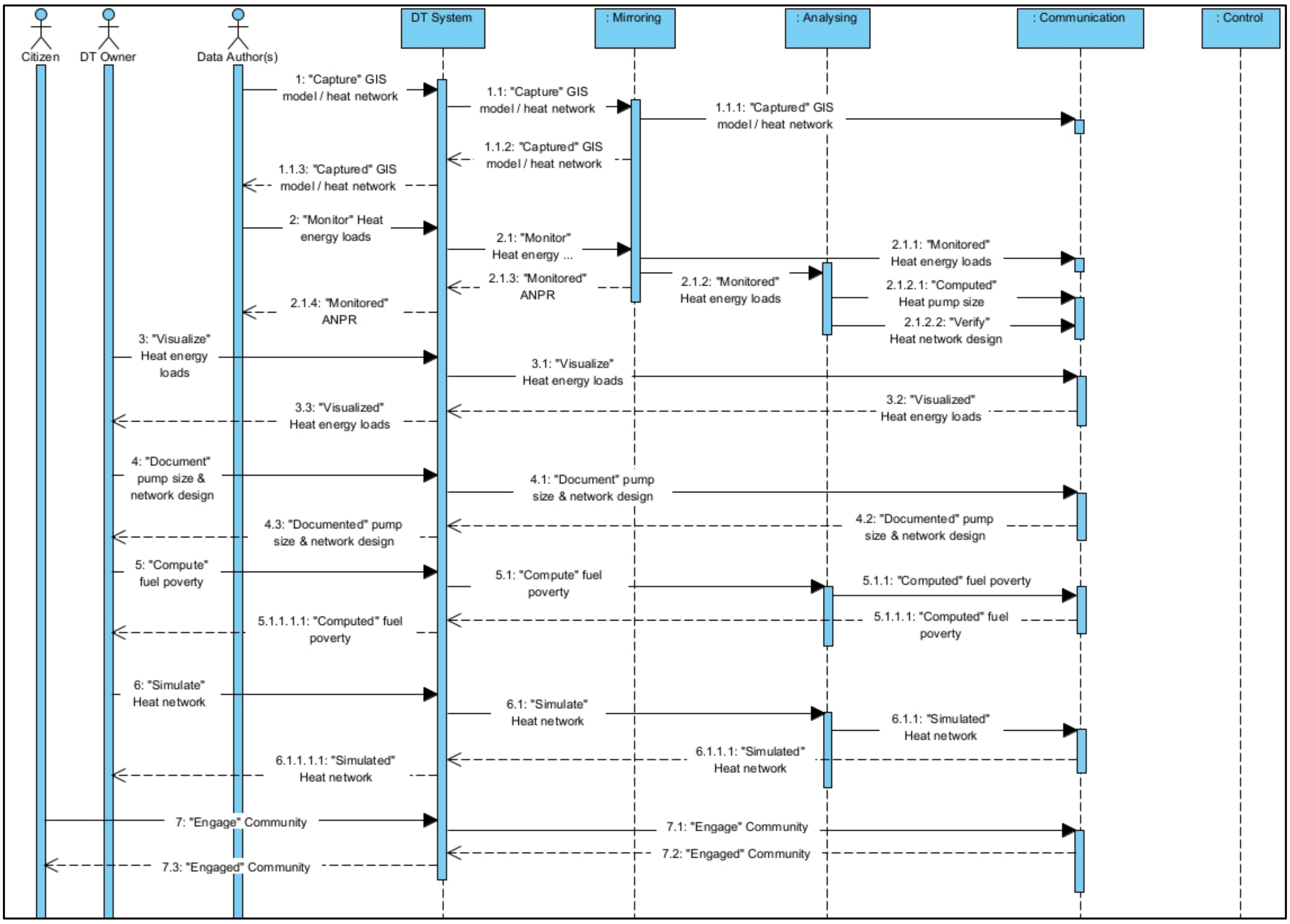

Figure 8: DT Case Study 03 Use Case Scenario

was challenging, time consuming. It also appeared that some valuable information regarding the involved stakeholders and the exact datasets used were either not stated or not explicitly clear in the textual documentation. All, thus, showed the necessity of a KM strategy and the value of using KB2DT in capturing such knowledge.

The next step, currently in progress, is building a prototype of KB2DT to demonstrate the usability of the system through more practical means. Further enhancements to KB2DT may include introducing an authorization layer to grant right level of access to stored DT knowledge to different users. Moreover, most of existing knowledge-based systems are developed and used as stand-alone software (Saibene, 2021) which can significantly limit their utilisation and consequently reduce know-how sharing and transfer. To overcome this issue and provide DT expertise in a more convenient way, KB2DT is developed following a Web-based architecture and thus, can be deployed on a cloud server. This should enable more accessibility and contribute to a broader sharing of DT knowledge. A long-term vision for KB2DT may involve full automation of the validation process currently carried out by human DT experts. This, however, will require a comprehensive ontology capturing the whole urban environment and the urban management domain concepts and relationships. This converges with the ultimate goal of the Information Management Framework [IMF] by the National Digital Twin [NDT], including both the Foundation Data Model [FDM] and Reference Data Library [RDL] (Hetherington & West, 2020).

Acknowledgments

None.

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