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An introduction and characterisation of non-identical digital twins in manufacturing systems

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Abstract. The digital twin (DT) has become a key component for the digitalisation, monitoring, and improvement of manufacturing systems. This has led to the development of various DTs for distinct workpieces, processes, and tools. While beneficial, these individual components need to be configured to form a system of DTs that represents the overall manufacturing system, a task that is nontrivial but necessary to realise a truly smart manufacturing system. This paper proposes an identification scheme to distinguish each unique DT within a system of DTs (Digital Twin System) from three aspects: the physical entity, the digital representation and connections. Based on it, non-identical DTs are proposed as different digital representations of the same element or elements in a manufacturing system. They are sorted into three classes, including homologous DTs, heterologous DTs, and exclusive DTs, based on their context and behaviour. Definitions and characterisations of three types of non-identical DTs are then discussed. Lastly, a case study of in-situ failure detection for material extrusion(MEX) additive manufacturing is demonstrated to explore affordances, challenges, and potential applications of non-identical DTs.

Keywords: Digital twin system, Non-identical digital twins, MEX additive manufacturing.

1 Introduction

A smart manufacturing system (SMS) is defined as the digitisation of every part of the manufacturing system to improve product quality and efficiency while reducing costs[1]. It can be achieved through the use of multiple digital twins(DTs) or a DT system which integrates multi-physics models, real-time data and information to map physical entities to digital space. This can assist with online monitoring, anomaly detection, predictive maintenance and decision-making[2].

As a rapidly developing technology, the definitions, concepts, reviews and applications of DTs have been widely researched over the last 20 years[3-5]. Most studies have focused on solving challenges in developing specific DTs at the unit level, system level or system of systems(SoS) level[6]. However, the relationships or differences among DTs in a DT system are often ignored.

Based on the context and behaviour of the DT, this paper proposes the concept of non-identical DTs, which refers to different digital representations of the same element or elements in a manufacturing system. In a DT system, there would be specific DTs for various products, processes, equipment, and other components. As for one DT, it is denoted as a specific DT, while two or more DTs are regarded as non-identical DTs. This paper mainly focuses on the identification of a specific DT and the classification of non-identical DTs. A case study is presented to illustrate non-identical DTs, and the potential applications, affordances and challenges are discussed.

The organization of this paper is as follows. In Section 2, a summary of related research is provided for the background. The identification scheme of DTs is presented and discussed in Section 3. A taxonomy of non-identical DTs is then demonstrated in Section 4. The potential application of three types of non-identical DTs on in-situ failure detection for MEX additive manufacturing is discussed in Section 5. Finally, the conclusions and future work are discussed in Section 6.

2 Related work

To provide context for the work presented in this paper, this section reviews the applications of DTs in the smart manufacturing system, as well as the essential components of a DT that are necessary for its identification at a system level.

2.1 DTs in manufacturing system

A manufacturing system is composed of various resources, such as human workers, machinery, equipment, materials, and other items to support the manufacturing activity. These resources are interlinked and mutually influenced by each other. According to the CIRP encyclopedia of production engineering, the main components of a manufacturing system are production machines, tools, fixtures, and other related hardware, assembly/disassembly, material handling system, industrial robots, human workers, and computer systems[7]. Meanwhile, ISO 23247 defines observable manufacturing elements(OMEs) in a manufacturing system to depict the physical world, including personnel, equipment, material, process, facility, environment, product, and supporting document[8].

As for the different OMEs in a manufacturing system, multiple DTs or a DT system are required to integrate them for smart manufacturing. Shao *et al.* proposed that various DTs can represent different focuses, aspects, or views in a manufacturing system and/or of a specific OME, in which case each DT is context-dependent and has its own focus[9]. Lu *et al.* discussed the influence of DTs on manufacturing assets, people, factories, and production networks in the context of smart manufacturing[10]. To model significant components in a smart manufacturing system and construct a real-time global view, Qamsane *et al.* introduced four individual classes of DTs: topology DT, machine asset DT, machine process DT and system process DT[11].

The above literature shows that multiple DTs or a DT system can be considered as the critical enabler to digitise various manufacturing resources in a manufacturing system. In addition, the integration of various DTs for different OMEs is essential to achieve wider applications, but seldom discussed.

2.2 Digital twin components

Over the last 20 years, academic and industrial practitioners have widely and deeply researched DTs to develop an accepted definition and structural model. Today, most researchers regard DTs as the digital representation of their physical counterparts, which follows the original model proposed in the early stage. There are three essential components of a DT: a physical entity, a digital entity and connections between them[12-13]. To meet new requirements for DTs and wider the application fields, Tao *et al.* extended the traditional three-dimensional DTs to five-dimensional DTs that add two more components: data and services[14]. The international organization for standardization(IOS) defined DT reference models for manufacturing, where there are three sub-entities in a DT entity: *(i,* an operation and management sub-entity maintains information, including digital modelling, presentation, representation, and synchronization; *(ii,* an application and service sub-entity provides functionalities including simulation, data analysis, and status monitoring; and, *(iii,* a resource access and interchange sub-entity provide access to functionalities of the digital twin entity and interfaces in support of interoperability[15].

Some researchers combine the idea of DTs with simulation technology and model-based system engineering(MBSE)[16]. Friederich *et al.* defined the concept of DTs as a natural extension of traditional simulation models, consisting of three constituent parts: real-world entity, data-driven simulation model and data[17]. Boschert *et al.* proposed that the DT is the linked collection of the relevant digital artefacts, including engineering data, operation data and behaviour descriptions via several simulation models[18]. Rossmann *et al.* proposed a new concept, "Experimental digital twins", as a new structuring element for simulation-based engineering processes, consisting of technical assets, a data processing system and a human-machine interface[19].

In manufacturing, a DT is mostly regarded as the digital copy of physical manufacturing elements. Even though there are many discussions about components or sub-entities in a DT, research on distinguishing a specific DT, especially in a manufacturing system with multiple elements, still needs to be completed. Moreover, identifying the unique DT is essential to clarify non-identical DTs in the manufacturing system.

3 Identification of digital twins

This section proposes an identification scheme based on the physical entity, digital entity and connections between them. It is derived from distinguishing between the observed contexts and behaviours of the digital twin system, and it is depicted in Figure 1.

The physical entity of DTs has been extensively studied in pervious research, with a focus on two main aspects: scope and objective .

- Scope - According to the magnitude of its physical counterpart involved in manufacturing, DTs can be divided into Unit-level DT (*e.g.,* a machine tool), System-level DT (*e.g.,* a production line), System of systems(SoS)-level (*e.g.,* a product life cycle)[6].

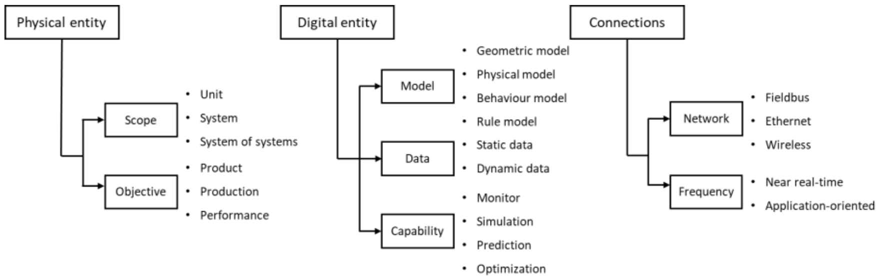


Fig. 1. The identification schema of digital twins

- Objective - A DT can be divided into product DT (*e.g.*, a physical product), production DT (*e.g.*, a manufacturing process), and performance DT (*e.g.*, an optimization process for the product and production system via a feedback loop) depending on the entity that is mapped into a digital representation[20].

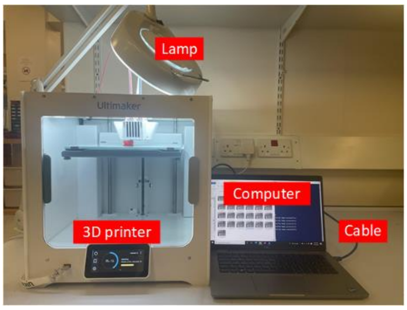
Three main methodologies commonly used in DTs include data-driven, model-based, and hybrid approaches[21], which rely on data and models as key components of the digital entity. Furthermore, the identification of a DT can be influenced by its capability, making it a critical attribute to consider.

- Model – In a DT, the virtual model is composed of sub-models in four dimensions: geometric models (e.g., a CAD model), physical models (e.g., a FEA model), behaviour models (*e.g.*, a simulation model) and rule models (*e.g.*, a decision-making model)[22].
- Data - Static data and dynamic data are two different types of data in DTs. Data or information from the design stage and process parameters are static data. Dynamic data varies with the manufacturing process, like real-time data from various sensors or the manufacturing machine's controller.
- Capability – Enabled by models and data with different types and fidelity, DTs can achieve different levels of capability, including monitoring, simulation, prediction, and optimisation.

As for the DT's connection, the method and frequency of synchronisation between the physical and digital entities can be utilised to identify a DT.

- Network - There are three different categories of industrial protocol networks: Fieldbus (*e.g.*, Profibus), Ethernet (*e.g.*, Ethernet cable), and wireless (*e.g.*, WiFi). Different networks can affect the sensitivity, compatibility and latency of data transmission in a DT.
- Frequency - Many DTs aim to reflect the current status of their physical counterparts, so near real-time is the expected frequency. Regarding other specific applications, the DT's frequency can be also application-oriented, like per minute, hour or day.

Based on the proposed identification schema, an XML file can be used for distinguishing DTs in a manufacturing system. Here is an example. As shown in Figure 2, a DT is developed to detect printing failures of the MEX additive manufacturing process for the Ultimaker S3, where the layer-to-layer image is captured from a Webcam and compared with the rendered image from a virtual environment to determine if the printing process is in a normal case. The identification information of the developed DT is shown in the XML file.



```
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            <Unit> Ultimaker S3 <\Unit>
        <\Scope>
        <Entity>
            <Process> Material extrusion process <\Process>
        <\Entity>
    </Physical entity>
    <Digital entity>
        <Model>
            <Geometric model> Pikachu CAD model <\Geometric model>
            <Physical model> Illumination models <\Physical model>
            <Behavior model> Layer-to-layer additive simulation <\Behavior model>
            <Rule model> An image comparison based decision-making method<\Rule model>
        <\Model>
        <Data>
            <Static data> Process parameters including layer thickness <\Static data>
            <Dynamic data> Online Layer-to-layer images and Z value of the extruder <\Dynamic data>
        <\Data>
        <Capability>
            <Simulation> Simulate the additive printing process per layer <\Simulation>
            <Monitoring> Monitor the geometirc contour of the printing part <\Monitoring>
    </Digital entity>
    <Connection>
        <Network>
            <Ethernet> Physical ethernet cable <\Ethernet>
        <\Network>
        <Frequency>
            <Application-oritend> Per second <\Application-oritend>
        <\Frequency>
    </Connection>
</identification of Digital twin>
```

Fig. 2. Identification of a DT for MEX additive manufacturing

4 Taxonomy of non-identical digital twins

In this section, the concept of non-identical DTs is introduced to characterise a collection of DTs within the context of an overall Digital Twin System (DTS) representing an entire manufacturing system. Based on the proposed identification scheme, non-identical DTs are divided into three types, defined in Table 1. The definitions and differences of these three types of non-identical DTs are discussed.

Homologous DTs represent twins that have the same physical entity, but differ in their digital representations and connections. A specific DT has an intrinsic level of fidelity based on its context and behaviour, which can be low, middle, high or mixed fidelity. The level of fidelity is relative to the capability present at the time of its creation. Meanwhile, it affects the cost and effort of the DT's development and ongoing maintenance. Given this, it can be asserted that an application-oriented evaluation system can be developed to analyse the requirements of the DT's application and suggest a threshold or optimal fidelity. Moreover, a simplification process can be implemented to trade the DT's fidelity for cost and effort when high fidelity is unnecessary. However, the challenges are that such a low-fidelity DT with limited accuracy should be determined based on the specific DT's purpose and, meantime, deliver comparable performance to what is considered to be an identical DT. As DT technologies continue to develop, more researchers are focusing on building DTs with the right level of fidelity instead of ultra-high fidelity[4, 23]. Moreover, the reference architectural model industries (RAMI) 4.0 can be referred to discuss the high and low fidelity models in a DT, particularly at the machine level[24].

Heterologous DTs represent distinct twins that consist of different physical entities. Although heterologous DTs may represent various physical counterparts, they may st-

Table 1. Three types of non-identical digital twins

	Homologous DTs	**Heterologous DTs**	**Exclusive DTs**
Description	Different twins of the same entity	Different twins of different entities	Different twins of opposite entities
Characteristics	Levels of fidelity	Mutual models, data, algorithms, or applications	Contrary situations
Methodology	Application-oriented evaluation system	Transfer learning, reconfigurable modules	Method of exclusive
Affordances	Decrease the cost and effort of developing a DT for a new manufacturing process		
Challenge	Deliver comparable performance	Extract common features	Clarify the boundary of two opposite situations
Application	★★★★	★	N/A

ill have potential relations between them, such as mutual models, data, algorithms, objects or standard interfaces. Since such ties exist, techniques such as transfer learning can be applied to gain knowledge from the resolution of one problem and apply it to a different but related problem[25]. For example, DTs of complicated products or processes could learn or use knowledge and information from those of simpler processes or artefacts by using transfer learning technologies. In this case, twinning those complicated products or processes based on the simpler ones might consume less cost and effort. Reconfigurable modules technologies can be used and reused to develop heterologous DTs that share the same interface, virtual environment or simulation capability. For instance, module type package (MTP)[26], AutomationML[27] can be used for this purpose. A meta DT, which is the abstract prototype of heterologous DTs, can also help develop a new DT or adjust an existing DT in a manufacturing system. However, it is still required to explore how to extract standard features between different products or processes and build a transfer learning-enabled relation. There is some research on using transfer learning technologies in a DT[28] and developing a dynamic DT for the reconfigurable manufacturing system[29].

Exclusive DTs are proposed as distinct twins of opposite situations. They focus on solving the case in the manufacturing process where dynamic changes or results are too complicated to be represented in a DT. In such cases, it might be easier to describe undesirable states than the physical characteristics necessary to determine the desired state. This could be a cost-effective and effort-effective method of developing a DT for a new manufacturing process. However, the critical point for exclusive DTs is to clarify the boundary between the two opposite situations. When preparing this publication, the use of exclusive DTs is a hypothesis, and the authors are unaware of applications based on this approach within the manufacturing field.

5 Case study

The scenario of detecting printing failures during the MEX process is considered for developing non-identical DTs. The workflow mainly involves extracting the model's contours from an image pair and calculating their similarity using Pearson's correlation coefficient (PCC). The image pair includes the real-time image captured by the mounted camera of the printer and the reference image derived from the virtual rendering environment. If there is an extra filament in the real-time captured image, as shown in Figure 3, the PCC value drops the set threshold, suggesting the possibility of a printing failure.

In this case, homologous DTs can be defined as a group of DTs that digitise the printing process of the Pikachu model at the same level of granularity, using geometric models with varying mesh numbers. The fidelity of such DTs is characterised by the attribute of mesh number. As shown in Figure 4(a), these mesh models represent the high-fidelity, middle-fidelity, low-fidelity and mixed-fidelity models. The mixed-fidelity mesh model of the Pikachu model has a clear boundary under this camera view and meanwhile a simplified geometry inside the boundary. It is suggested that it is unnecessary to use the high-fidelity model to detect the extrusion and layer shift errors. The benefits of using DTs with such lower fidelity, specifically the mesh number of its geometric model, are also analysed in terms of data storage and simulation time. The threshold or optimal fidelity of this DT can be explored by comprehensively considering cost and performance.

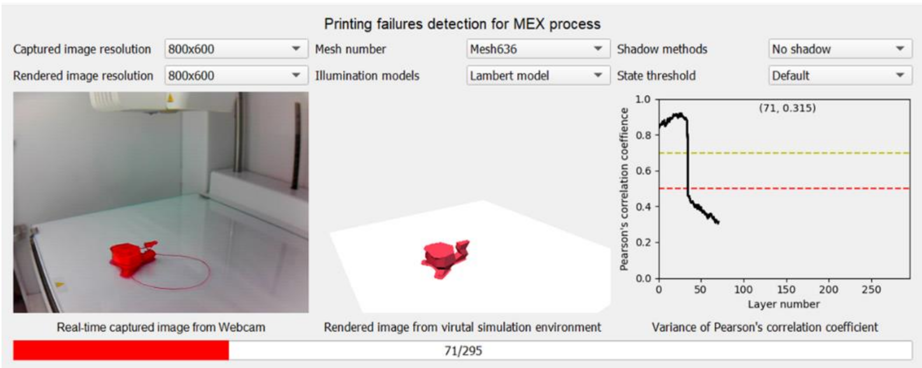

Fig. 3. An image-based DT for detecting real-time printing failures

To detect real-time printing failures in the MEX manufacturing process, heterologous DTs can also be utilized through a framework based on transfer learning technologies, as depicted in Figure 4(b). For this approach, a CNN-based model is trained using an image dataset that contains similar failures from other DTs. This well-trained CNN-based model can then be applied directly or used as a baseline model for this specific case. The Spaghetti Detective, an open-source project, has already developed a successful method of detecting critical "spaghetti" failures using a CNN-based network called YOLO[30]. This method is convenient, practical, and general, as long as a camera monitors the printing process with a suitable view. However, the possible challenge is that the proposed CNN-based model may not be able to detect such type of printing failures successfully if there are not enough extra filaments present in the image.

Exclusive DTs are proposed as a potential solution to detect failures during the MEX manufacturing process. By simulating opposite situations of a normal printing process in a virtual environment, such DTs can assume what will happen if an extrusion error occurs. As shown in Figure 4(c), an image with an extra filament is synthetically generated in the virtual environment using physical simulation. However, creating an image dataset that includes all possible situations with the extrusion error is a massive challenge for this approach.

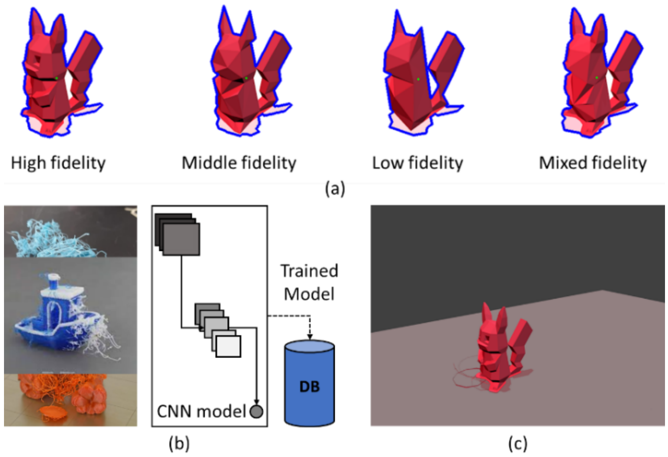

Fig. 4. Potential applications of non-identical digital twins

6 Conclusion

This study proposes an identification scheme for distinguishing between DTs within a digital twin system from three perspectives: the physical entity, digital representation and bidirectional connection. Homologous, heterologous, and exclusive DTs are proposed as three types of non-identical DTs. Their definitions, characteristics, methodologies, affordances, challenges, and current applications are discussed. A case study illustrates the potential application of non-identical DTs in detecting online printing failures during the MEX additive manufacturing process.

While the results obtained by the case study are specific and have limited generalizability, future work will aim to propose a more comprehensive and general identification of DTs in a manufacturing system. Applications based on three types of non-identical DTs are expected to be realised in the following work.

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