Automatic Verification and Validation of Automatically Generated Simulation-Based Digital Twins for Discrete Material Flow Systems

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List of Abbreviations

CPS Cyber-Physical System. 1

DES Discrete-Event Simulation. 1

DM Digital Model. 1

DMFS Discrete Material Flow Systems. 1

DS Digital Shadow. 1

DT Digital Twin. 1

IoT Internet of Things. 1

ML Machine Learning. 1

SBDT Simulation-Based Digital Twin. 1

V&V Verification and Validation. 1

Chapter 1

Introduction

1.1 Initial Situation

Digital Twins (DT) are a key technology at the front of the fourth industrial revolution, coined Industry 4.0. The latter term is characterized by the interaction of cyber-physical systems (CPS), the Internet of Things (IoT), and cloud computing to create smart factories with the goal of automation and efficiency (Oztemel & Gursev, 2020). Companies pursue this ideal by trying to remain competitive through the adoption of innovative technologies that promise enhanced productivity and reduced operational costs. One such technology promising this is the DT. It can be defined as a virtual representation of physical assets enabling real-time monitoring and optimization (Tao et al., 2018). The DT bridges the connection between the two entities with a bi-directional data flow to exchange information and to influence the behaviour of the physical asset (Grieves, 2014). This technology in Industry 4.0 connects the physical and digital worlds through real-time data integration, simulation, and optimization (Judijanto et al., 2024).

Although this field is rapidly evolving, a unified definition of DT has yet to be established. The term was first introduced by Michael Grieves in 2002, defining it as a digital representation of a physical object or system (Grieves, 2014). However, the concept has evolved since then, encompassing a broader range of applications and technologies. Going back through the literature, there are three terms used to describe similar characteristics of DT: Digital Model (DM), Digital Shadow (DS), and Digital Twin (DT), see Figure 1.1 (Jones et al., 2020; Zhang et al., 2021).

The DM represents the most basic form. It contains manual data connections between physical and digital entities. These connections can be temporarily shifted

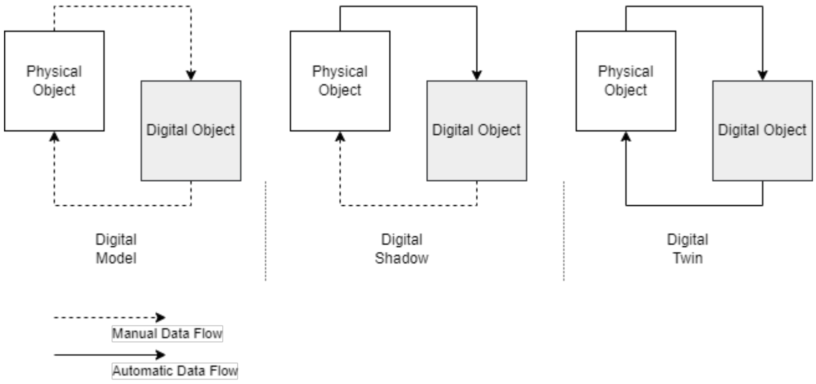

Figure 1.1: Comparison of Digital Shadow (DS), Digital Model (DM) and Digital Twin (DT) as presented by Kritzinger (2018). This distinction is crucial for understanding validation requirements across different digital representation types.

or even disconnected. There is no control of the digital object over the physical entity. It rather is a simple or complex model *describing* the modelled object. It can not make decisions by itself to influence the physical object. The reason lies in the potential outdated data the digital part possesses or in the fact that it does not contain logic to control the data flow back to the physical part by itself. The control and the obligation to interpret the results is completely in the hands of the modeller. The DS is a more advanced version of the DM. It is a digital representation of the physical object, which is continuously updated with real-time data. The DS can be used for monitoring, analysis and simulation purposes. It can predict the future state of the physical object based on the current state and historical data. However, the DS is not able to influence the physical object. The control is, similar to the DM, still in the hands of the modeller. A DS is mainly used for simulation and in the literature often confusingly classified as a DT. The DT is the most advanced version of the triplet. It is a digital representation of the physical object, which is also continuously updated with real-time data. The DT can be used for monitoring, analysis, and *control* purposes. It can predict the future state of the physical object based on the current state and historical data. The DT can also influence the physical object by sending control signals to it. The control is partially or completely in the hands of the DT. The DT thus *can* serve more purpose than modelling or simulating the physical object. It may serve as an autonomic system, updating itself or by help of the modeller (Kritzinger et al., 2018).

Digital twins are applied across various sectors, including manufacturing, defense, automotive, and recycling. This thesis focuses on manufacturing, particularly discrete material flow systems (DMFS). These systems process discrete objects (parts) that move along transportation routes or conveyor lines—either at regular or irregular intervals—integrating both production and logistics operations (Arnold & Furmans, 2005; Schwede & Fischer, 2024). A core simplification in their modeling is the abstraction of material flow as a sequence of discrete events, similar with the principles of discrete-event simulation (DES) (Kovacs & Kostal, 2016; Robinson, 2014). DES is particularly well-suited for analyzing complex systems where state changes occur at discrete points in time, such as arrivals, departures, and processing steps (Robinson, 2014).

In hindsight, DM played a crucial role in the design, planning, and control of DMFS, primarily through applications such as material flow simulations, logistic assistance systems, and digital factory implementations (Thiede et al., 2013). However, advancements in both DS and DT have enabled a revolution from isolated, usecase-specific models toward complete digital representations that span the entire lifecycle of DMFS (Abdoune et al., 2023). This transition is largely driven by the increasing demand for predictive capabilities by stakeholders and automated decision support in manufacturing systems, reflecting the cornerstones of Industry 4.0 (Frank et al., 2019). A second driver of DT innovation lies in the widely available data from IoT devices and sensors. Unlocking these potentials in model training and real-time adaption of the DT is crucial for its modelling capabilities (Tao et al., 2018).

In practice, the automated data transfer between the digital model and the physical system is of secondary importance for DMFS management. Unlike in time-critical applications, human decision-makers remain an integral part of the control loop, ensuring that real-time automation is not always necessary (Schwede & Fischer, 2024). Consequently, for this thesis, digital simulations and digital twins will be treated as equivalent concepts.

Beyond merely replicating the current state and managing historical data, digital twins serve a crucial function in predicting system behavior and evaluating potential modifications. The widespread adoption of DES within digital twins highlights the central role of simulation-based digital twins (SBDT) in DMFS (Lugaresi & Matta, 2021). As Schwede and Fischer emphasize, SBDTs provide decision support for optimizing cost and performance in highly competitive manufacturing environments. While current SBDTs are primarily developed and updated manually by domain experts, emerging research explores how machine learning (ML) can enhance predictive accuracy and automate model updates by automatically learning model characteristics, reducing costs and development time.

Thus, the progression from digital models to simulation-based digital twins reflects an ongoing shift towards data-driven, predictive, and increasingly automated representations of DMFS, ensuring more informed decision-making throughout the whole system lifecycle (Boschert & Rosen, 2016; Lim et al., 2020).

1.2 Problem

Despite the transformative potential of DT, their implementation can be challenging. The creation and maintenance of accurate Digital Twins require substantial investments in technology and domain knowledge. This investment yields no return if the resulting model fails to accurately represent the modelled entity or delivers incorrect results. Automatic generation may be an elegant solution, but possesses the risk of overfitting or biased predictions (Geman et al., 1992). Manufacturing data used as training data must be preprocessed and cleaned thoroughly. The DT per definition has to be able to perform real-time decision making without excessive time lags. This yields the requirement to extract, transform, clean and load (ETL process, Vassiliadis et al., 2002) data on the fly, performing inference fully in memory. All these hurdles are challenges to automatic learning (Ribeiro et al., 2016; Zhao et al., 2024). As industries integrate DT into their production processes, establishing trust becomes fundamental as well (Arrieta et al., 2020; Trauer et al., 2022). To gain widespread acceptance, the technology must demonstrate accuracy, transparency, and cost-efficiency (Shao et al., 2023; Wright & Davidson, 2020). Without these qualities, organizations will likely fall back to familiar methods, potentially building resistance to technological advancement (Lapointe & Rivard, 2005).

Even if the automatic learning of the DT was performed successfully, the question of its correctness, precision and robustness remains unanswered. These questions are tackled by validation, verification and uncertainty quantification frameworks (VVUQ) (Sel et al., 2025). Ensuring the validity, reliability, and accuracy of a Digital Twin is critical, yet traditional VV approaches rely heavily on manual expert involvement and case-specific reference values (Bitencourt et al., 2023; Hua et al., 2022). This creates inefficiencies, particularly in the context of automated DT generation, where such manual processes conflict with the goal of reducing development effort. Hua et al., 2022 even argue that there are no robust and standardized VVUQ methods for Digital Twins. One hurdle to standardized VVUQ frameworks is the lack of a clear definition for validity and verification in the context of Digital Twins (Bitencourt et al., 2023).

For discrete material flow systems, these challenges are even more pressing due to their processual nature and inherent stochastic elements. Manufacturing processes may fail due to anomalies, resource constraints or human error. VVUQ approaches have to anticipate these risks. When DTs for these systems are generated automatically, conventional validation approaches become problematic, as they negate much of the efficiency gained through automation. This creates an apparent paradox: Automated Digital Twin generation reduces initial development effort but potentially increases subsequent validation complexity, mitigating efficiency gains through automation. State of the art VVUQ frameworks have to uphold the efficiency gains earned while ensuring validity and reliability of the Digital Twin.

1.3 Objective

The thesis thus addresses this paradox by developing a data-driven framework for automated VVUQ of automatically generated, simulation-based DTs which have been learned from data. The focus lies on DMFS due to their practical relevance and dynamical, processual nature. The endeavor can further be concretized by the following research questions (RQ):

- **RQ1:** How can automated validation and verification processes for digital twins be efficiently implemented?
- **RQ2:** Which data-driven approaches are best suited to identify discrepancies between simulated behavior and real operational data in discrete material flow systems?
- **RQ3:** To what extent does the developed framework improve the quality and reliability of digital twins compared to traditional VV methods?

This thesis addresses these questions by proposing that object-centric event logs—the same data structures often used to generate DT in manufacturing—can serve as the foundation for an automated, use case-independent validation and verification framework. Such an approach would maintain the efficiency benefits of automated generation while ensuring the resulting Digital Twins meet necessary quality standards. The development and monitoring of generic, statistically grounded reference values is a key aspect of this approach. Such key indicators need to have an underlying distribution and have to be quantifiable. The framework will be evaluated using a case study from the discrete material flow domain, providing empirical evidence of its effectiveness in improving model accuracy and efficiency.

1.4 Structure and Methodology

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