

System Variations and Their Impact on the Validation of Digital Twin Models in Dynamic Manufacturing Environments

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Abstract—Digital Twins, as near real-time virtual replicas of physical systems, provide insight into systems' behaviors, supporting optimization of manufacturing processes. The dynamic nature of modern manufacturing systems, however, poses unique challenges for validation of the underlying simulation models of the corresponding Digital Twins. Model validation, as an integral part of Digital Twin frameworks, ensures that Digital Twin models accurately reflect their real-world counterparts over time. In today's flexible manufacturing systems, frequent technological upgrades, workforce changes, and operational modifications can all play a part in impacting Digital Twins' accuracy. Consequently, Digital Twins require robust validation processes capable of detecting and reflecting these variations in manufacturing systems. In this paper, we present a comprehensive overview of the diverse types of system variations in manufacturing environments, categorizing them into machine-intensive, labor-intensive, and hybrid manufacturing systems. We analyze how these variations influence Digital Twin validation and highlight key challenges in maintaining Digital Twin fidelity in evolving manufacturing contexts. Finally, we discuss future research directions to enhance validation methodologies, ensuring that Digital Twins remain reliable and adaptive amidst continuous system variations.

Keywords— *Digital Twin, Reconfigurable Manufacturing Systems, Model Validation, Manufacturing environment*

I. INTRODUCTION

The rapid evolution of the market, consumer demands, and technologies has led to a major shift in manufacturing [1]. This transition towards an agile and dynamic manufacturing, generally known as Industry 4.0, aims to optimize manufacturing processes by utilizing technological advancements such as Internet of Things (IoT), autonomous robots, and simulation [2].

Simulation, specifically Digital Twins (DTs), as complex and dynamically evolving simulation models, can ensure optimized, reliable, and productive manufacturing processes [3]. DTs can be used in what-if analysis, cross-validation checks, and manufacturing testing, making the transition towards smart and dynamic manufacturing possible.

DTs' potential relies on the fidelity of the underlying models to their physical counterparts which can be achieved through robust validation processes. However, the flexibility and reconfigurability of modern manufacturing pose significant challenges for DT validation. Modern

manufacturing's ability to quickly respond to changes in product design, production requirements, and market demands is realized through technological upgrades, changes in the workforce, and modifications in how the operations are done [4]. In reconfigurable manufacturing environments, where changes can happen frequently and unpredictably, DTs must be able to detect these changes and maintain their models' accuracy compared to the corresponding real-world systems to provide adequate support. In this paper, we use the term *variation* to encompass both intentional and unintentional changes in manufacturing systems. Decision-making based on invalid or outdated DT models can potentially lead to reduced efficiency and costly errors. Therefore, precise validation processes are critical in ensuring that DT models correctly reflect these variations and the corresponding manufacturing systems (MSs).

Variations in MSs can differ in terms of their frequency, predictability, and their impact on the respective systems. Some variations occur frequently, while others may be rare. The nature of these variations can influence corresponding DTs and shape the validation approach to detect and reflect these variations in an effective and timely manner. However, we have not identified a study on the impacts of dynamics in manufacturing environments on validation of DTs. In this paper, we review the literature on reconfigurable manufacturing and categorize manufacturing environments into three types: machine-intensive, labor-intensive, and hybrid. We analyze the types of variations that can occur in each and highlight how variations in manufacturing impact DT model validation, along with the challenges that arise. With this, we aim to establish a foundation for future research and discussions on the topic of validation of DT models, as understanding both deliberate and unintended variations in MSs is critical for developing robust DT model validation methodologies.

The paper is organized as follows. In Section 2, we review the background and related work on validation of DTs and variations that can occur in manufacturing environments. In Section 3, we present and discuss the challenges in validation of DTs that arise from variations in manufacturing environments. Finally, we conclude our discussion and suggest future research directions.

II. BACKGROUND AND RELATED WORK

In this section, we first review the existing literature on validation of DTs. We then provide an overview of the

variations that can occur in MSs as identified in the literature. These variations are categorized based on the manufacturing environments in which they are most likely to occur: technological variations (machine-intensive), variations in human behavior (labor-intensive), and variations based on interaction between humans and machines (hybrid).

A. Validation in Digital Twins

Maintaining accuracy of DT models and ensuring they remain accurate reflections of their real-world counterparts is essential for DTs' functionality. Model validation is the process of confirming a model's satisfactory accuracy, within its domain, with its intended application [5]. While multiple simulation model validation techniques have been proposed [6], research on continuous, near real-time validation of DT models remains an emerging topic.

Recent studies have introduced efforts towards continuous validation of DT models. Hua et al. proposed a DT model validation approach utilizing human expert knowledge and data collected from IoT devices [7]. Similarly, Lugaresi et al. exploited time series analysis to propose a continuous validation comparing output of simulation models to the data from corresponding systems to obtain similarity levels [8]. Mertens and Denil utilized approximation functions and anomaly detection to continuously compare DT models with their physical counterparts [9]. Additional approaches include machine learning and control charts [10], automated periodic key performance indicators (KPIs) measurement [11], and particle filtering [12]. In addition, in our earlier work [13], we introduced a modular validation approach, building on the two-phase validation framework by Friederich and Lazarova-Molnar [14] to detect and recalibrate variations in underlying DT models.

Model validation is an integral part of DT frameworks [15, 16]. These model validation processes are very complex as the continuous reflection of real-world systems in DTs requires mechanisms to detect and react to the variations in the systems. Variations in systems can significantly impact model validation processes, necessitating thorough investigation into their implications.

B. Technological Variations in Manufacturing

The evolution of MSs and the move towards the goals of Industry 4.0 has been made possible by the advancements in digital technologies [17]. The advanced machinery and modern equipment, as well as integration of information technology and the vast gathering of data have paved the way for machine-driven smart MSs. However, with utilization of the new technologies, their subsequent effects on MSs and their corresponding DTs must be considered, substantiated and further explored.

Smart machine-driven MSs consist of physical layer, logical layer, and communication layer [18]. Manufacturing cells, automated guided vehicles, and automated storage and retrieval systems lie in the physical layer. They can be modified, updated, or replaced depending on the production demands and manufacturing reconfigurability needs [19]. Machines behave independently, and, as such, their variations are also independent [20]. Common variations in smart MSs include repositioning machines or their axes to improve workflow efficiency, integrating sensors to enhance processes, and replacing equipment completely.

As smart MSs undergo variations, their corresponding DTs must be updated to maintain their accuracy. The independent behavior and diversity of the variations make validation a complex challenge, and robust validation processes are needed to detect and reflect the variations to the manufacturing processes in the DT models.

C. Human Characteristics and Individuality

In labor-intensive manufacturing environments, where production processes heavily rely on human labor with minimal machine support [21], variations in human conditions and characteristics can have a significant impact on the production processes. Human operators' skills and training, stress and fatigue, and psychological conditions all play a part in the overall manufacturing productivity, as we elaborate in the following.

In labor-intensive MSs, human learning is critical for performance of the systems [22]. Workers' skill levels and knowledge increase over time as they gain more experience, affecting MSs' performance and efficiency. However, learning curves for all individuals are different. Previous training, cognitive abilities, and task complexities can influence how an individual worker performs and can directly impact the whole manufacturing process. Labor-intensive manufacturing productivity can also be affected by human workers' physical conditions. Human fatigue is a major contributor to quality deficits in manufacturing [23]. Workers' age, physical limitations, and movement patterns can shape how both workers and the overall MS perform. Finally, in addition to the physical conditions, psychological conditions can impact workers and manufacturing performance. Stress levels, motivation, and emotional intelligence can play a role in MSs' performance [24]. Thus, Layer et al. argue that humans' perceived quality of work life, dependent on their job satisfaction, supervision, and empowerment, affects their performance [25].

These human factors can alter the manufacturing process and create significant challenges for maintaining accuracy of corresponding DT models. Unlike machines, human performance cannot be easily quantified, and validation processes need to incorporate mechanisms to measure these qualitative variations to ensure DTs continuously represent their real-world counterparts.

D. Human-Machine Collaboration and Effects

Modern MSs are moving away from separated workspaces between humans and machines to collaborative workspaces where humans and robots closely interact and work hand in hand to achieve higher efficiency, productivity, and flexibility [26]. The emergence of collaborative robots (cobots) has further helped shape hybrid manufacturing and the way workers and machines interact, making a more balanced environment. However, the communication and integration of humans and machines, the allocation of tasks and workloads, and safety concerns can impact an MS, as we detail below.

In dynamic manufacturing, human-machine interactions are frequently shifting. As workers and machines continuously exchange information, their interactions and task responsibilities are dynamically adapted based on real-time conditions [27]. This constant interaction and exchange of information affects the manufacturing performance. For example, while workers are better suited for creative tasks, the workers still need to understand the type of interaction,

repetitive nature, operations and shortcomings of machines which could increase their mental workload, influencing their and the system's performance [28]. Furthermore, flexible task allocation, where the goal is to optimize workload between workers and machines, is challenging and affects the system as ignoring the interactions between workers and machines in task allocation policies results in suboptimal joint human-machine performance [29]. In a hybrid environment, workers and machines cannot be regarded as fully independent entities and one's performance can affect the other. Malfunctions in machines can slow down workers' performance, or lack of qualification of workers can lead to breakdowns of the system, affecting the overall performance [30]. Lastly, as workers and machines are intertwined and are sharing a workspace, safety and its implications on the system must be considered. Workers' trust in systems' safety defines their interaction with robots and affects their overall performance. Robots can also change their behavior depending on their real-time interaction with workers to ensure workers' safety [31].

Thus, the interaction between humans and machines in hybrid MSs adds another layer of complexity to validation of DT models for this type of MSs. Validating DT models in hybrid environments requires both separate validation of human and machine components as well as validation of their intricate interactions, ensuring emerging behavior from their collaboration is reflected in the DT models.

III. IMPLICATIONS OF MANUFACTURING VARIATIONS ON VALIDATION IN DIGITAL TWINS

In the following, we identify possible variations in MSs from literature, and explore their implications, for both intended and unintended variations, on DT models' validation. Further, we discuss the challenges and possible mitigations for model validation within different manufacturing environments.

A. Implications of variations in manufacturing on Digital Twin validation

As noted previously, variations in MSs are inevitable due to the dynamic nature and evolving manufacturing demands. These variations, which vary from a simple repositioning to a complete shop floor overhaul, can have a significant impact on the corresponding DT models and their validation [32, 33]. For example, machine overhauls can affect underlying reliability models and their validation [13].

To find variations in manufacturing systems, we used Science Direct and Google Scholar search engines to explore the literature. Furthermore, we used the keywords 'Digital Twin', 'Manufacturing', and synonyms of the word 'change' to find the related articles. Based on the related articles, we identified several variations in manufacturing systems and categorized them based on the manufacturing environments, machine-intensive, labor-intensive, or hybrid. For instance, in machine-intensive environments, Tao and Zhang describe how radical changes in the production system lead to reconstruction of the corresponding DT model [32]. Similarly, for labor-intensive environments, Pena et al. demonstrate how workers' skill levels evolve at different rates, and it creates a challenge for validation of the corresponding DT model as individual learning curves must be incorporated in the DT model

validation process [34]. Furthermore, Wang et al. highlight how, in hybrid manufacturing environments, safety measures result in machine and human behavior variations, implying that DT model validation mechanisms must incorporate effects of safety measures.

It is important to note that modern MSs can adaptively shift between machine-intensive and hybrid approaches based on production needs. This flexibility means that variations and their corresponding model validation implications cannot be exclusively categorized in a single manufacturing environment. Therefore, the categorization is based on the environments where variations are most likely to occur. In Table I, we showcase the identified variations in MSs and show how they can affect the DT model validation process. The list is not exhaustive as manufacturing and application of Digital Twins in manufacturing is rapidly evolving, creating variations and validation challenges not introduced in the list. Moreover, we relied solely on published research which may not fully encompass industry implementations.

Traditional model validation techniques are typically all-at-once approaches incapable of continuously detecting variations in the system. In addition, they often treat models as static entities while DTs' evolving nature demands identification and reflection of variations in the real system to maintain DT models' accuracy. Therefore, DT models require continuous validation methods that can dynamically address both intended and unexpected system variations and reflect them in the corresponding underlying DT models, moving beyond the limitations of traditional static validation techniques.

TABLE I. EFFECT OF VARIATIONS IN MANUFACTURING ON MODEL VALIDATION

Type of Variation	Manufacturing Environment	DT Model Validation Implication
Variations in machine positioning [35]	Machine-Intensive	Detecting the underlying variations and the relationship among machines
Variations of equipment [36]	Machine-Intensive	Readjusting of metrics and introducing new parameters
Equipment replacement [32]	Machine-Intensive	Re-extracting or reconstructing a new model
Human operator's skill level and experience variation [34]	Labor-Intensive	Incorporating individual's learning curve
Variations in human operators' physical state [37]	Labor-Intensive	Integrating humans' physical condition, limitation, and fatigue models
Variations in human operators' psychological state [24]	Labor-Intensive	Integrating psychological metrics, and emotional models
Variations in human-machine interaction and behavior [27]	Hybrid Environment	Integrating human-robot interaction models
Variations in task allocation [38]	Hybrid Environment	Incorporating workload distribution and role assignments
Safety measures affecting performance [39]	Hybrid Environment	Integrating safety models and mechanisms

Table I illustrates the diverse and complex nature of variations across different manufacturing environments: from technological equipment variation in machine-intensive environments, to qualitative human behavioral variations in labor-intensive settings, and to variations in the interactions between humans and machines in hybrid manufacturing environments. The implications of these variations on validation of DT models highlight that validation requirements are context dependent, and no single approach can adequately address them. For example, DT model validation in machine-intensive environments can rely on abundance of data for detection and reflection of underlying variations while in labor-intensive manufacturing human behavior must be integrated in the process [40]. Therefore, tailor-made and adaptable validation processes are necessary. We elaborate these findings in more detail in the following subsection.

B. Discussion

Robust DT model validation processes need to be able to detect variations in manufacturing environments. Next, we discuss the implications, challenges and possible solutions in incorporating them in DT validation mechanisms of different manufacturing environments.

1) Machine-Intensive Manufacturing Environment

DTs' underlying models need to evolve together with their physical counterparts, and this can only be achieved through rigorous validation. The challenge, however, is that static approaches are insufficient to capture and reflect variations in near real-time and continuous validation methods capable of adapting to system variations are needed [7]. Machines and technological equipment are frequently going through modifications and upgrades of different natures to deal with the rapidly changing demands. Correct capturing of these variations brings up certain challenges for DT validation process. In the following, we go more in depth on these challenges:

- Variations resulting from reconfigurations of machines and equipment: Detecting such variations presents validation challenges as not all variations happen similarly or impact the system equally. For this reason, model validation processes not only need to detect these variations, but they also need to assess the impact of these variations on the whole system. This can be achieved through utilization of model partitioning, intermediate validation points [13], and sensitivity analysis [41]. Furthermore, introduction of validation frequency can help with detection of variations as they may occur with varying frequencies. Therefore, validation frequency can decide how often the system needs to be investigated for different variations [14].
- Variations due to equipment addition and replacement: When new equipment is added or existing equipment is fully replaced, validation mechanisms must accurately detect these variations and trigger appropriate updates or a complete reconstruction of the DT model. Human expert knowledge is a valuable source to overcome this challenge. However, as DTs strive for near-real-time reflection and responsiveness, validation processes based on human expertise may be a hindrance. Data-driven methods or systematic fusion of human expert

knowledge with data can help make near-real-time detection and reconstruction of DT models possible [42]. Additionally, predefined thresholds and parameters can support decision-making by indicating when model adjustment is no longer feasible, and reconstruction of a model is necessary.

2) Labor-Intensive Manufacturing Environment

Detecting variations in machines' performance is largely quantitative as most data and metrics can be directly collected. In contrast, detecting variations in humans' behavior and performance presents a significantly more complex challenge [3]. Unlike machines, humans' individuality and qualitative characteristics introduce substantial variability, complicating the validation process of DT models for such systems. Below, we outline two key human-related challenges in DT model validation:

- Variations in human operators' skill levels: Unlike machines, where the initial performance metrics are defined, human performance evolves over time. Operators begin with varying skill levels and experience and learn at different paces. Validation mechanisms must account for these learning dynamics and incorporate them into DT models. Ideally, this would involve highly detailed digital representations of human operators to continuously track and update their learning curves [34]. However, as this level of detail is often not feasible, alternative approaches such as parameter estimation and machine learning can be employed to model and maintain human learning curves and their impact on the system and the corresponding model.
- Variations in humans' physical and psychological states: Humans' physical conditions and fatigue levels as well as emotional moods can impact their performance, which also need to be captured by DT model validation mechanisms. These variations are difficult to model as human responses to identical tasks fluctuate and do not follow identical patterns every time. To address this uncertainty, validation mechanisms must integrate behavioral, physical, and psychological metrics, while simultaneously navigating challenges related to data availability and privacy [37].

3) Hybrid Manufacturing Environment

In hybrid environments, in addition to the behavior and variations in machines and humans, cascading effects of one on the other must be considered. Here, we discuss how, in a shared workspace, human-machine interaction and interconnectivity changes the manufacturing process and challenges its DT validation:

- Variations in human-machine interaction: As humans and machines work together, validation processes cannot treat them as separate entities. For instance, introduction of a new cobot may change the way a human operator interacts with the system. The operator may develop new behavioral patterns based on the cobot's behavior while the cobot's performance may be affected based on the operator's actions. Validation mechanisms must integrate interaction models to understand and detect the variations in behavior between machines and humans.

- Variations in task allocation: Validation processes need to incorporate workload distribution models and safety measures in the process. Depending on the demand, workload distribution between humans and machines may shift and validation processes need to incorporate distribution patterns and role assignments to be able to detect and reflect the variations in DTs [38].
- Variations due to implementation of safety measures: Interaction of machines and humans may change depending on the safety measures, changing system's performance [39]. For example, a cobot performance may vary if human operators are in proximity or humans may adjust their behavior when nearing cobots and machines. Therefore, validation mechanisms must include safety models and limitations to detect trust variations and their effects on the system.

Taking advantage of DTs' capabilities relies heavily on having accurate reflections of the real-world systems. To ensure DTs' validity, developing complex validation mechanisms, capable of determining and scheduling ongoing validation based on frequency, significance, and impact of variations in the system, is critical.

IV. SUMMARY AND OUTLOOK

As manufacturing systems evolve to cope with the dynamic demands of the market, utilizing tools and technologies to optimize manufacturing processes has become critical. Digital Twins, as near real-time replication of real-world systems, are a great asset in supporting optimization. The potential of Digital Twins, however, hinges upon rigorous validation processes ensuring their underlying models remain accurate reflections of their real-world counterparts over time.

We explored the types of variations that can occur in different manufacturing environments and how they can impact Digital Twin validation processes. In machine-intensive manufacturing, variations to machines, from small adjustments such as machine calibration to significant alterations like complete machine replacement, impact manufacturing systems, and validation processes must be able to detect these minor or major modifications. In labor-intensive manufacturing, humans' skills, physical and psychological state play a critical role, and Digital Twins validation mechanisms must overcome privacy and data availability concerns to be able to integrate different human states in the process. Finally, in a hybrid environment, where the participation of machines and humans is mostly balanced, the complexity of validation increases as variations in machines and humans cannot be fully separated. Validation must consider interactions between humans and machines, effects of task distributions, and how safety measures affect each entity's behavior. Robust validation mechanisms must utilize data, as well as human expert knowledge, to detect criticality of variations, their impact on the overall system, and frequencies with which they occur and should be evaluated for validity.

As a result of our analysis and discussion on variations in manufacturing systems and their implications for Digital Twin validation, we attempted to provide possible mitigations and directions to address the identified challenges, namely:

- *Partitioning and intermediate validation points:* As complex systems consist of many parts and processes, breaking down the system and introducing intermediate key performance indicators can help in detecting underlying variations and the targeted validation of the corresponding Digital Twins.
- *Criticality detection:* Alterations and fluctuations do not impact systems equally. As such, uncertainty analysis and impact grading can be used to detect and consider criticality of the variations in the validation process.
- *Dynamic validation frequency:* Detecting variations in systems is challenging because the patterns of variations do not exhibit the same behavior. To correctly detect variations in systems based on their unique characteristics, dynamic validation frequencies can be utilized to tailor the validation process based on different criteria such as time needed for data accumulation or criticality of a variation.
- *Fusion of human expert knowledge with data:* Expert knowledge is invaluable for validation, especially in systems where data is scarce. Therefore, combining expert knowledge with data can be a great asset in validation processes.
- *Parameter estimation for human behavior modeling:* Complete virtual replication of human behavior is not feasible. Therefore, techniques such as particle filtering can be utilized to estimate and validate the nuances of human behavior in Digital Twins [43].
- *Integration of task distribution and human-machine interaction modeling:* In systems, where humans and machines perform tasks collaboratively, tasks distribution and human-machine interactions are dynamically shifting. Modeling adaptive interactions can aid validation processes by detecting variations and reflecting them in the Digital Twin models.

Although recent studies have highlighted the importance of maintaining DT models validity over time and explored continuous validation, the lack of research in addressing validation challenges, especially in labor-intensive and hybrid manufacturing systems, persists. For future work, we suggest research on dynamic adjustment of frequency of validation, criticality detection, and incorporating human behavior models in the validation process.

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