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ScienceDirect

Procedia Computer Science 238 (2024) 623–630

Procedia Computer Science

www.elsevier.com/locate/procedia

The 7th International Conference on Emerging Data and Industry (EDI40), April 23-25, 2024, Hasselt, Belgium

Validation of Digital Twins in Labor-Intensive Manufacturing: Significance and Challenges

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Abstract

Digital Twins allow for designing, operating, and optimizing running systems by replicating the operations of the physical components in a digital environment. Interconnectivity between Digital Twin models and corresponding real-world counterparts facilitates continuous examining of the actual system, resulting in nearly real-time analysis and decision-making support. Validation is an integral part of Digital Twins as underlying models must accurately reflect the corresponding physical systems according to predefined objectives. The near real-time nature of Digital Twins demands a continuous validation process to ensure models' accuracy. Labor-intensive manufacturing, where humans are at the heart of manufacturing processes, is a sector that encompasses a wide range of industries, from toys and apparel to medical devices and automotive components. This sector continues to play a vital role in emerging economies, offering employment opportunities that mitigate poverty and enhance social stability. Enabling Digital Twins for labor-intensive manufacturing systems opens many opportunities towards humancentricity and improvement of well-being of human operators. In these systems, however, human data must also be considered for Digital Twin development and the corresponding validation processes. Handling human data further complicates the creation and validation of Digital Twins. To the best of our knowledge, there has not been a comprehensive study on the validation of Digital Twins in labor-intensive manufacturing. In this paper, we review Digital Twin validation in manufacturing, focusing on systems that feature data from human operations. As a result, we outline the current challenges of validation of Digital Twins in labor-intensive manufacturing environments and suggest future research directions.

Keywords: Continuous validation; Digital Twin; Labor-intensive manufacturing; Industry 5.0

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1877-0509
10.1016/j.procs.2024.06.070

1. Introduction

The never-ending development of new technologies has led to increased gathering of data and information. This information can be used in industry to assist in decision making and optimization. Utilizing data and technology in moving toward smart manufacturing is one of the main pillars of the fourth industrial revolution. One powerful technology employed in industry, in line with achieving smart manufacturing, is simulation, providing insights by modeling real-life systems and analyzing their behavior.

Since 2003, the concept of Digital Twin (DT) as a digital equivalent to a physical product has been introduced and defined [7]. Simply put, DTs can be regarded as more complex and detailed simulation models that evolve with their physical counterparts. In their most basic characterization, DTs consist of a physical entity, a virtual mirror replication of the physical model, and the connection and communication between the two objects [34]. DT capabilities can be utilized in manufacturing to ensure reliable, optimized, and productive processes. They can be used in what-if analysis and cross-validation checks [19], validation of manufacturing systems from design to operation [1], as well as optimizing production with manufacturing testing and product validation [12].

Despite the advancements in technology and the move toward automation, humans still play an important role in manufacturing. Labor-intensive manufacturing continues to be a major part of global manufacturing especially in developing countries like Indonesia, where most manufacturing relies on human labor [8]. Moreover, UNIDO's report on the impact of the recent pandemic on labor-intensive manufacturing industries such as apparel, textiles, and furniture attests to the fact that human operators are indispensable in many industries [25]. Integration and reflection of both humans and machines in implementation of DTs can aid monitor production activities, enhance machine efficiency, and more importantly achieve operation safety and enhance the health and safety of involved humans [13].

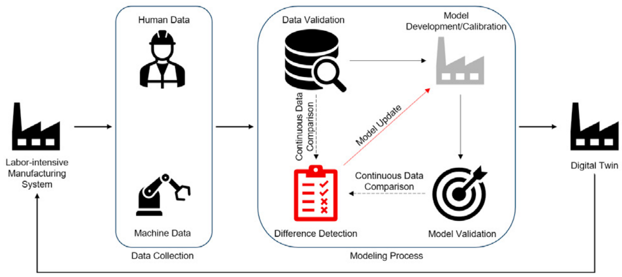

Fig. 1. Digital Twin development of labor-intensive manufacturing system with continuous validation.

Realizing the full potential of DTs and implementing them in manufacturing is dependent on having a high-fidelity DT, which is achieved through rigorous validation processes. DT validation is a challenging problem to address as the nature of DTs demands an ongoing validation process to enable nearly real-time virtual mirroring of the system. In labor-intensive and human-centric manufacturing, human operators and their well-being are an essential part of the manufacturing process. Validating human related data and DT models based on humans and their inherent uncertainties poses a significant challenge. Figure 1 shows a general DT modeling process with integrated continuous validation, tailored at labor-intensive manufacturing systems (LIMSs). Data from both human operators and machines is continuously collected and validated. We denote by human related data, data that can be collected from or generated by human operators. This data can be obtained non-intrusively through IoT devices or voluntarily through operators. Human activity and productivity metrics, health and safety, and behavioral data are instances of human related data. Machine data refers to data collected from machines in manufacturing processes, for instance, production data, machine performance, and maintenance data. Both human and machine data are used for both model extraction and calibration. The model validation process continuously checks for discrepancies between the DT model and data from the real system, and in case of discrepancies, the DT model is updated to mirror the latest state of the actual system. Although many studies on validation of traditional simulation models are available, focused research on continuous validation of DTs, more specifically in manufacturing, have been limited. In this paper, we review the current literature and draw attention to the challenges of validating DTs in LIMSs, where humans are integral in the manufacturing processes. Human operators' unpredictability and flexibility adds another layer of complexity and uncertainty, both in model extraction and validation process of DTs [9]. Privacy concerns need to be considered adequately too. This paper serves as a starting point for future research and discussion on the critical topic of continuous validation in LIMSs.

The paper is organized as follows. In Section 2, we review the background and the related work on validation of DTs in manufacturing. We identify the main challenges with validation of DT in labor-intensive manufacturing in Section 3. Finally, we conclude our findings and provide future research directions.

2. Background and Related Work

In this section, we describe labor-intensive manufacturing, provide an overview of validation of traditional simulation models, define and describe DTs, and provide a review of the current literature in validation of DTs. Finally, we highlight the discovered research gaps.

2.1. Labor-intensive Manufacturing

Labor-intensive manufacturing relies heavily on human labor with minimal machine involvement in the production process. It is the opposite of capital-intensive manufacturing, where the production process is mostly performed by machines with minor human involvement [33]. Many industries, such as apparel, footwear, pottery, wood, and textiles, as well as manufacturers in developing countries, depend on manual human labor [17]. In industries like jewelry manufacturing, human labor is indispensable and cannot simply be replaced by automation [18]. Moreover, from an efficiency standpoint, replacing human labor with automation may not always be the most optimized option considering cost and time. Labor-intensive manufacturing allows for more flexibility as humans are more tolerant of change. Humans, unlike machines, are a more flexible resource. Depending on the task at hand, human operators can be trained or substituted. Even though human adaptability is advantageous, the unpredictability and sentient nature of humans makes them a challenging resource to monitor. Therefore, capturing and analyzing human behavior and input is vital in optimizing production as they are the main contributor in labor-intensive manufacturing.

2.2. Validation of Traditional Simulation Models

Schlesinger et al. define simulation model validation as “substantiation that a computerized model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of the model” [30]. In other words, a model is deemed valid if, according to the model’s purpose, it mirrors the characteristics and processes of its real-life counterpart to an acceptable degree of accuracy. According to Sargent [29], conceptual model validation and operational validation are part of a modeling process with data validity as the central core ensuring the model is built and validated based on robust data. Conceptual model validation deals with the correctness of assumptions while operational validation focuses on accuracy of the model output compared to the real system.

Sargent describes several validation techniques used in model validation. The methods are implemented either subjectively or objectively. Subjective validation can be done by the model development team in the development process, stakeholders, model users, with knowledge of the real-world system, or an independent third-party validation team while objective validation refers to statistical approaches and tests. In the following, we name and briefly describe some of these techniques:

- Animation: An animated representation of the model is presented. By visualizing the simulation run, behavior of the model and its changes through time are easier to understand and detect.
- Event validity: Significant occurrences are compared in similarity to the events in the real system.
- Face validity: Human expert knowledge is used to check the validity of the model. People with knowledge about the domain review the model and give verdict on its validation.
- Historical data validation: Data collected over time from the real system can help validate the model if the model is able to reproduce the same output as the data recorded.
- Sensitivity analysis: This technique helps in finding the significance of input parameters. By changing the value of input parameters, the effects of the change on the output of the model are tested and analyzed.

- Predictive validation: In this technique, instead of reproducing the output of the system, the model predicts system's behavior and if the predicted output is the same as the eventual system output the model is considered valid.
- Turing tests: The discrepancy between the model output and the system output is measured by expert knowledge. If the experts are unable to distinguish between the outputs, the model is considered valid.

Traditional validation techniques are limited in their ability to provide near real-time responses. Subjective validation implies a delay in evaluation as the validation process relies heavily on human intervention with restricted automation while objective approaches depend on availability of sufficient historical data. Moreover, as traditional modeling is static, validation is a one-time process during or after the development and does not consider the changes to the system. DTs strive for near real-time replication, which requires more dynamic approaches in ensuring a timely and accurate validation.

2.3. Digital Twins

DTs are extensions of simulation models, aimed at dealing with more complex and sophisticated systems as are common at present. A DT model is a replica of a real-world system in the virtual world mirroring the modules and processes of the physical object. Depending on the integration level between the physical object and its virtual counterpart, a DT can be further classified as a digital model, digital shadow, or a digital twin [16], detailed as follows:

- A digital model has no automated data flow between the physical and virtual objects.
- A digital shadow has a one-way data flow between the physical and virtual objects.
- A digital twin has a fully automated two-way data flow between the physical and virtual objects.

In this paper, we focus on digital twins, where the data flow is fully integrated between the objects, meaning a change in the physical object affects the virtual object. In other words, the DT is continuously updated to reflect the actual state of its physical entity. Internet of Things (IoT) and sensor technology are key enablers of real-time data transmission between the physical and the virtual object paving the way for developing a DT model and close to real-time analysis and decision-making support.

In the context of manufacturing, a DT model can be utilized to monitor and control operations and enhance productivity, maintenance, and reliability. ISO 23247 provides a four-part generic framework (general principles, reference architecture, digital representation, and information exchange), for developing case-specific DTs in manufacturing, applying IoT devices in data collection and transmission [31]. The standard provides guidelines for developing DTs; however, it lacks focus on validation of DTs. Developing a DT is objective specific, and its validation is also dependent on these objectives as a complete representation of a physical system is not feasible. For example, developing a DT to address human well-being requires its own relevant data and development process compared to a DT for energy efficiency or production optimization. Therefore, validation for these cases would need different data and different performance measures.

2.4. Validation of Digital Twins

It is essential that DTs represent the physical system accurately over time. To confirm that a DT model is built right and conforms to the actual system with sufficient accuracy, the model must go through a validation process. Different validation methods have been proposed in literature. However, most validation methods are applicable to traditional simulation models where the resulting data are available only after the simulation run which means by the time the data are analyzed, the presented outcome might not reflect the current state of the real-life system [11]. DTs, on the other hand, highly depend on an ongoing validation process to continuously reflect the system and provide close to real-time resulting data. Thus, the validation is not a choice, but a strong enabler and prerequisite for DTs.

The need for constant communication and data transmission between the physical object and its DT model makes the validation process an integral part in developing a DT. By definition, a DT without a continuous validation process would become a digital model. Hua et al. proposed a framework for ongoing validation using real system data collected from IoT devices combined with human expert knowledge [11]. A two-step validation method in which the initial model is validated using traditional validation techniques, and in the second phase the output of the model is compared with the output of the system based on data streams to ensure ongoing validation of the model is proposed by Friederich and Lazarova-Molnar [5]. Lugaresi et al. also utilized data gathered from IoT devices for online validation of DTs. By treating the gathered data as sequences in a time-series format, they were able to compare the sequences of data captured from the system and its DT to obtain the similarity level of the two to validate the DT even with a limited dataset [21]. A workflow is presented by Mertens and Denil using approximation function and comparing real system data with the simulated data to continuously validate DTs [23]. Assuming a validated initial DT exists, a three-step approach to periodically validate DTs is proposed by Henrique dos Santos et al.; K-nearest neighbor classifier and p-control chart are integrated to assess validity of digital models based on defined evaluation variables [28]. Overbeck et al. [26] also proposed a periodic validation method by automatically measuring and comparing key performance indicators (KPIs) such as normalized root mean squared error of the outputs of the DT and the real system. Particle filtering is another approach for continuous calibration as Ward et al. [35] have used this methodology in tracking changing parameter values and calibrating the DT accordingly. While other studies, such as [22] and [10], can also be extended and applied to DT validation, to the best of our knowledge, publications on the study of continuous validation of DTs in manufacturing are limited to the noted literature. Table 1 provides a comparison of the reviewed literature in validation of DTs in manufacturing.

As we noted in Subsection 2.2, data validation is critical for model validation since validating a model based on invalid data would yield an inaccurate model, and most methodologies from the literature that we reviewed assumed availability of perfect data. Moreover, most of the reviewed methods aim at complete automation of the validation process with minimal human expert knowledge integration, ignoring a valuable information source that can be highly beneficial for both data and model validation.

Table 1. Comparison of previous work on digital twin validation.

Work	Data validation	Automation/Human-input	Type of validation
Validation of Digital Twins: Challenges and Opportunities [11]	Data are validated before model validation process	Semi-automated/Expert knowledge input	Face validity – Historical data validation
A Framework for Validating Data-Driven Discrete-Event Simulation Models of Cyber-Physical Production Systems [5]	Perfect data are assumed	Semi-automated/Expert knowledge input	Face validity – Historical data validation – Predictive validation
Online validation of digital twins for manufacturing systems [21]	Perfect data are assumed	Complete automation/No human input	Event validity
Digital-twin Co-evolution using Continuous Validation [23]	Availability of validated data is considered	Complete automation/No human input	Predictive validation
Digital Twin simulation models: a validation method based on machine learning and control charts [28]	Validated data are assumed	Complete automation/No human input	Predictive validation
Development and analysis of digital twins of production systems [26]	High-quality validated data is assumed	Complete automation/No human input	Event validity – Historical data validation
Continuous calibration of a digital twin: Comparison of particle filter and Bayesian calibration approaches [35]	Perfect data are needed as the method does not respond well to noisy data	Complete automation/No human input	Sensitivity analysis – Novel particle filtering approach

Validation is a critical element of the DT framework. As humans play a significant role in labor-intensive manufacturing, their roles, operations, and expert knowledge need to be considered in DT validation. Existing literature, however, lacks focus on the impact of human operators on DT development and validation.

3. Challenges in Validation of Digital Twins for Labor-intensive Manufacturing Systems

Human operators are a fundamental element of labor-intensive manufacturing. DTs of LIMSs must accurately reflect humans as well as the machines involved in the manufacturing process. However, the coexistence, cooperation, and collaboration between human operators and machines in human-centric and LIMSs bring about a set of societal and technological challenges [20]. In this section, we detail the challenges in validating DTs in labor-intensive and human-centric manufacturing.

3.1. Data Availability

Developing and validating DTs hinge upon data [36]. The more data from a system is available, the more the possibility of an accurate DT of the system. Validation of DTs can be accomplished by comparison of the data collected from the real system to the output of the DT [15]. If data from the actual system is insufficient and unavailable, the comparison and validation evaluation of the two entities cannot take place. The challenge in the case of LIMSs is gathering data as the data may be unavailable or hard to obtain since capturing data generated by human operators is accompanied with legal and privacy concerns as well as variability and complexity of humans in general. Furthermore, each human operator may have its own specific characteristics, unlike machines, where all machines of a same type exhibit same or similar performance characteristics. For example, different human operators may have different performance levels on an identical task depending on their age, physical ability, and even their attitude [14]. Therefore, data gathered from each human operator is unique and makes data accumulation difficult. Moreover, continuous flow of data is hindered by availability of human operators which makes the on-going validation process of the DT challenging. Although IoT devices and sensors can aid in data gathering from humans, health, privacy, and safety concerns must be addressed.

3.2. Data Validation

Data of good quality is essential in DTs as a DT can only be as good and valid as the data it is based on [3]. In a continuous validation process, the DT model is continuously (or with a high frequency) compared to the real-world system for discrepancies, based on predefined key performance measures. If the comparison is based on corrupt data, the DT itself can become compromised and invalid which could lead to decision support that is damaging to the performance of the physical system. In LIMSs, where human safety is critical, making decisions based on DTs with invalid underlying models may lead to safety hazards and accidents. Hence, the correlation between data validation and DT validation must always be considered.

Current literature on DT validation treats these two processes as two separate units, and because of the cost and time-consuming nature of data validation process, presence of validated data is already assumed. The challenge is to incorporate data validation in the DT continuous validation process making sure model validity is determined based on robust data [29]. For example, a DT can still be deemed valid if its output data conforms to the collected data it is compared to. However, if the collected data itself is unvalidated, the DT, though valid by comparison, may not be a correct reflection of its real-world counterpart. In LIMSs, in addition to IoT devices and sensors, human operators are also generating data through their operations. Overcoming data validity issues such as noise and missing values in sensor data as well as quantifying and validating human data and behavior continuously are of utmost importance in ensuring the DT's accurate reflection of the system.

3.3. Data Privacy

Availability of sufficient data is a necessity for continuous validation of DTs. However, humans' trust in the system and their willingness to cooperate makes collecting data from humans challenging. A way to build trust is to ensure the privacy of the data collected from humans [32]. The relationship between humans and the system must be transparent. Humans need to know what the system needs from them, and most importantly how the system gathers and processes the data provided by humans [6]. It is, furthermore, essential to differentiate between privacy and security. For example, a system may be protected against threats but may still leak personal and sensitive data [24].

Therefore, the challenge arising from the need for privacy is to find data privacy methods that can extensively protect sensitive data while maintaining data integrity and model validity. Redaction processes, such as data anonymization may increase the privacy level, as well as present new challenges for validation. For instance, the HuMAN privacy and trust framework [27] provides guidelines on data privacy. However, following the guidelines may impact the model validation process as all traces of a data element can be deleted. Increasing privacy, while maintaining validity, aids in growing the trust between humans and machines which results in more data collection and ultimately an accurate DT.

3.4. Human Automation Balance

Automation is an inseparable part of industry. It enables a consistent, robust, and intelligent manufacturing performance. However, in LIMSs where automation is overshadowed by human labor, the input from the experts is invaluable and cannot be neglected. In the context of DT validation in labor-intensive and human-centric manufacturing, human knowledge must be integrated with automation in the DT validation process. Aligned with the goals of Industry 5.0, the aim is to find the right balance between automation and human input [2].

Although existing literature on DT validation is focused mostly on fully automated validation approaches, expert knowledge of procedures in the manufacturing process may facilitate the validation more than an extensive automated analysis. Since data in LIMSs is typically scarce, integrating expert knowledge is especially valuable in the validation process. Instead of striving for complete automation, we should preserve the human knowledge, as proposed as the first step validation in the two-phase validation framework [5], and use data visualization and other data representation aids to assist humans in their judgment and decision-making on validation [4]. Effectively and systematically integrating human input and expert knowledge along with automation in finding optimized validation methods is the challenge that must be met.

4. Summary and Outlook

Digital Twins enable mirroring real-life systems in a virtual world. The dynamic nature of Digital Twins reflects the characteristics and properties of a system in near real-time. More specifically, in a manufacturing environment, the live communication capability opens the door for optimization, decision support, evaluating different production setups, and enhancement of human well-being. However, taking advantage of these opportunities relies on having a validated Digital Twin. In addition, human labor is still an indispensable resource in many industries and is the main driving force of manufacturing in developing countries, but also in specific industries worldwide. Validating Digital Twins in labor-intensive environments, where manufacturing processes are dependent on humans, is an extremely challenging process. Human's knowledge, input, and generated data must be precisely considered when developing and validating Digital Twins. While studies on validation of Digital Twins in manufacturing have been recently published, it is safe to say that the literature on validation of Digital Twins in a labor-intensive manufacturing environment is scarce.

In this paper, we reviewed the current literature on validation of Digital Twins in manufacturing comparing them in three main categories: data validation, automation, and type of validation. The comparison showed that proposed methodologies assumed data validity with little or no focus on human input and expert knowledge. Based on our findings, we identified four key challenges in validation of Digital Twins in labor-intensive manufacturing: data availability, data validation, data privacy, and human automation balance. Addressing challenges concerning data and human input in validation of Digital Twins helps in general adoption of Digital Twins in labor-intensive and human-centric manufacturing especially in small manufacturing enterprises and is in line with the objective of Industry 5.0.

Acknowledgements

This research is part of the ONE4ALL project, funded by the European Commission, Horizon Europe Programme under the Grant Agreement No 101091877.

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