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A FRAMEWORK FOR VALIDATING DATA-DRIVEN DISCRETE-EVENT SIMULATION MODELS OF CYBER-PHYSICAL PRODUCTION SYSTEMS

Jonas Friederich

Mærsk Mc-Kinney Møller Institute
University of Southern Denmark
Campusvej 55
Odense, 5230, DENMARK

Sanja Lazarova-Molnar

Institute AIFB
Karlsruhe Institute of Technology
Kaiserstr. 89
Karlsruhe, 76133, GERMANY

ABSTRACT

In recent years, there has been a significant increase in the deployment of Cyber-physical Production Systems (CPPS) across various industries. CPPS consist of interconnected devices and systems that combine physical and digital elements to enhance the efficiency, productivity, and reliability of manufacturing processes. Due to the continuous and fast-paced evolution of the behavior of CPPS, there is an increasing interest in generating data-driven Discrete-event Simulation (DES) models of such systems. The validation of these models, however, remains a challenge, and traditional approaches may be insufficient to ensure their accuracy. To address this challenge, we propose a framework for validating data-driven DES models of CPPS. We emphasize the importance of continuously monitoring the validity of data-driven DES models and updating them when necessary to ensure their accuracy over time. We, furthermore, demonstrate our proposed approach through a case study in reliability assessment and discuss challenges and limitations of our framework.

1 INTRODUCTION

Simulation modeling is the process of creating an abstracted digital version of a real-world system that can be used to study and predict how the system will behave under different conditions. However, for simulation models to be useful, it is essential to validate them. Validation not only ensures that the model accurately represents the real-world system being studied, but also builds confidence in the model's results, identifies potential errors or omissions that need to be corrected, and improves overall understanding of the system (Sargent 2010; Law 2019). Decision-makers can use validated simulation models to make informed decisions based on reliable information, which can lead to improved system outcomes and reduced risks. Cyber-physical Production Systems (CPPS) are a new and emerging application area for simulation modeling, posing unique challenges to conventional simulation modeling and model validation.

CPPS refer to advanced manufacturing systems that integrate physical components with digital technologies and automation, resulting in more efficient, flexible, and customizable production processes. In recent years, there has been a significant increase in the deployment of CPPS across various industries (Monostori 2014; Uhlemann et al. 2017). One of the main drivers for this increase is the need to improve productivity and efficiency in manufacturing processes, which can be achieved through the integration of digital technologies and automation. Additionally, the rise of Industry 4.0 and the Internet of Things (IoT) has provided new opportunities for manufacturers to collect and analyze data in real-time, enabling better decision-making and predictive maintenance (Lasi et al. 2014). Another important driver is the demand for more flexible and customizable production systems to meet the changing needs of consumers and the market. Finally, concerns over environmental sustainability and the need to reduce energy consumption

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have also contributed to the adoption of cyber-physical systems, as they can help optimize resource usage and reduce waste.

The continuous and fast-paced evolution of the behavior of CPPS has sparked an increasing interest in data-driven simulation modeling of these systems. Event logs provide a detailed account of the events occurring in a CPPS, including timestamps, activities, resources, and their interrelationships. This information can be used to automatically generate discrete-event simulation (DES) models of the system, using Process Mining (PM) techniques (Friederich and Lazarova-Molnar 2021). PM has been applied in various ways to extract DES models from event logs, such as during the conceptual modeling phase (Abohamad et al. 2017) or for automatic extraction of Digital Twins (Lugaresi and Matta 2021; Friederich et al. 2022) and reliability models (Friederich and Lazarova-Molnar 2022) of manufacturing systems.

Figure 1 outlines the general process for data-driven simulation modeling and analysis of CPPS. The process involves extracting data capturing manufacturing processes of a CPPS from various sources, such as IoT sensors or information systems like Manufacturing Execution System or Enterprise Resource Planning. Next, the data is used to extract simulation models using, for example, PM techniques. Following, these models then need to be validated to ensure their robustness. Simulation and data analytics are then employed to support decision-making regarding system configuration, purchase decisions, or maintenance scheduling (Friederich and Lazarova-Molnar 2021).

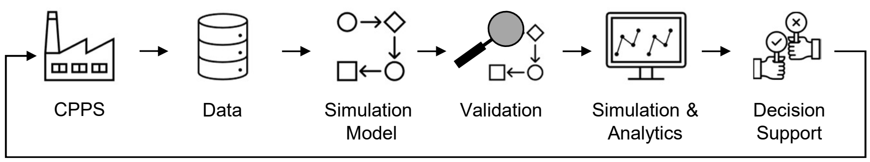

Figure 1: Data-driven simulation modeling and analysis of CPPS.

Lazarova-Molnar and Li (2019) discuss the potential of data for derivation of simulation models. The authors stress the fact that, such models also require new frameworks on how to systematically validate them. In Hua et al. (2022), the authors discuss several challenges facing the model validation within digital twins. Furthermore, they propose an initial framework to define basic rules of digital twin model validation and introduce a systematic approach to validation that seamlessly combines expert knowledge and data gathered from available IoT devices. Lugaresi et al. (2022) propose a method for ongoing validation of digital twins in manufacturing that uses sequences of data for the physical system and compares it to the output of the digital twin.

While some of the above mentioned contributions discuss or propose a specific method for validation of data-driven simulation models, a structured approach is still missing in the literature. Especially in the context of CPPS, validation of data-driven simulation models is a critical yet unsolved challenge, primarily due to the rapidly evolving behavior of these systems. Without frequent updates, simulation models can become outdated, rendering them useless. Existing validation techniques have mostly been developed for static simulation models that do not account for frequent changes in the system's behavior. Additionally, these techniques rely heavily on human expertise and input, creating a bottleneck for data-driven model validation. To address these challenges, we propose a novel framework for validating data-driven DES models of CPPS. Our framework leverages the abundance of data generated by CPPS to partly automate the validation process by identifying discrepancies between the model's behavior and the actual behavior of the system. This approach eliminates the need for manual validation and allows for the frequent updating of simulation models. We believe that our framework will significantly improve the accuracy and reliability of data-driven simulation models of CPPS.

The paper is organized as follows. First, in Section 2, we review current approaches for validating and verifying simulation models. Next, in Section 3, we focus on the specific challenges of validating and verifying data-driven simulation models. In Section 4, we propose a novel framework for automatic operational validation of DES models of CPPS. We then present an illustrative case study from the reliability modeling domain demonstrating the effectiveness of our framework in Section 5. In Section 6, we discuss our findings and provide an outlook for future research in this area.

2 CURRENT APPROACHES FOR VALIDATION AND VERIFICATION OF SIMULATION MODELS

The validation and verification of simulation models is a well-established research problem within the simulation community. In this paper, we adopt the paradigm proposed by Sargent (2010), which relates validation and verification to the model development process. As shown in Figure 2, the model development process includes three phases: *analysis and modeling*, *implementation*, and *experimentation*. During the analysis and modeling phase, a conceptual model is created based on the real system being studied. This conceptual model is then transformed into a simulation model in the implementation phase. Finally, the simulation model is used to analyze the real system and draw conclusions during the experimentation phase.

Conceptual model validation involves verifying that the theories and assumptions underlying the conceptual model are correct and that the model representation of the real system is appropriate for the intended purpose of the simulation study. *Simulation model verification*, on the other hand, is concerned with ensuring that the programming and implementation of the conceptual model are correct. *Operational validation* determines whether the output behavior of the model is accurate enough for the intended purpose of the model over the domain of its applicability. Lastly, *data validation* focuses on verifying that the input data used for model building, evaluation, and testing are accurate, complete, and representative of the real system being modeled.

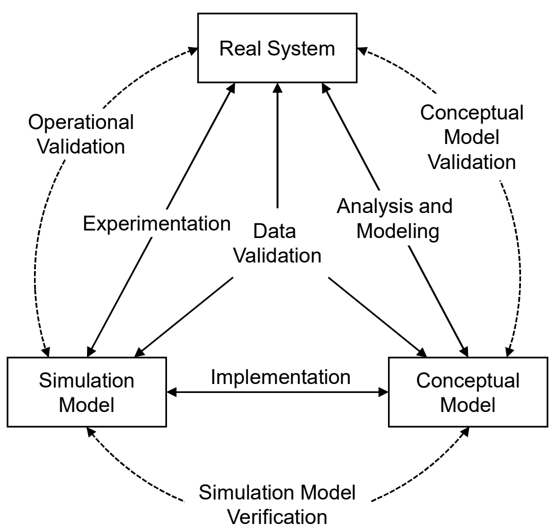

Figure 2: Simplified simulation modeling process (adopted from Sargent 2010).

There are several commonly used techniques and tests for verifying and validating simulation models, which are often used in combination to evaluate both submodels and the overall simulation model. Below, we describe some of these techniques and tests:

- *Animation:* A visual representation of the simulated system is created and its behavior is animated over time. This technique helps in identifying unexpected behavior or bugs in the simulation model and allows users to explore different scenarios and test the model's robustness. Animation also facilitates communication of simulation results to stakeholders who may not have a technical background.

- *Face Validation*: Feedback from domain experts with knowledge of the simulated systems is obtained. These experts evaluate the model's assumptions, logic, and structure to determine whether it appears reasonable and appropriate for the system being studied. Face validation helps identify potential issues or inconsistencies in the model, providing valuable feedback for improving its accuracy and predictive capability.
- *Sensitivity Analysis*: The impact of small changes in input parameters or model structure on the simulation output is tested. Sensitivity analysis helps in identifying the most critical factors that affect the model's output and assesses the robustness of the model.
- *Historical Data Validation*: The model's output is compared to actual data collected from the system being studied. This technique involves testing the model's ability to reproduce the behavior of the real system and evaluating its accuracy by comparing its predictions with actual data. By using historical data, the model's assumptions, logic, and structure can be evaluated against real-world observations, allowing for refinement and improvement of the model.
- *Turing Test*: The model's ability to mimic human-like behavior in a way that is indistinguishable from that of a human expert with knowledge of the system being modeled is evaluated. This involves comparing the model's output to that of the human expert and determining whether the expert can reliably distinguish between the system's behavior and the behavior produced by the model.

3 VALIDATION AND VERIFICATION OF DATA-DRIVEN SIMULATION MODELS

In this section, we provide an extension to the commonly used validation and verification paradigm by Sargent (2010) to address the unique challenges of data-driven simulation modeling. As shown in Figure 3, the data-driven model development process comprises five phases: *customization*, *implementation*, *model generation*, *experimentation*, and performing *actions/changes*.

In the customization phase, the conceptual models and design patterns describing a system are tailored to suit the specific domain of interest. Popular conceptual modeling formalisms used in simulation, such as stochastic Petri nets, are employed to represent domain-specific design patterns. For instance, in manufacturing, such design patterns could determine how a queue of a production resource is modeled, its capacity or fault model. Since each system within a domain may have unique characteristics and requirements, the conceptual models and design patterns need to be customized by domain experts accordingly.

In the implementation phase, advanced data-driven modeling methods are implemented that use Data Mining techniques. These data-driven modeling methods utilize the domain-specific design patterns and the data collected from the real system to generate a simulation model. For example, Lugaresi and Matta (2021) use Data Mining to extract digital twins of manufacturing systems, Lazarova-Molnar et al. (2020) extract Fault trees from time series data of a system, Mesabbah et al. (2019) use Process Mining for automated simulation modeling of hospitals, and Friederich and Lazarova-Molnar (2022) use Process Mining for data-driven reliability modeling of manufacturing systems.

The model generation phase involves the actual generation of a simulation model of a real system using the data-driven modeling methods. The data-driven modeling methods perform both topological modeling of a real system using the customized design patterns as well as parameterization of the resulting simulation model. The generated simulation model can then be used to conduct experiments by defining different scenarios and inputs, and then running the model to observe and analyze the outputs. The results of these experiments can provide valuable insights and inform decision-making in real systems. For example, a simulation model of a manufacturing system can be used to evaluate the impact of changing production parameters, such as the speed of a production line or the allocation of resources, on system performance metrics such as throughput or resource utilization. The simulation can be run with different parameter values to assess the effect of each change on the system. The results of these simulations can then be used to identify the optimal parameter settings that maximize system performance or minimize costs.

Data are needed for all stages of the model development process. *Data validation* is a crucial step in developing a reliable and accurate simulation models, especially in the context of CPPS. The purpose of

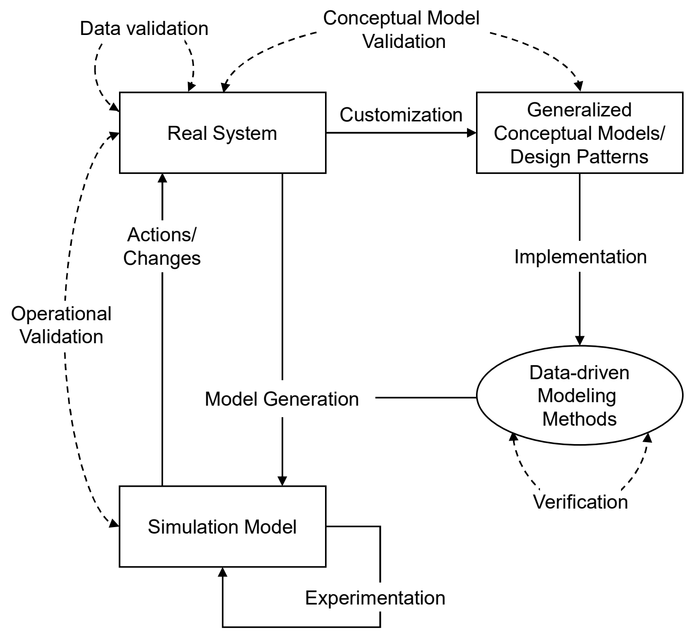

Figure 3: Simplified data-driven modeling process.

data validation is to ensure that simulation models accurately represent the real systems' behaviors and characteristics. To achieve this, it is critical that the input data generated by the real system is also validated to ensure that it accurately reflects the system's variability, complexity, and stochastic behavior. If the input data is inaccurate, the resulting simulation model will also be inaccurate, leading to incorrect conclusions and decisions. Data validation typically involves a range of activities, including checking for missing data, identifying outliers and errors, assessing the representativeness of the data, and comparing the data to other sources. Statistical methods may also be used to identify and correct errors in the input data.

Conceptual model validation is the process of evaluating whether the conceptual models and design patterns accurately represent the real system components and whether they are appropriate for the intended purpose of the model. It involves assessing if the model's level of detail and aggregation relationships align with its intended purpose and if the structure, logic, mathematical, and causal relationships are appropriate. Face validation is a commonly used technique for this type of evaluation. However, other techniques such as comparison with similar models can also be used to validate the conceptual models and design patterns.

Once the data-driven modeling methods have been implemented, *verification* is performed, which is the process of checking whether the computer programming and implementation of the generalized conceptual models and the model extraction algorithms are correct. Various techniques and methods for verification can be employed, including having the implementation checked by a subject-matter expert or utilizing interactive debuggers. Additionally, software engineering methods can also be utilized in the verification of data-driven modeling methods. This includes techniques such as code reviews, unit testing, and integration testing. These methods help to identify and fix errors in the implementation of the extraction algorithms, ensuring that they match the specifications and assumptions of the generalized conceptual models.

The *operational validation* involves determining whether the data-driven simulation model's output behavior is accurate enough for the intended purpose and over the domain of the model's intended applicability. In this paper, our primary focus is on techniques for operational validation of data-driven simulation models of CPPS. According to (Sargent 2010), the operational validity mainly depends on whether the real system is observable or not, where observable means the possibility of collecting data on the operational behavior of the system. Since abundant data on the operational behavior of the real system of CPPS are available for building simulation models, the operational validity of observable systems such as CPPS is assessed using statistical tests and procedures, by comparing the output behavior of the model and the real system for various sets of experimental conditions.

4 OPERATIONAL VALIDATION OF DATA-DRIVEN DISCRETE-EVENT SIMULATION MODELS OF CPPS

In this section, we present our framework for the operational validation of data-driven DES models of CPPS. Figure 4 provides an overview of the framework, which consists of the two phases *validation of initial model* and *validation of model at run-time*. In the first phase, the validity of a newly generated model is evaluated to ensure that the model is safe to deploy in a production environment to support decisions. In the second phase, the deployed model is validated to ensure continuous validity. In the following Subsections 4.1 and 4.2, we elaborate on these two phases in detail.

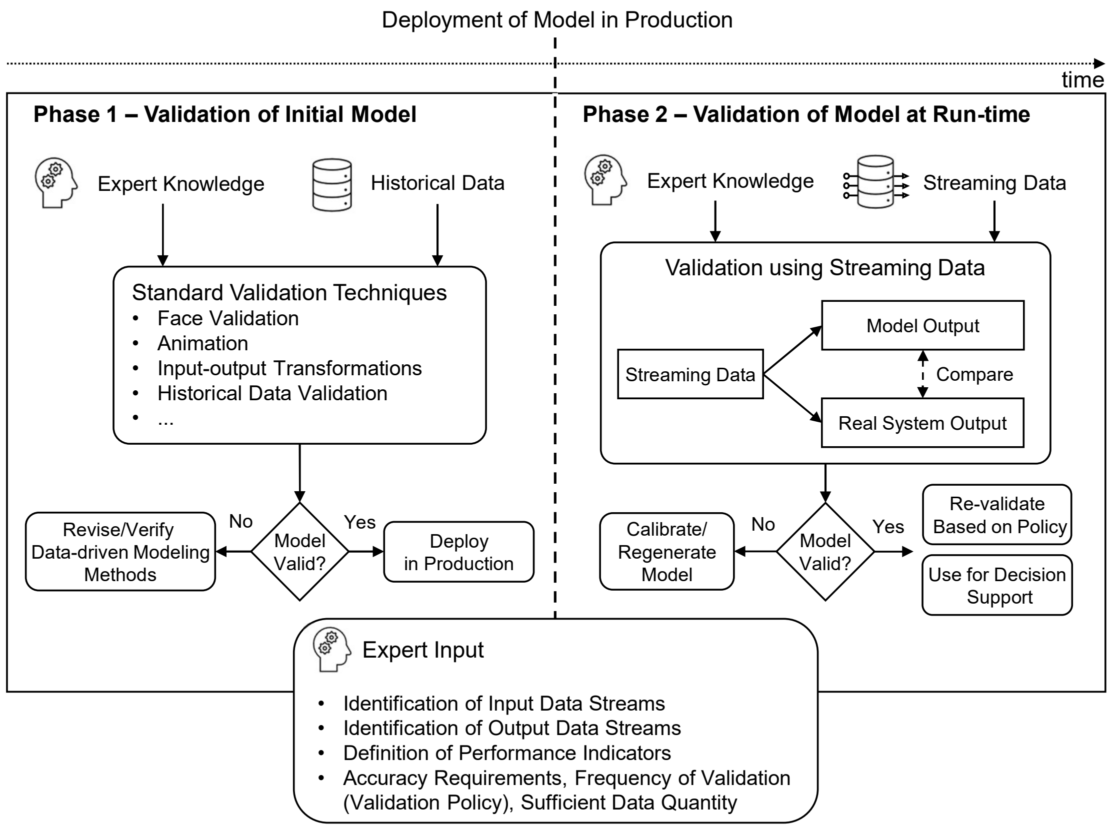

Figure 4: Operational validation of data-driven simulation models in two phases.

For both validation phases, input from domain experts, such as production managers or engineers, is essential. This input includes the identification and definition of input and output data streams used for validation, the definition of key performance indicators (KPIs), and the definition of accuracy requirements, frequency of validation, and sufficient data quantity.

Input and output data streams of a CPPS typically include a wide range of data types, such as sensor data from machines and equipment, production data, maintenance and repair data, logistics data, and other related data sources. Input data streams include, for example, orders, production schedules, raw material data and quality control data, while output data streams include, for example, material flow, production rates, product quality data, maintenance and repair data, logistics and supply chain data.

KPIs for a CPPS are metrics that are used to measure the performance of the system and can be derived from the production output data and used to assess the validity of the data-driven model. KPIs that can be used for the validation process of data-driven simulation models are, for example:

- **Production volume**: Total amount of production orders completed over a given period of time.
- **Throughput**: Number of production orders that can be produced or processed by the system over a given period of time.
- **Cycle time**: Time it takes for a single production order to move through the manufacturing process.
- **Work-in-Progress (WIP)**: Amount of inventory in the system at any given time.
- **Equipment downtime**: Amount of time that equipment in the manufacturing system are not operational due to breakdowns, maintenance, or other reasons.
- **Overall Equipment Effectiveness (OEE)**: Measure of how efficiently equipment is being used in a production process.

Accuracy requirements for data-driven simulation models of CPPS can vary depending on the specific application and purpose of the model. For instance, in some cases, a high degree of accuracy may be necessary to ensure safety or to prevent financial loss, while in others, a lower level of accuracy may be acceptable. Some factors that may affect the required level of accuracy include the complexity of the system, the potential impact of errors, and the criticality of the system. Additionally, the accuracy requirements may differ between the two validation phases. In the first phase, a higher level of accuracy may be necessary to ensure that the model is safe to deploy, while in the second phase, a lower level of accuracy may be acceptable as long as it does not compromise the safety or efficiency of the system.

The frequency of validation refers to how often a data-driven simulation model which is deployed in production is validated against the real-world system. The choice of validation frequency depends on the criticality of the decision-making that relies on the simulation model, as well as the rate of change in the system being modeled. If the validation frequency is too low, the simulation model may not accurately reflect the current state of the system, potentially leading to incorrect decisions. On the other hand, if the validation frequency is too high, the validation process may become too time-consuming and resource-intensive, resulting in decreased efficiency. In the case of a CPPS, where the production process and the machinery involved can change rapidly due to factors such as machine breakdowns or changing production schedules, a higher validation frequency may be necessary. This ensures that the simulation model accurately reflects the current state of the system and that decisions made based on the model are valid. However, a higher validation frequency also requires more data collection and processing, which can be a challenge for large-scale CPPS with high volumes of data. In such cases, it may be necessary to strike a balance between the validation frequency and the available resources for data collection and processing.

In addition to expert judgment, we propose four more rigorous approaches for determining the validation frequency:

- **Empirical Testing**: In this approach, various frequencies of validation are tested, and the results are compared. The optimal frequency could be determined as the one that provides the best balance between model accuracy and computational resources.
- **Machine Learning-Based Optimization**: Machine learning techniques can be utilized to dynamically adjust the frequency of validation. A learning algorithm can be designed to learn from the previous simulations' accuracy and computational costs to adjust the validation frequency.
- **Statistical Process Control (SPC) Methods**: SPC methods can be used to monitor the changes in the system, triggering a model validation when the system exhibits behavior that is statistically different from its expected behavior. This ensures that validation is carried out when significant changes occur in the system, thus balancing resource consumption and accuracy.
- **Predictive Modeling**: A predictive model can be developed which uses information about the system, the simulations, and their outcomes to predict when a validation would be most beneficial.

This model can guide the validation scheduling, again balancing the trade-off between resource consumption and accuracy.

Defining sufficient data quantity for validation is an important aspect in ensuring the accuracy of data-driven simulation models of CPPS. If the data quantity is too small, the model may not accurately reflect the system behavior and may lead to incorrect decisions. On the other hand, if the data quantity is too large, it may lead to unnecessary computational costs and delays in decision-making processes. Therefore, it is important to define the appropriate data quantity for validation based on the model's intended purpose, complexity, and the availability of data. In general, the data should be representative of the system behavior and cover a sufficient range of operating conditions. The required data quantity can also vary depending on the frequency of validation. If the model is validated frequently, a smaller data quantity may be sufficient. On the other hand, if the validation frequency is low, a larger data quantity may be necessary to ensure the model's accuracy over a longer period of time.

In general, there are several factors that can make a data-driven simulation model of a CPPS invalid. Some examples are inaccurate or incomplete data, insufficient data, model overfitting, model complexity, model assumptions, or changes in the real system.

4.1 Phase 1 - Validation of Initial Model

The first phase of the operational validation framework for data-driven simulation models of CPPS involves validating the initial model to ensure it is safe for deployment in production to support decisions. This validation process leverages both expert knowledge of the system and historical data to ensure that the model accurately represents the real-world CPPS. Standard validation techniques such as face validation, animation, input-output transformation, and historical data validation are utilized during this phase to identify any potential issues or discrepancies with the model. If the model is found to be valid, it can be deployed in production to support decision-making processes. However, if the model is deemed invalid, additional investigations need to be conducted to identify the root cause of the issue. This includes validating and revising the data used to generate the model as well as the generalized conceptual models and design patterns used for implementation of the data-driven modeling methods, and verifying the implementation of these methods.

4.2 Phase 2 - Validation of Model at Run-time

The second phase of the operational validation framework for data-driven simulation models of CPPS is the validation of the model at run-time. This phase ensures the ongoing validation of the deployed model. During this phase, the output of the model is compared with the actual output of the real system based on data streams collected during the production process. Any discrepancies found are rectified by adjusting the model parameters, inputs, or logic. These adjustments may be automatic or require intervention from domain experts. Additionally, the validation of the model at run-time may involve updating the model to account for changes in the production process, such as changes in the environment or equipment. This can be done by either calibrating the model parameters or by regenerating the model.

There are three policies according to which the validation of a data-driven simulation model at run-time is ensured (Figure 5):

- **Validation on Demand/Condition-based Validation**: An expert determines the best time to validate the model based on domain knowledge or when the validation is triggered based on the condition of the system or its components.
- **Periodic/Time-based Validation**: A domain expert determines a specific schedule for model validation.
- **Continuous Validation**: The model is continuously validated.

These policies have different computational complexities, so it is crucial to determine the appropriate policy for the system or component being validated.

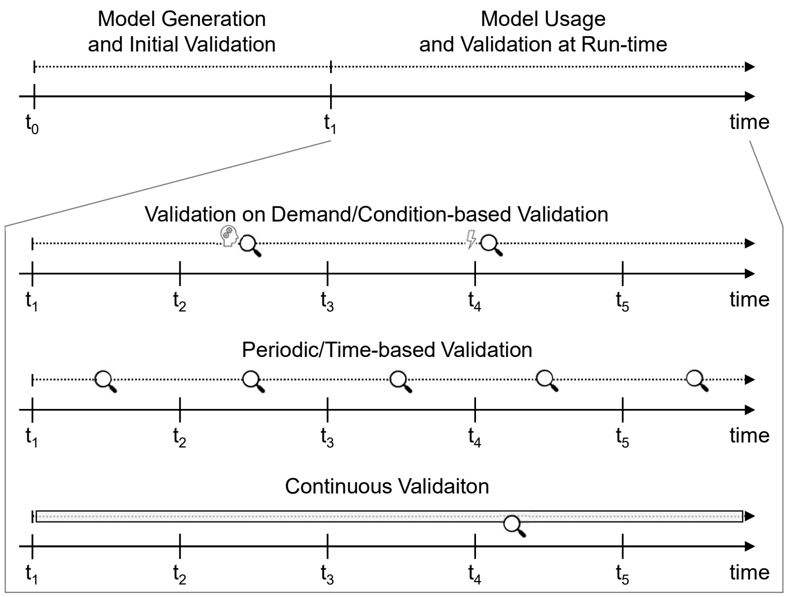

Figure 5: Policies for the validation of a model at run-time.

To conduct an objective comparison between the output of a data-driven simulation model and the actual output of a real system, statistical techniques such as confidence intervals or hypothesis tests can be utilized. These methods enable the comparison of means, variances, or distributions of key performance indicators (KPIs) or output variables of a simulation model and the real system. In highly dynamic systems like CPPS, the observation window plays a critical role in determining the accuracy of the validation results. For instance, in a flexible production line where machines switch between producing different products, the activity times of machines may vary, resulting in different cycle times for different products. Thus, to ensure the accuracy of a data-driven simulation model, the validation run should focus on data collected during the production of a specific product, depending on the required level of detail for the model.

5 CASE STUDY

To demonstrate our framework for operational validation of data-driven simulation models, we conducted a case study using a data-driven reliability model of a CPPS. The manufacturing system used in the case study is a simple flow line consisting of two production cells that sequentially process new production orders scheduled by a MES. We recorded an event log that captures material flow and a state log that captures changes in the operating state of the two production cells (i.e., idle, working, failed, repaired) over a time period of 40 days. Tables 1 and 2 show an extract of the recorded event and state log of the system.

We applied the approach presented in Friederich and Lazarova-Molnar (2022) to extract a reliability model from a subset of the first 10 days of the recorded event and state log. Figure 6 depicts the extracted model using stochastic Petri net as the modeling formalism. In the model, the arrival times of new production orders and the operations of the two production cells are represented as timed transitions. To model cell failures and repairs, each production cell is equipped with a dedicated fault model. When a cell fails, a token in the failed place prevents the operation transition from firing until the cell is repaired. We extracted the material flow logic from the event log using Process Mining techniques. To estimate the repair, failure, and operating distributions for each cell, we analyzed the state changes recorded in the state log. Similarly,

Table 1: Recorded event log.

timestamp	order ID	resource	event
...	...	...	
2023-02-03 16:21:12	154	MES	new order
2023-02-03 16:21:12	154	cell 1	operation
2023-02-03 16:22:34	155	MES	new order
2023-02-03 16:22:56	154	cell 2	operation
2023-02-03 16:22:56	155	cell 1	operation
2023-02-03 16:23:13	154	MES	order completed
2023-02-03 16:23:45	155	Cell 2	operation
2023-02-03 16:24:01	156	MES	new order
...	...	...	...

Table 2: Recorded state log.

timestamp	resource	state
...	...	...
2023-02-12 08:45:13	cell 1	idle
2023-02-12 08:45:13	cell 1	busy
2023-02-12 08:45:34	cell 2	failure
2023-02-12 08:46:24	cell 1	idle
2023-02-12 08:54:45	cell 2	repaired
2023-02-12 08:54:45	cell 2	busy
2023-02-12 08:54:45	cell 1	busy
2023-02-12 08:55:34	cell 1	idle
...	...	...

we estimated the arrival time distribution for new production orders based on the *new order* events in the event log.

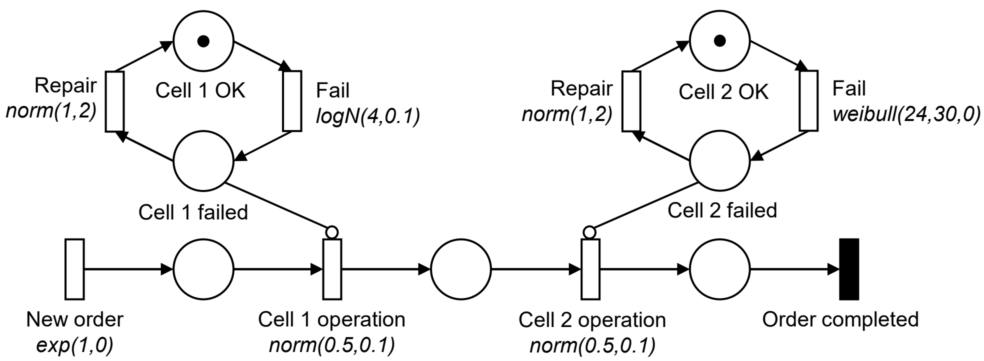

Figure 6: Extracted reliability model of the case study system.

After extracting and validating the initial reliability model, we applied the proposed validation policies at model run-time. We streamed the remaining 30 days of production data recorded in the event and state log to emulate a live production scenario. Our validation KPI was the total system downtime (in hours) in the last 24 hours, which we calculated at the end of each day. Figure 7 displays the results obtained from applying the different validation policies. For condition-based validation, we set a trigger to validate the model if a decline in the KPI was observed over the past three days. For periodic validation, we scheduled the validation to occur every fourth day. For continuous validation, we validated the model each time a new KPI measurement became available. Note, that there was a significant decrease in the KPI between days 10 and 15, as depicted in the Figure.

We conducted 50 simulation replications for each model validation iteration to generate the confidence intervals depicted. When the recorded KPI was outside the confidence interval bounds, we calibrated the reliability model using data from the past 24 hours. As expected, the continuous validation policy provided the best results and kept the reliability model consistently accurate. We also found that the periodic validation policy kept the model reasonably accurate. In contrast, the condition-based validation policy struggled to capture the latest changes in the real system accurately, as shown in Figure 7.

6 DISCUSSION AND OUTLOOK

The increased use of data-driven simulation modeling in CPPS has proven to be a valuable tool for analyzing and optimizing complex production systems. By leveraging the large amounts of data generated by CPPS, data-driven simulation models can provide accurate representations of systems' behaviors and

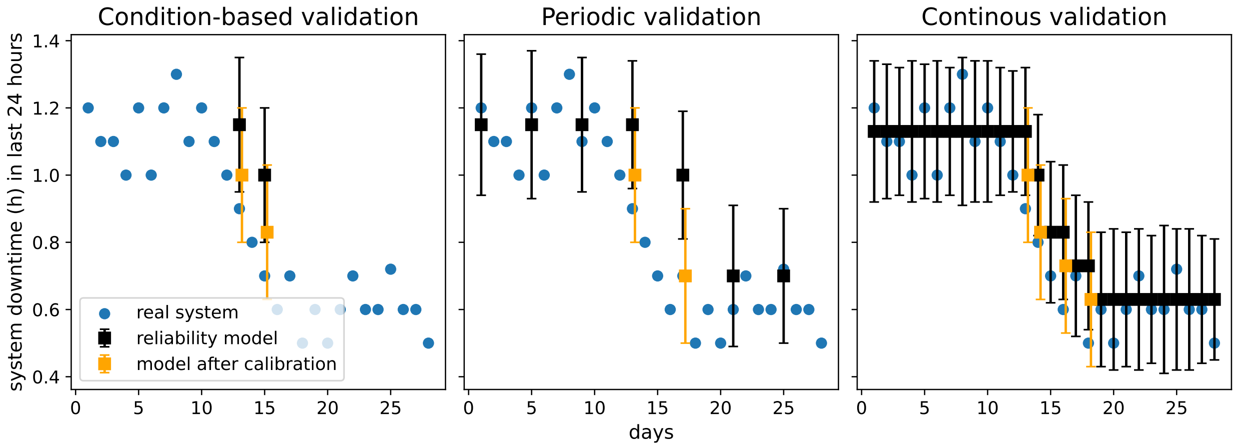

Figure 7: Validation and calibration of the reliability model following the three validation policies.

enable prediction of systems' performance under various operating conditions. This capability allows for the identification of potential bottlenecks, optimization of system parameters, and evaluation of different production scenarios. However, validating these models is still an open challenge that needs to be solved to ensure the accuracy of the models over time.

In this paper, we propose a framework for validation of data-driven DES models of CPPS. Our framework takes advantage of the large amounts of data generated by CPPS to validate simulation models that are generated in a data-driven manner. The framework consists of two phases, validation of the initial model and validation of the model at run-time. Validation of the initial model uses standard validation techniques to determine whether the model can be deployed to support decisions in production. Validation of the model at run-time is conducted using streaming data. In case of an invalid model, the model is calibrated or regenerated using recent data collected from the real system. We propose three validation policies for the ongoing operational validation of data-driven simulation models. Finally, we applied our proposed framework to a case study in reliability assessment, demonstrating the effectiveness of validation at model run-time.

There are several challenges and limitations associated with the validation of data-driven simulation models of CPPS, including:

- Limited availability of data that accurately represents real-world CPPS operation.
- Data quality issues, such as incomplete or inconsistent data that can affect model accuracy.
- Difficulty in selecting appropriate validation KPIs that accurately capture CPPS performance.
- Need for careful selection of appropriate validation policies based on the characteristics of the CPPS and the simulation model.
- Limited generalizability of data-driven simulation models, as they are often specific to a particular CPPS and may not be easily transferable to other systems.
- Need for continuous model calibration and updating to ensure model accuracy over time.
- Limited ability to capture complex, dynamic relationships within CPPS, such as emergent behaviors and feedback loops, using data-driven models alone.

These challenges and limitations need to be addressed in order to build a robust validation framework. In future, we plan to address some of these challenges and limitations and aim to test our framework on other manufacturing systems with various complexity.

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AUTHOR BIOGRAPHIES

JONAS FRIEDERICH is a PhD student at the Mærsk Mc-Kinney Møller Institute, University of Southern Denmark. In 2020, he obtained his Diplom in Information Systems from the Technical University of Dresden, Germany. His research interests cover Modeling and Simulation, Process Mining, Machine Learning and Computer Vision. His email address is jofr@mmmi.sdu.dk.

SANJA LAZAROVA-MOLNAR is a Professor at the Institute of Applied Informatics and Formal Description Methods, Karlsruhe Institute of Technology. She is also a Professor at the University of Southern Denmark. She is a Senior Member of The Institute of Electrical and Electronics Engineers (IEEE), and currently serving as Director-at-Large on the Board of Directors of The Society for Modeling & Simulation International (SCS). Furthermore, she is Chair of IEEE Denmark and Vice-Chair of IEEE Denmark Women in Engineering Affinity Group. Her email address is sanja.lazarova-molnar@kit.edu.