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► **To cite this version:**

Erik Flores-García, Goo-Young Kim, Jinho Yang, Magnus Wiktorsson, Sang Do Noh. Analyzing the Characteristics of Digital Twin and Discrete Event Simulation in Cyber Physical Systems. IFIP International Conference on Advances in Production Management Systems (APMS), Aug 2020, Novi Sad, Serbia. pp.238-244, 10.1007/978-3-030-57997-5\_28 . hal-03635628

**HAL Id: hal-03635628**

**<https://inria.hal.science/hal-03635628>**

Submitted on 30 Jun 2023

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# Analyzing the Characteristics of Digital Twin and Discrete Event Simulation in Cyber Physical Systems

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**Abstract.** Digital Twins (DTs) are described as the next wave in simulation, a critical component of Cyber Physical Systems (CPS), and a key enabler for data-driven decision-making. Yet, the literature presents limited understanding about the characteristics of DTs and their relation to current simulation capabilities. Addressing this problem, the purpose of this study is to analyze the characteristics of DTs and simulation models for CPS in production logistics. This study reviews extant literature on DTs and presents findings from a single case study at a South Korean manufacturing company developing a DT including Discrete Event Simulation (DES). The findings of this study highlight the importance of DES in DTs focusing on increased production logistics performance. The results of this study indicate that the use of DES may promote the development of DTs, but be insufficient in the characterization of DTs for CPS in production logistics.

**Keywords:** Digital Twins, Discrete Event Simulation, Production Logistics.

## 1 Introduction

Digital Twins (DTs) are proposed as the next wave in simulation and optimization technology, extending simulation along the life cycle of products and production systems [1]. Research posits that DTs are essential for Cyber Physical Systems (CPS) and data-driven decision-making [2–3]. The benefits of DTs facilitating data-driven decision-making along the value chain include facilitating product customization, flexibility, operation and monitoring leading to increased performance [4]. However, the literature presents limited understanding about the characteristics of DTs and their relation to current simulation capabilities [2]. This situation is problematic because inadequate understanding of the characteristics of DTs and simulation may translate to increased costs when implementing DTs and limited benefits to key stakeholders along the value chain [5]. Addressing this problem, the purpose of this study is to analyze the characteristics of DTs and simulation models for CPS in production logistics. This study presents findings from a case study at a manufacturing company developing a Discrete Event Simulation (DES) model in a context of DTs for CPS. These findings of this study contribute to existing understanding by describing the limitations and coincidences between

the characteristics of DTs and DES for CPS in production logistics which may be essential for increased performance.

## 2 Frame of Reference

### 2.1 *Characterizing Digital Twins in Cyber Physical Systems*

The literature describes CPS as the integrations of computation and physical processes [5]. CPS and DTs share common principles including the interconnection and interoperability of a physical shop floor and corresponding cybershop floor [6]. However, CPS and DTs refer to distinct constructs with unique compositions, cyber-physical mapping, control and core elements [3]. For example, data and models are the core elements of DTs, which differ from the core elements of CPS (e.g. sensors and actuators). Data and models in DT play an important role helping interpret and predict the behavior of the physical world based on data. Currently, literature focused on DTs supporting data-driven decision-making for production logistics in CPS follows three lines of inquiry: Firstly, studies providing a general understanding of DTs [7]. Secondly, conceptual studies proposing the models, operating mechanisms, or architectures for DTs [8]. Thirdly, studies exploring the use of DTs in practical applications [9]. The study of DTs is a dynamic field. One of the more recent reviews [10] presents the characteristics of DTs shown in Table 1.

**Table 1.** Characteristics of Digital Twins in Cyber Physical Systems based on [10].

Characteristic	Description
Networking Devices	Physical or cloud-based communication devices for data exchange
Synchronization	Real-time convergence of physical systems and its digital counterpart
Multi-Communication Environment	Communication processes between production systems, environment, domain experts and DTs for interaction and operation
Data Storage	Acquiring historic static data of products, processes, production planning and ontologies for data comprehension
Data Analysis	(De)coding and analyzing data for integrating multiple data sources
Information Selection	Identifying, extracting and storing useful information
Pattern Identification	Identifying changes and trends by analyzing data
Self-Adjustment	Self-adaptation and parametrization capabilities following production system changes during its lifecycle
Predictive Analytics	Predicting future status and important changes of production systems
Prescriptive Analytics	Specifying high-value alternatives given objectives, requirements, and constraints
Optimization	Achieving best outcomes while addressing data uncertainty
Closed Loop Feedback	Feedback to production systems and to other DTs, using interfaces to access the computed information
Simulation	Representing current status and what-if scenarios

## 2.2 *Characterizing Discrete Event Simulation in Production Logistics*

DES is one of the most commonly used techniques for understanding the dynamics of production logistics [11]. DES involves the experimentation of a simplified imitation of a production system as it progresses through time, for the purpose of understanding and/or improving that system [12]. Recent publications reviewing DT literature underscore the importance of DES in data-driven decision-making [8]. The literature presents alternative processes for developing DES models, but largely coincide on the activities of structured process [13]. Beginning with a clear problem definition, DES in production logistics frequently focus on operational performance including work in progress, lead-time, throughput, or utilization of resources. In addition, DES involves activities specifying the useful information according to the purpose of a model and acquiring data from multiple sources (e.g. ERP systems and domain experts). Frequently, DES depends on multiple sources of communication, data storage systems, and statistical analysis to synthesize and comprehend the interrelation of variables and outputs. Increasingly, DES research emphasizes the need for identifying a best alternative (optimization), and increasing understanding of results to non-experts (for example through 3D visualization).

## 3 **Method**

To meet its purpose, this research is based on a single case study. This study adopts case study research because of its appropriateness for investigating novel scientific inquiries with scant theoretical background [13]; namely, the need for empirical insight about DTs for CPS in production logistics [3]. Case selection followed from the correspondence between four DT implementation features [8] and the attributes of DTs at a manufacturing companies. These features included an explicit description of acquired dataset and acquisition protocols, specification of simulation model objectives, cloud usage, and control of the real system from the DT. Data collection occurred between July 2019 and February 2020 including participant observation, company documents, and DES models. Data analysis relied on a comparison between identified characteristics of DTs and DES described in the frame of reference and collected data.

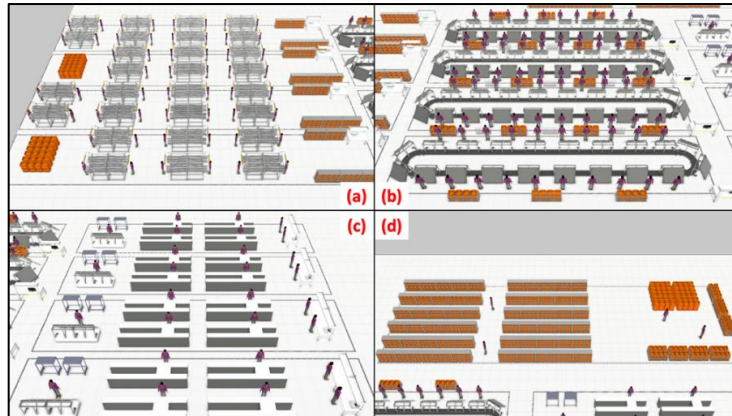
## 4 **Empirical Results**

The manufacturing company is a global producer of wire harnesses and electronic components for the automotive industry that undertook the development of a DT based on CPS principles. The purpose of the DT involved improving performance in the areas of production logistic, quality, and production control based on data-driven decision-making. The development of the DT focused on the assembly process of wire harness products including sub-assembly, main assembly, inspection, and product buffer areas.

Acquired data sets for the DT included CAD files for factory layout, bills of materials and processes, production cycle times and disturbances, and real time data of resources (machines, assembly stations, forklifts, and buffers). Data was acquired via

systems for Enterprise Resource Planning (ERP), Manufacturing Execution (MES), and Real Time Location (RTLS) systems. The DT enabled cloud services such as facilities/configuration engineering service, smart quality prediction service, production control service and production logistics management service.

The DT included quality predictive model, production optimal control model and DES model. The purpose of the quality model was that of identifying and prescribing actions for correcting quality problems. The purpose of the production control model included determining the optimal production process based on production environmental conditions for improving production throughput. DES included a 3D visualization of material flow with the purpose of predicting resource utilization and production throughput. Managers and operators performed control of the real life system based on the visualization of the system behavior and guidelines presented through user interfaces included in the DT. Figure 1 presents the DES model visualization of sub-assembly, main assembly, inspection, and product buffer included in the DT.



**Fig. 1.** DES model visualization of (a) sub-assembly, (b) main-assembly, (c) inspection, and (d) product buffer included in the DT.

The DES presented a simplified imitation of the production process. Managers identified parameters including utilization rate, idle rate, poor quality rate, production throughput, and buffer levels for calculating production logistics performance. Production staff examined information, selecting or excluding data, required as input data. A multi-communicational environment was essential for DES. For example, historical data stored in ERP and MES systems and the outputs of the production control and quality models provided inputs to and facilitated the verification and validation of the DES model. In addition, the knowledge of domain experts was crucial for modeling the production process. DES produced two types of results. First, DES predicted future status of production logistics performance based on demand and operational prognosis. What-if scenarios including changes in demand or resources enabled this type of predictive analysis. Second, DES utilized optimization algorithms linking various design variables (e.g. buffer size or number of forklifts) to the production logistics perfor-

mance. Adopting optimization in DES helped identify and prescribe high-value alternatives and their trade-offs including for example minimum buffer sizes and production lead-time and maximum production throughput. Feedback from DES to the performance of the production system depended on the interpretation of production staff and their corrective actions based on quantitative data analysis and 3D visualization.

## 5 Analysis

The purpose of this study is to analyze the characteristics of DTs and simulation models for CPS in production logistics. The findings of this study suggest that the use of DES may promote the development of DTs in CPS for production logistics. This study reveals that eight characteristics of DTs were facilitated by DES in production logistics including: multi-communication environments, data storage, data analysis, information selection, predictive and prescribe analytics, optimization and closed loop feedback shown in Table 2. This finding coincides with current research showing that manufacturing companies benefit from the prescriptive analysis of DES when securing multi-communication, data storage, data analysis, and information selection competences [14]. Additionally, publications report on advanced in optimization, prescriptive analytics, and close loop feedback in DES [8]. These findings are encouraging for companies that currently embrace DES in the analysis of production logistics. These companies may hold a critical advantage for understanding the benefits of DTs and data-driven decision-making including: processes and technologies increasing data quality, or data analytic capabilities essential for increased production logistics performance.

Data shows that a DT is not a collection of self-standing technologies or simulation models. In agreement with previous studies [15], the findings suggest that interconnection of characteristics were critical to meet the DTs goal of increasing production logistics performance. For example, case data revealed that achieving quality prediction and production optimization for smart automated-manual production required fulfilling 14 DT characteristics described in literature and shown in Table 2. This finding suggest that the benefits of DTs, including data-driven decision-making for production logistics, depend on fulfilling individual DT characteristics and establishing a link between these. This finding underscore the importance of identifying the elements, processes and operating mechanisms and their interrelation required for fulfilling the characteristics of DTs in CPS for production logistics [14].

The findings of this study suggest that DES is supportive but not sufficient for developing a DT in production logistics. DTs include a complex human, machine, material, and environment interaction throughout the lifecycle of a production system. Achieving this interaction requires the coordination and linkage between relevant data and models to fulfill the purpose of a DT [3]. Empirical data presented in Table 2 reveal the absence of networking devices, synchronization, pattern identification, and self-adjustment in the DES model. The absence of these four characteristics do not constitute a failure to the success of a DES project, but do limit the characteristics of DTs in CPS aimed at improving production logistics performance [8]. In addition, data suggests that DES may facilitate one, or several, characteristic of DTs, but the use of DES brings no

assurance that DT characteristics will be fulfilled. For example, information selection which is both a characteristic of DTs and DES found in case data as shown in Table 2. In DES, information selection is an iterative activity traditionally entrusted to simulation specialists and domain experts [12]. However, DTs require extracting useful information in a manner that reduces cost storage and computational processing but does not compromise the volume of data and dynamic services [6]. This finding is important because it underscores the need for increased understanding of shared characteristics between DTs and DES, and the extent of their fulfillment towards a common goal.

**Table 2.** Case analysis of DTs and DES characteristics for CPS in production logistics

Observed DT characteristics	Observed DES characteristics
Networking Devices	x
Synchronization	x
Multi-Communication Environment	x ERP, EMS, simulation models, domain expert knowledge
Data Storage	x Historical data for DES model inputs
Data Analysis	x Production logistics resource utilization, quality rate, production throughput, and buffer levels
Information Selection	x Non-automatic identification of useful information
Pattern Identification	x
Self-Adjustment	
Predictive Analytics	x What-if scenarios with changing production demand and resources
Prescriptive Analytics	x Identifying high-value alternatives including minimum buffer size and resource quantity and maximum production throughput
Optimization	x Linking design variables to production logistics performance
Closed Loop Feedback	x Staff-dependent, based on DES output and 3D visualization

## 6 Conclusions

This study analyzed the characteristics of DTs and simulation models for CPS in production logistics. This study indicated that the use of DES may promote the development of DTs, but may be insufficient towards their characterization. Future research could verify the findings of this study with additional cases, and understand the precedence of DT characteristics and their alignment to current DES capabilities at manufacturing companies.

## Acknowledgement

This research was supported by the Ministry of Trade, Industry and Energy (MOTIE) in South Korean and the Korea Institute for Advancement of Technology (KIAT) through the International Cooperative R&D program [P0009839] and the Fostering Global Talents for Innovative Growth Program [P0008746]. In addition, this study is part of the Cyber Physical Assembly and Logistics Systems in Global Supply Chains (C-PALS) project funded by Eureka SMART and Vinnova.

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