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CHALLENGES OF DISCRETE EVENT SIMULATION IN THE EARLY STAGES OF PRODUCTION SYSTEM DESIGN

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This study analyzes the challenges of applying discrete event simulation in the early stages of production system design. Highlighting the implications of new production processes and technologies leading to improved competitiveness, this study provides novel contributions to the understanding of discrete event simulation based on three case studies of the transformation of legacy production systems in the heavy vehicle industry. The findings of this study show that equivocal or ambiguous understanding about new production processes or technologies, and uncertainty about necessary data input and the interrelation of subsystems in production, are critical in addressing discrete event simulation-related challenges. These findings highlight the need for an established process to manage assumptions and simplifications during the design, development, and deployment of discrete event simulation models as a countermeasure against uncertainties, improving manufacturing system design and practice.

Keywords: production system design; discrete event simulation; case study; innovation; uncertainty; equivocality

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1. INTRODUCTION

Recent publications have highlighted the importance of embracing new production processes and technologies as a key to manufacturing competitiveness (Spring et al. 2017). According to Giffi *et al.* (2016), this ability is essential for manufacturing companies to meet current demands including digitalization, increased flexibility, product customization, and sustainability requirements. Modeling and simulation are fundamental in the analysis of new production processes and technologies. Accordingly, a great deal of production system design literature emphasizes the importance of discrete event simulation (DES) (Fowler et al. 2015), which consists of modeling a series of events as state changes occur at discrete points in time (Law 2015), and can support decision making because of its ability to dynamically evaluate changes (Aickelin et al. 2018). Consequently, the benefits of DES include increased system knowledge and understanding, readily comprehensible visualization of results, and improved communication of decisions about a production system between different functions within a firm (Kasie et al. 2017).

Despite these benefits, the use of DES in the design of production systems, although increasing, is still sporadic (Negahban and Smith 2014). Accordingly, researchers have expended considerable efforts to identify the challenges of DES in the design of production systems (Fowler and Rose 2004; Wang and Chatwin 2005; Mönch et al. 2011). These efforts have led to increased understanding, but many unknowns remain. In particular, few studies to date have investigated the challenges of DES in the early stages of production system design. This limitation is understandable because of the contextual circumstances in these early stages, such as the lack of information, which compromises the validity of generated models and the credibility of the results (Oberkampf et al. 2002). However, increased interest in the use of DES in the early stages of production system design to enable the introduction of new production processes or technologies calls for a revision of the current body of knowledge (Javahernia and Sunmola 2017). Addressing this knowledge gap is essential for two major reasons: first, early insight into new elements in a production system are necessary to identify potential problems that may lead to failure; and second, obtaining knowledge about DES challenges in the early stages of design may be fundamental in streamlining simulation-based production systems engineering, which is necessary for the development of future production systems (Schluse et al. 2018).

Therefore, the objective of this study is to analyze the challenges of applying DES in the early stages of production system design. This objective is pursued in the context of the introduction of new processes or technologies in production systems. Accordingly, this study addresses the following research question: “What DES challenges are identified in the evaluation of new production processes or technologies in the early stages of production system design?” This interest in new production processes and technologies led us to consider three real-time case studies performed at a leading manufacturer of heavy vehicles who transformed its legacy production systems by introducing multi-product assembly lines. The results of this study reveal how two of these cases succeed in designing, developing, and deploying DES models in the early stages of production system design and the other did not. This study contributes to the body of existing knowledge by synthesizing empirical findings and literature focused on DES challenges, providing novel contributions to the current understanding of DES applications. In short, the findings of this study reveal the causes and impacts of equivocal or ambiguous understanding of new production processes or technologies in relation to challenges in DES application. Additionally, the results of this study demonstrate the impact of uncertainty in the development of DES models that can affect not only the input data (as has been previously disclosed), but also the interrelation of subsystems during production. This study also demonstrates the need for a process to manage assumptions and simplifications as countermeasure against uncertainties in DES models. Finally, this study identifies the need for a structured process for DES design, development, and deployment to resolve the lack of DES knowledge in manufacturing organizations. The results of this study are essential because they suggest that DES use in the early stages of production system design can enable the introduction of new production processes or technologies. Yet, in order to do so, practitioners must first be aware of additional DES challenges. The remainder of this paper is accordingly structured as follows. First, the research background from the literature is presented. Then the research method for analyzing the case studies is described. Empirical findings are then discussed and later analyzed, and finally, the conclusions of this study are drawn.

2. RESEARCH BACKGROUND

To address its research question, this study analyzes current understanding about the use of DES in the design of production systems. In addition, this study considers previously identified challenges of using DES in production system design, which have typically been concerned with more detailed and later production system design stages than the early stages considered in this study.

2.1 Production System Design and DES

Production system design is defined as the conception and planning of the overall set of elements and events constituting a production system, together with rules for their relationships in space and time (CIRP 1990). Indeed, the design of a production system is not solely constituted by the definition of the elements within it, but also by the processes that characterize the system (Bellgran and Säfsten 2010). Although trial and error remain the most frequently employed method to design production systems at manufacturing companies, the research literature strongly suggests the use of a more structured process (Rösiö and Bruch 2018).

A process-based perspective in the design of a production system refers to both the series of actions that lead to the conception of the system and the coordination of work activities required during production system design (Gu et al. 2001). Designing a production system involves a continuum of stages that include initiation by defining a problem, a pre-study analyzing the background of the problem and formulating objectives, conceptual design and evaluation of design alternatives, and definition and selection of a detailed design all of which are illustrated along the vertical axis of Figure 1. The ultimate objective of production system design is to develop and provide adequate manufacturing operations for the value-added product realization process, as indicated along the horizontal axis at the bottom of Figure 1. Examples of production system design are given by Bellgran and Säfsten (2010), Bruch and Bellgran (2013), and Rösiö and Bruch (2018), among others.

Discrete event simulation is one tool that can be used during the various stages of the production system design. In a DES model, the subject system is modeled as a series of events (Law 2015), and changes to the modeled system are evaluated dynamically (Aickelin et al. 2018). The use of DES can be separated into the three process phases of design, development, and deployment (Fowler and Rose 2004), as illustrated by the steps linked to the production system design shown in Figure 1. In the early stages of production system design, the DES design phase consists of the development of a specification that includes project customers, goals and deliverables, the definition of a project team and plan for model development, and conceptual models. The DES development phase consists of the establishment of a number of model development options, including non-simulation alternatives, selecting the identifying entities and activities, as well as determining and collecting input data and the methods to be used for model verification and validation. Finally, the DES deployment phase consists of activities including experimentation, simulation output analysis, data maintenance and model integration, as well as presentation and use of simulation results for the intended customer base of the project.

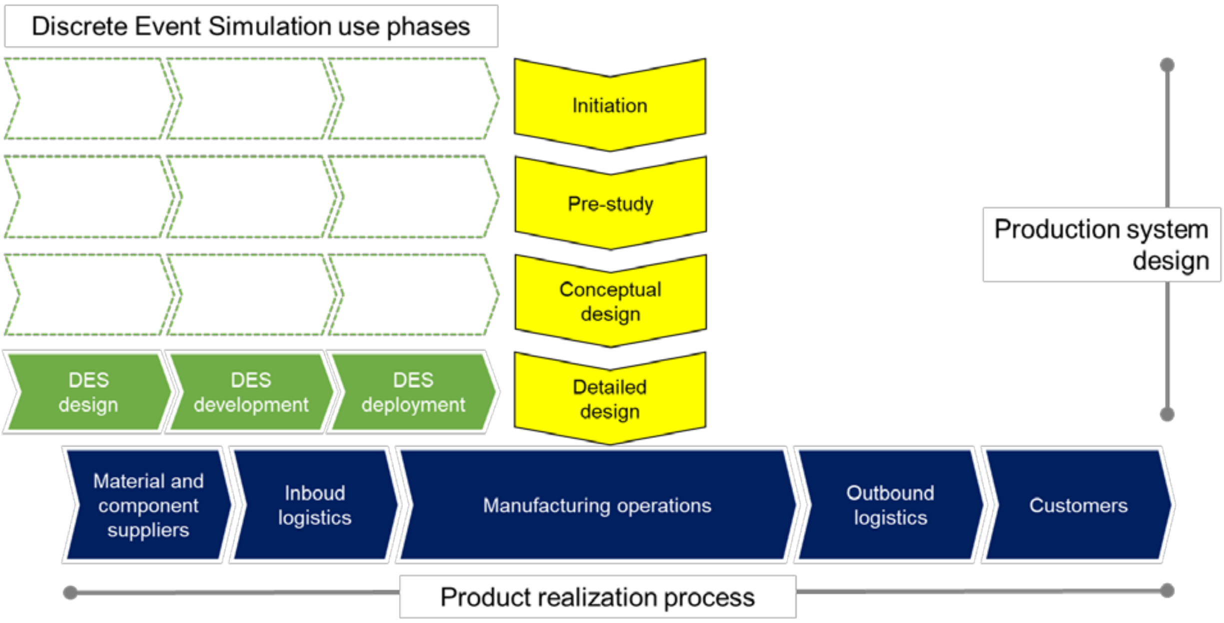

Figure 1. Relationships between DES use phases, production system design, and the product realization process

2.2 Challenges in DES Use

Although DES is the most popularly applied technique in the design and operation of production systems, the full potential benefits of DES for manufacturing companies remain to be realized (Jahangirian et al. 2010; Fordyce et al. 2015). To address this issue, considerable research has been conducted in effort to pinpoint the challenges of DES use in production system design (Fowler and Rose 2004; Wang and Chatwin 2005; Heilala et al. 2010; Fischbein and Yellig 2011; Mönch et al. 2011). Table 1 classifies the challenges of DES in production system design based on Fowler and Rose (2004). This table includes three additional challenges not present in Fowler and Rose (2004): the development of simulation and production system knowledge, software diversity and lack of standardization (Wang and Chatwin 2005), and trade-off considerations and non-intuitive decisions (Mönch et al. 2011).

Literature describing the challenges of DES has preponderantly centered on difficulties of developing DES models. These difficulties stem from the fact that a single DES model is often incapable of supporting all production system design decisions and that detailed questions about the performance of a production system will arise during the design process (Fowler and Rose 2004). Additionally, the difficulty of DES modelling arises from the need to build trustworthy DES models for factory management in order to commit to production system design decisions (Fischbein and Yellig 2011). This situation underscores the criticality of the issues that arise in determining which elements of a production system to represent in order to provide a successful implementation of the DES model to support production system design decisions (Wang and Chatwin 2005).

Relevant literature based on specific manufacturing contexts provides different perspectives on the challenges of using DES in the design of production systems. Fowler and Rose (2004) addressed the challenges of DES use for decision support in current and future production systems. Heilala *et al.* (2010) analyzed the support of production system design and operations decisions based on DES use. Wang and Chatwin (2005) and Fischbein and Yellig (2011) described the key issues in successful DES model implementation and the difficulties in supporting decisions for production system evaluation, respectively. Finally, Mönch *et al.* (2011) provided an analysis of a production system grounded in a logistic point of view.

Recent findings indicate that DES may be useful in the early stages of production system design, particularly when introducing new production processes or technologies (Javahernia and Sunmola 2017). In these early stages, manufacturing companies could benefit from the use of DES to examine, test, and analyze new production processes or technologies, exploit opportunities, avoid costly mistakes, and otherwise improve production system design (Montoya-Weiss and O'Driscoll 2000). However, the early stages of production system design are frequently hampered by two outstanding issues that become more critical when introducing new production processes or technologies: the existence of multiple or conflicting interpretations about what and how a new production processes or technology will achieve its purpose, referred to as equivocality (Eriksson et al. 2016), and the difference between existing and required information about an activity, referred to as uncertainty (Rönnberg et al. 2016). However, extant literature presents only a limited understanding of these challenges from a DES perspective.

Table 1: Challenges when using DES in production system design at manufacturing companies, adapted from Fowler and Rose (2004), Wang and Chatwin (2005), and Mönch *et al.* (2011).

DES model phase	Challenge
Design	• Decision support restricted by question-specific model formulation. What is the problem and how is it addressed? • Representation of production system dynamics and complexity • Validity of model detail level • Simplification of production system complexity and factor interdependence • Non-uniform abstraction level for model simplification • Modelling combinatorial explosion of options in a production process • Incomplete and conflicting production system knowledge • Development of simulation and production system knowledge • Software diversity and lack of standardization
Development	• Model verification and validation • Model development time • Input data collection and analysis • Input data availability and quality
Deployment	• Model interoperability and information sharing between models • Industry acceptance of DES • Communication of results for effective decision making • Simulation model maintenance • Consideration of trade-offs and non-intuitive decisions • High cost and low reusability of models

3. METHOD

To meet its objective, this study employed a case study method. This choice was informed by three criteria. First, production system design is a complex process consisting of multiple activities occurring over time, and case studies are well-suited to study such phenomena as they develop (Yin 2013). Second, case studies are well-suited to investigate phenomena in their natural setting and without control over behavioral events (Eisenhardt 1989). This was important because we expected DES challenges to arise naturally as part of the idiosyncrasies of production system design. Third, the choice of method was considered important when investigating the connection between the subject of study and the circumstances under which a study is conducted (Voss et al. 2002), specifically the relationships between the DES challenges and the early stages of production system design. The selection of cases was based on two criteria: production system design projects focusing on the transformation of legacy systems by introducing new production processes or technologies, and projects planning the use of DES. After the selection of cases, this study focused on a comparison of the identified challenges from the three selected cases with challenges identified in previous research on the use of DES in later stages is illustrated in Figure 2.

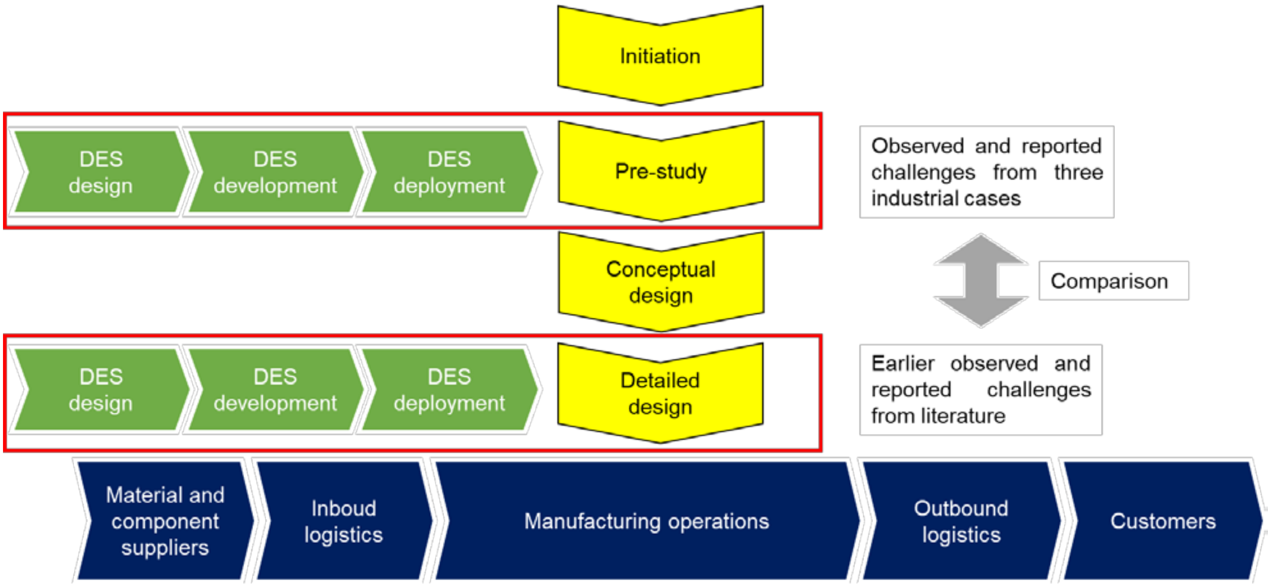

Figure 2. Comparison of challenges in early phases, identified in the three subject cases, with previously reported challenges in later stages of production system development.

This study followed and collected data from the three subject cases between 2014 and 2016. Case 1 was followed for 12 months, Case 2 for 14 months, and Case 3 for 5 months. Data collected from each case included interviews, participant observations, and company documents including DES models. Five interviews were conducted for each case and interviewees were selected on the basis of their participation in each production system design project. In this study, interviews were conducted with a manufacturing research manager, two logistics developers, two consultants, six manufacturing engineers, two project managers, a manufacturing engineering manager, and one production engineering manager. Interviewees described the reasons behind the start of production system design, the activities included in the design of the production system, and the conclusions and consequences of the designed production system. Interviews lasted between 38 and 120 minutes and were recorded and transcribed. Interviewees were individually contacted at a later date and shown the transcribed texts for approval. Data collected through participant observations (Adler and Adler 1994) included weekly project meetings, workshops, informal conversations, and shop floor visits. Company documents related to each production system design project were analyzed, including five DES models (A–E) developed in Case 1, and two DES models (G and H) developed in Case 3. All DES models were developed in ExtendSim 9.1 with visual representation using Automation Study. The purpose of collecting these diverse data was to deepen understanding of the consequences of introducing new production processes or technologies in the early phases of production system design.

Data analysis followed three streams of concurrent activities based on Miles et al. (2013): data condensation, data display, and conclusion drawing. Each case was first treated individually as a separate study. Then a cross-case analysis was employed to gain a comprehensive understanding across cases (Yin 2013). The analysis was based on the previously identified challenges in using DES in manufacturing application by Fowler and Rose (2004), Wang and Chatwin (2005), and Mönch *et al.* (2011), as summarized in Table 1. Conclusions were then made based on a comparison of previous findings with the results of the cross-case analysis.

4. EMPIRICAL RESULTS

This section presents the empirical results from the three analyzed cases including the design, development, and deployment of DES models in the early stages of production system design. The findings for each case are organized into three sections: background information describing the three cases and their objectives in using DES models; the manner in which DES models supported decision making in the early stages of production system design; and reports on the challenges of DES use in the early stages of production system design.

4.1 Background

This study followed three cases (Cases 1, 2, and 3) at a leading heavy vehicle manufacturer involving the design of multi-product assembly systems. Case 1 focused on the production of heavy vehicles, Case 2 on vehicle transmissions, and Case 3 on vehicle cabins. These cases were developed at three different manufacturing sites and are described in Table 2. The manufacture of heavy vehicles involves producing customized products designed to operate under extreme conditions. Leadership in this industrial segment is defined by specialized product families targeting solutions tailored to specific market requirements. Traditionally, heavy vehicle manufacturing systems are characterized by the manual assembly of products. Heavy vehicles are typically produced in assembly lines that specialize in the production of one product family and operate independently. In this industrial segment, production systems are capital intensive and planned production volumes do not exceed a thousand products a year. These characteristics, coupled with the large size of the products, result in spacious and underutilized production systems that threaten the competitiveness of heavy vehicle manufacturers. To address this issue, the subject manufacturing company launched a global effort focused on the introduction of new production processes and technologies to transform existing legacy production systems into multi-product assembly systems.

The objectives of these transformations are best explained by the manufacturing research manager in Case 1: "*There was a vision to utilize our production system in a more efficient way. We believed it was important to provide a better utilization of our industrial footprint, decreasing delivery time to customers with standardized production of products, and increasing the flexibility of production systems*." Senior management identified the lack of knowledge in the development of multi-product assembly as a crucial problem. Accordingly, the manufacturing company spent considerable resources, acted preemptively, and front-loaded activities into the early design stage of the production systems. A central aspect of this work included the use of DES to support decision making, test ideas, evaluate the effects of decisions, and increase understanding of multi-product assembly processes.

Table 2. Description of Cases 1, 2, and 3

	Case 1	Case 2	Case 3
Product	Heavy vehicles	Vehicle transmissions	Vehicle cabins
Plant location	North America	Latin America	Sweden
Product families	5	5	3
Employees on site	900	780	350
Design team members	Project manager Manufacturing research manager Site manager Production engineers from six sites Logistics developers Product design managers R&D staff Consultants Simulation specialists	Project manager Production managers Site manager Production engineers from five sites Product design engineers Logistics developers R&D staff Consultants Simulation specialists	Project manager Manufacturing research manager Site manager Production engineer manager Production engineers from one site Product design engineers Logistics developers R&D staff Consultants Simulation specialists
DES models developed	5	0	2

4.2 Supporting the Early Phases of Production System Design using DES

Case 1 included the development of five DES models (Models A, B, C, D, and E), described in Table 3, that represented a production system for the multi-product assembly of five families of heavy vehicle products. These models supported decision making in two ways. First, the DES models summarized loose discussions when limited information was available. To this extent, Model A provided a visual representation of the production process for Case 1 and facilitated the selection of a layout from five possible alternatives. An image of Model A is presented in Figure 1. Second, the DES models quantitatively evaluated the performance of the production system of Case 1 throughout the early stages of design. This evaluation was conducted in Models B to E. Figure 2 shows an image of Model D, which evaluated the operational performance of the designed production system. Interview data revealed that these models were considered crucial to the success of Case 1, as in the following statement by one of the production engineers of Case 1, "*without simulation, we could not evaluate whether the designed production system met the operational objectives of management. Had we not used (discrete event) simulation, we would have had to rely on best guesses and our gut feeling.*" Supported by these DES models, the design team identified problems in the early design stages of the production system, proposed solutions, and evaluated their consequences.

Table 3. Description of DES models developed in the early stages of production system design of Case 1

	Model objective	Input data	Evaluation parameters	Model outcome
Model A	Visual representation of two alternative production processes	Takt time, assembly stations, product demand	Qualitative-based discussion within design team	Selecting a production process and developing a layout
Model B	Evaluation of designed production system	Yearly product demand, production process, cycle times	Production throughput, lead time, and utilization of assembly stations	Identifying and proposing solutions to production process bottlenecks
Model C	Evaluation of designed production system based on data from selected site	Yearly product demand, production process, cycle times, disturbances	Production throughput, lead time, and utilization of assembly stations	Identifying and proposing solutions to production process bottlenecks
Model D	Evaluation of assembly line staffing alternatives	Yearly product demand, production process, cycle times, disturbances, assembly staff assignment rules	Production throughput, lead time, utilization of assembly stations and assembly staff	Establishing rules for assignment of assembly staff and need for additional improvements to achieve operational objectives
Model E	Evaluating effects of four production process enablers	Yearly product demand, production process, cycle times, disturbances, assembly staff assignment rules, logistics, common assembly tools, instructions, autonomous vehicles in assembly	Production throughput, lead time, utilization of assembly stations and assembly staff	Early design finalized and ready for continued on site testing

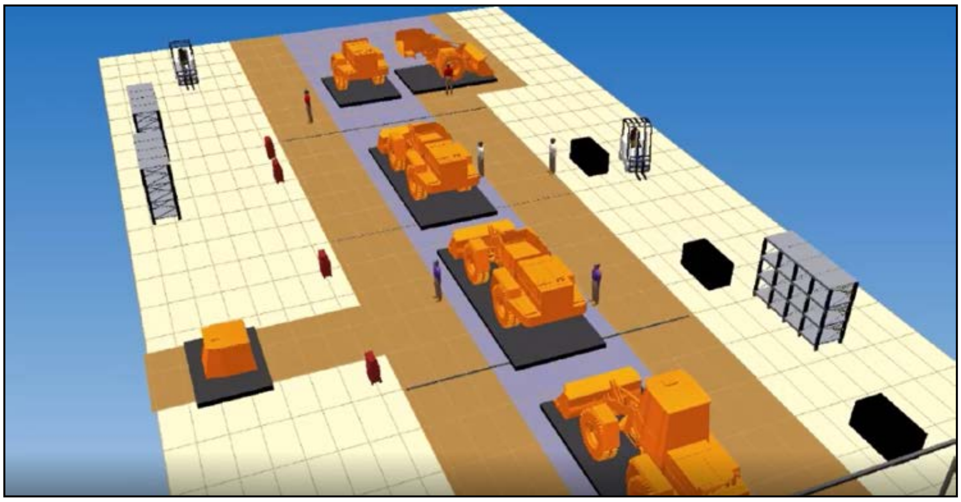

Figure 3. Visual representation of the production process in Model A of Case 1

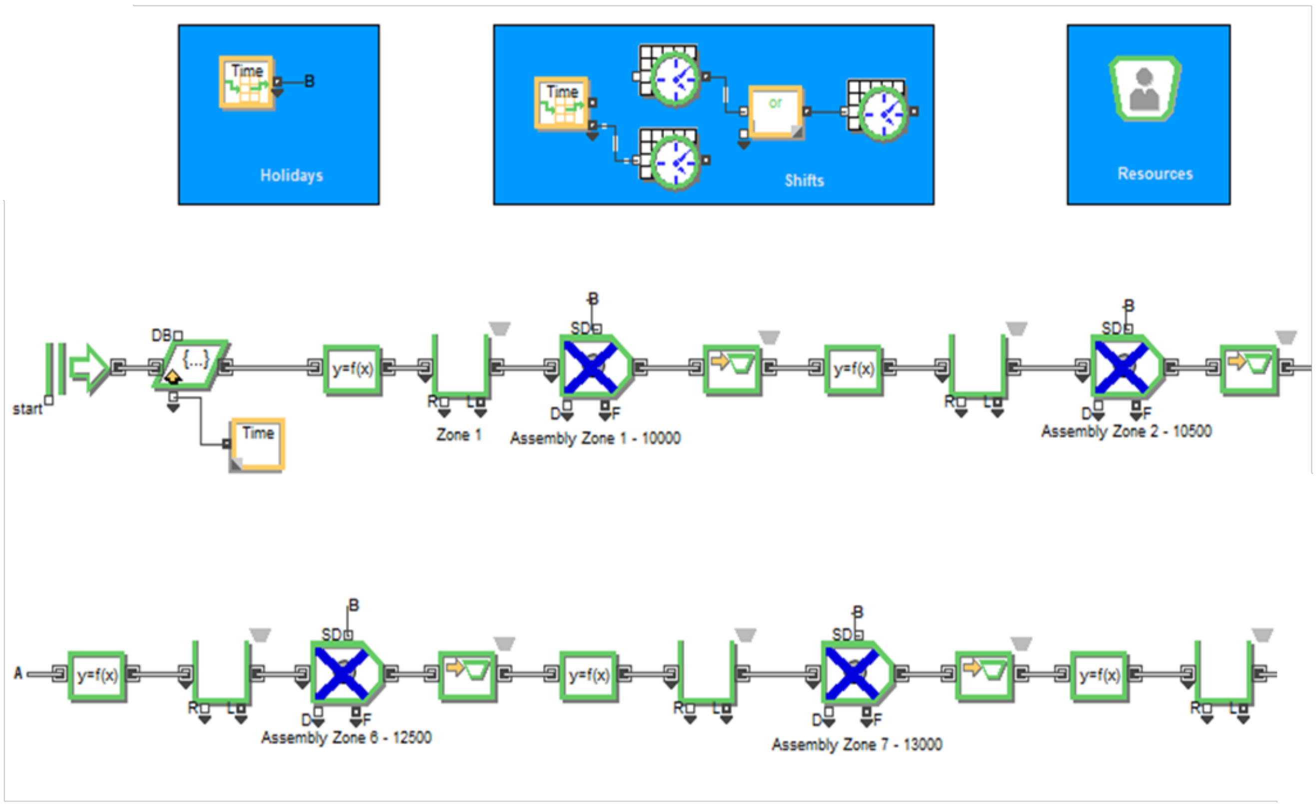

Figure 4. Evaluation of designed heavy vehicle production system in Model D for Case 1

Case 2 failed to successfully design, develop, and deploy a DES model (Model F) due to aspects of its project management structure detailed later in this paper. Model F was intended to quantitatively evaluate the performance of a production system designed to produce five families of vehicle transmissions. This model was necessary because the design team could not dynamically evaluate whether the designed production system achieved the operational objectives set by senior management. This dynamic evaluation was important for two reasons. First, the demand of vehicle transmissions varied over the course of a year to the point that additional resources were sometimes necessary in the production process. Second, the design team could not judge the consequences of changes in one part of the production system and its effects across other sub systems or processes using tools other than DES.

Case 3 included the development of two DES models of a system designed to produce three families of vehicle cabins (Model G and H). Model G represented the existing production system and Model H represented the designed production system. Descriptions of Models G and H developed in Case 3 are presented in Table 3. These two models together supported decision making in the early stages of production system design by comparing the operational performance of the existing and designed production systems. The models were critical in convincing senior managers that a multi-product assembly system could accommodate an increase in product demand and meet operational performance objectives. Additionally, the design team of Case 3 experimented with "what if" scenarios that were likely to occur in the near future, such as introducing new products and changes in product demand, which could not be evaluated dynamically with any other available tools. Figure 5 shows an image of Model G, which was used to compare the operational performance of an existing vehicle cabin production system to that of the newly designed multi-product assembly production system.

Table 4. Description of DES models developed in the early design of Case 3

	Model objective	Input data	Evaluation parameters	Model outcome
Model G	Analyze current vehicle cabin production system in three independent assembly lines	Yearly product demand, production process, cycle times, disturbances	Production throughput, lead time, utilization of assembly staff	Quantitative comparison between current and future production systems. Selection of a multi-product assembly system
Model H	Analyze future vehicle cabin production system in a multi-product assembly line	Yearly product demand, production process, cycle times, disturbances, and one additional product	Production throughput, lead time, utilization of assembly staff	

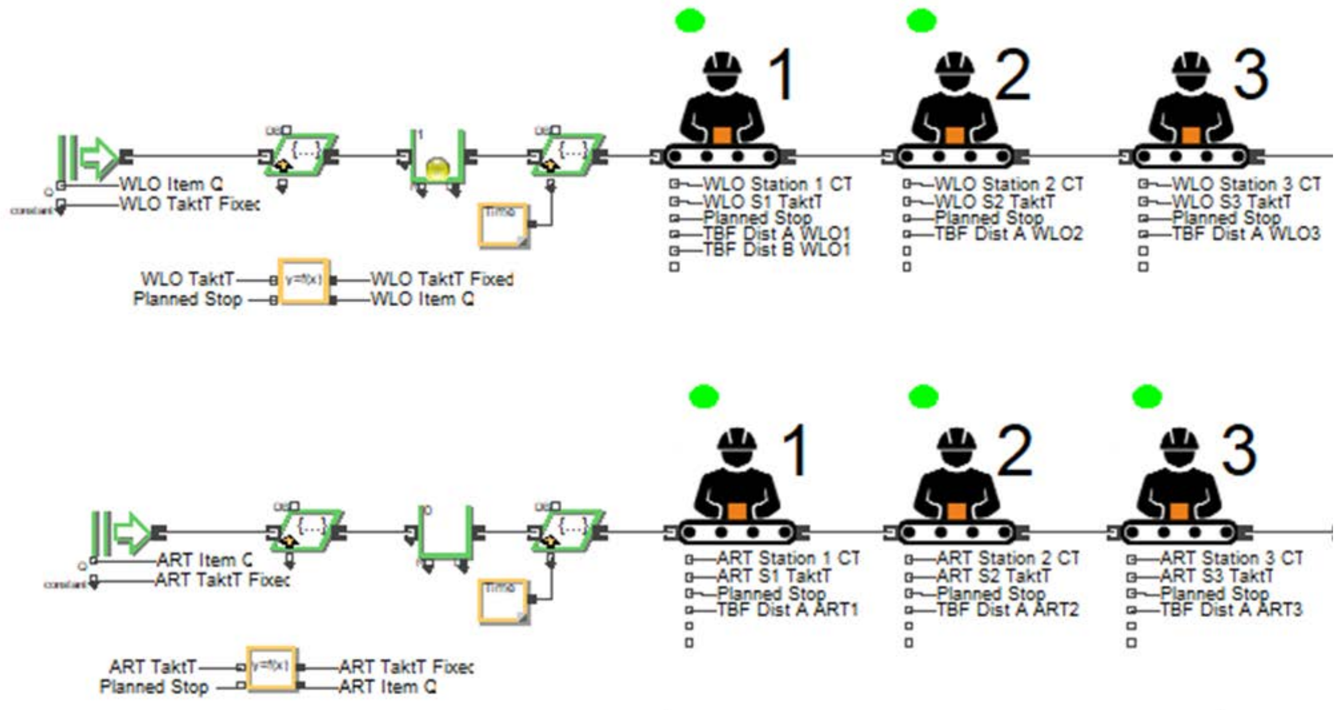

Figure 5. Evaluation of current vehicle cabin production system in Model G for Case 3

4.4 Challenges of DES Use

The empirical data reveal several challenges when using DES to support decision making in the early stages of production system design. Some of these challenges were common to all cases, while others were case specific. The observed challenges of DES use can be classified into the previously defined model design, development, and deployment phases.

4.4.1 DES Model Design Phase

The DES model design phase includes activities that define the DES project team, model goals, plan for model development, and conceptual models. In the case studies, the definition of a DES project team was based on the availability of resources. The project managers of Cases 1 and 2 had access to only one simulation specialist each. Therefore, the design of DES models required the joint effort of all participants in the design teams. On the other hand, Case 3 included a DES project team of three simulation specialists who supported the early stages of production system design. Project managers in all cases held responsibility for enforcing the use of DES in addition to supervising the design of the production systems. However, the project manager of Case 1 was the only project manager with DES experience.

Two perspectives existed in relation to the planning of DES models during the early stages of production system design. In Cases 1 and 3, DES models were planned and developed in the context of a structured production system design process, and the project managers were supportive of the use of DES. In these cases, the production system design processes indicated points in time for the design of DES models. However, the production system design processes did not specify the responsibilities or activities for the design, development, or deployment of the DES models, nor did it require communication between the DES specialists and the design teams. Instead, the project managers of Cases 1 and 3 determined responsibilities, activities, and communications independently. The project managers of Cases 1 and 3 encouraged weekly meetings between DES specialists and the design team throughout the early stages of production system design. Additionally, the project managers assigned responsibilities to design team members related to DES. Design team members participated in the formulation of problems, objectives, data collection, and presentation of model results. However, differing approaches existed on how DES was used in the early stages of production system design: while the project manager of Case 1 specified the use of DES throughout the early stages of production system design with no limit to the number of DES models, the project manager of Case 3 limited the use of DES to two models. In Case 2, the DES models were planned in a context that included a production system design process that was not consistently followed and a project manager unfamiliar with DES. The production system design process did not specify any time for the development of DES models, so the design team formally requested the development of a DES model only after finalizing an initial draft of the production system design, and at a time close to the delivery of final results to senior management. The data also indicate that the Case 2 project manager gave a higher priority to activities in the early stages of design other than the design, development, or implementation of DES models.

Empirical data from interviews, company documents, and field notes agree on the criticality of one challenge above all others in the DES model design phase. This challenge involved defining the problems in production system design, and then translating these problems into DES models, a situation that occurred in Cases 1, 2, and 3. This challenge originated from ambiguous or equivocal interpretations of the capabilities, functionalities, and physical description of a multi-product assembly system between different members of the design teams. For example, design team members described problems related to conflicting interpretations and a lack of consensus about the initial steps in the early stages of production system design. Additionally, team members described difficulties in sharing their interpretations with stakeholders from different backgrounds. The following excerpt from our interview with the project manager of Case 1 is representative of the challenge of defining and translating problems into DES models, which were also apparent in Cases 2 and 3, "*A problem for us was determining whether we were designing a production system that would be adequate for the needs of our site and met the objectives set by senior management. We could of course come up with a solution. But would we be doing the right thing? Where we on the right track? No one really had an answer for that, and it was difficult for us to agree on a first step. This project was a big jump from business as usual. What things to consider? Were we missing something? We were very worried about this*."

Our data reveal that the challenge of defining and translating problems into DES models occurred frequently during the early phase of production system design, every time a DES model was developed in Cases 1, 2, and 3. Two examples from Case 1 demonstrate this. First, a great deal of time was required to come to an agreement about the steps in the heavy vehicle production processes necessary for the visual representation of Model A. Second, a difference of opinions existed within the design team over the definition of enablers and their representation in Model E. These challenges were similar to those experienced by the design team in Case 3 when defining a production processes that was common to all vehicle cabins for Model H.

These ambiguities and disagreements hindered the definition of problems in production system design and their translation to DES models, increasing the abstraction of the DES models. For example, members of the design teams in Cases 1 and 3 could not initially agree if the design would initiate from detailing one production subsystem at a time or from presenting a holistic perspective of the entire production system to be later detailed at the sub system level. Consider the following excerpt from our interview with the project manager of Case 3, "*You can ask everyone in our project how to design this production system. Everyone will give you a different opinion. What should we choose? It's not only about the pieces. The important part is the system around you. Specifying a level of detail that agrees with all our concerns is not easy*."

4.4.2 DES Model Development Phase

The DES model development phase involved selecting and identifying entities and activities, determining and collecting input data, and verifying and validating the DES models. Empirical data show that the most important challenge in the DES model development phase was the difference between available and required data to build a simulation model. This challenge was common to all cases in this study and is exemplified by this interview excerpt with the project manager of Case 2, "*There were many unknowns in this innovative project. This was very different from doing business as usual, and very different from designing a completely new production system with many resources at our disposal. We had to transform our existing production systems into something we had never done before. We were doing this (transformation) for the first time with no recipe.*" Problems related to the lack of data occurred between the development of a conceptual model and the DES model deployment phase throughout the early stages of production system design.

The challenge of a lack of data originated from the absence of a real-life production system from which to develop the DES models. This challenge affected three aspects of the input data necessary for DES model development. First, it was difficult to determine which products would be produced by the multi-product assembly system. The design teams began their work with no clear idea of the product that would be produced, therefore, they proposed a logic for the selection of product families, and then justified a choice of products. Only then could the design teams specify the production process and demand for products in the multi-product assembly system. Second, it was difficult to establish a common production process for the multi-product assembly system. Once product families were selected, the design teams proposed a production process that complied with all product families. This was problematic because there existed a lack of clarity regarding the interrelation of subsystems that supported common production processes. Additionally, design teams were aware of disturbances affecting existing production systems but did not know how these would influence a multi-product assembly system. Third, it was difficult to define parameters to evaluate the operational performance of the multi-product assembly system and compare these to existing production systems. Design teams found that operational performance was measured differently at different sites. Proposing performance measures that evaluated the designed production systems and compared them against existing ones was not intuitive, and establishing clear parameters for evaluation required the approval of various global manufacturing sites and different levels of seniority.

To mitigate this lack of data, the design teams made assumptions and simplifications. Initially, these were based on rough estimates of existing production processes similar to those of the designed systems and required the approval of experts from various sites. The design teams maintained these assumptions and simplifications until activities from the production system design revealed additional information. To reduce assumptions, the design teams iteratively revised their data during the early stages of production system design. These iterations were characterized by questioning prior assumptions, comparing assumptions with new data generated from design activities, and gaining approval from experts.

The design teams of Cases 1, 2, and 3 applied two different approaches to collect input data for model development during the early stages of production system design. The design teams of Cases 1 and 3 first agreed on the type of data and its definition, then collected data for the DES models. These two steps were repeated for every DES model, and the quantity and detail of the data increased over time. Conversely, the design team of Case 2 collected all possible data related to the production of vehicle transmissions, and only then defined the inputs for their DES model. However, the design team of Case 2 realized that not all collected data was suitable for DES model development and that additional data was necessary. Activities related to assumptions, simplifications, and collection of data were time consuming, threatening the timely development of DES models in Case 1 and 2, and preventing the complete development of DES models in Case 2 altogether.

4.4.3 DES Model Deployment Phase

The DES model deployment phase involved experimenting, analyzing, and implementing model results to inform decision making. Empirical data show that a challenge common to all cases in the DES model deployment phase was the limited knowledge of DES processes among members of the manufacturing company. With the exception of the DES specialists in Cases 1, 2, and 3 and the project manager in Case 1, all other members of the design teams had no previous experience with DES.

The time allocated to the design, development, and deployment of the DES models was insufficient due to the limited knowledge of DES in the design teams of Cases 1, 2 and 3. Eventually, DES specialists held workshops with design team members and explained the basic principles of DES, its operation, and potential benefits for the design of production systems. These workshops were not originally planned as part of the early design stages of production system design, but were necessary to provide input for Cases 1, 2, and 3. Similar workshops were held every time a new DES model was designed for Cases 1 and 3. These workshops focused on clarifying whether the DES models could address issues of concern identified by the design teams.

Additionally, the design teams required support from simulation specialists to analyze and interpret the results of the DES models, adjust model values, and set up experiments. This was problematic because in some instances, minor adjustments were necessary, but design team members had to wait for the assistance of simulation specialists. Furthermore, communication of results to inform effective decision making was limited by the lack of DES knowledge in all cases. Design team members relied on simulation specialists to present DES model findings, and these findings were presented to members of the manufacturing organization at meetings, which targeted staff from different backgrounds and levels of seniority. Simulation specialists were solely responsible for adjusting the findings of the DES models to address the concerns of these staff members.

An additional challenge encountered in the deployment phase was the low re-usability of DES models in Cases 1 and 3. The DES models were used once and then developed sequentially as new information became available. Earlier DES models shared no information with newer ones; once a DES model was finalized and its findings presented, the models were updated to the point that they were completely different from the originals. This occurred for two reasons. First, the DES models specified the interrelation of subsystems within the production systems in greater detail as more information became available in the early stages of production system design. For example, though Models B, C, D, and E in Case 1 all evaluated the operational performance of the heavy vehicle multi-product assembly system, the details describing the interrelation of elements in the production system differed considerably as a consequence of new findings uncovered during the design of the production system. Second, new concerns and objectives often arose during the early stages of production system design. For example, in Case 1, Model A focused on a visual representation of the production process with the objective of initiating discussions with the design team, while Model B focused on producing a quantitative analysis in which the visual representation of the production process was not critical. A similar situation existed in Case 3, in which Model G represented the existing production system, while Model H represented a completely different multi-product assembly production process. Notably, the project managers in Cases 1 and 3 assigned simulation specialists to pressing issues, and no resources were available to re-use previously developed DES models. Furthermore, the DES models developed during the early stages of design were not utilized afterwards because the simulation specialists participating in Cases 1 and 3 were assigned to other projects before the later design stages.

Finally, the consideration of trade-offs and non-intuitive decisions differed across the evaluated cases in the DES model deployment phase. In Case 1, the design team developed an initial draft for a production system (Model A) that was evaluated using a DES model to identify problems and propose solutions. These steps were repeated for every DES model in Case 1 throughout the early stages of production system design (Models B, C, D, and E). In Case 3, the design team developed an initial designed draft of the production system. Based on prior experience, the design team reflected on potential challenges to the operational performance of this draft design. Members of the design team then worked on a final version of the production system, and the operational performance of this system was evaluated in DES Model H.

4.4.4 Summary of Challenges Identified Throughout the DES Use Phases

Based on data collected from Cases 1, 2, and 3, and described in Sections 4.4.1–4.4.3, Table 5 presents the identified challenges of applying DES in the design, development, and deployment phases of each case. The list of challenges is synthesized from the existing literature presented in Section 2.

Table 5. Challenges of applying DES to support production system design decisions in all evaluated cases.

	Challenge	Case 1	Case 2	Case 3
Design	Decision support restricted by question-specific model formulation	√	√	√
	Representation of production system dynamics and complexity			
	Validity of model detail level		√	
	Simplification of production system complexity and factor interdependence			√
	Non-uniform abstraction level for model simplification	√		√
	Modelling combinatorial explosion of options in a production process			
	Incomplete and conflicting production system knowledge	√		√
	Development of simulation and production system knowledge	√		√
	Software diversity and lack of standardization			
Development	Model verification and validation	√	√	√
	Model development time	√	√	
	Input data collection and analysis	√	√	√
	Input data availability and quality	√	√	√
Deployment	Model interoperability and information sharing between models	√		
	Industry acceptance of DES	√	√	√
	Communication of results for effective decision making	√		√
	Simulation model maintenance			
	Consideration of trade-offs and non-intuitive decisions			√
	High cost and low reusability of models	√		√

5. DISCUSSION

The empirical data indicate that DES models were crucial in supporting decisions in the early stages of production system design when introducing new production processes or technologies in heavy vehicle manufacturing. Our results make new contributions to the current understanding of DES applications, and reveal the presence of equivocality and uncertainty to be two very critical factors driving the challenges of applying DES in this context. While our results suggest that equivocality and uncertainty may be unavoidable, activities undertaken during the design, development, and deployment of DES models can moderate their negative effects. Accordingly, manufacturing companies can potentially avoid many previously identified challenges of applying DES in the early stages of production system design. The findings of this study highlight that in order to avoid DES-related challenges, manufacturing companies would likely benefit from structured processes and increased institutional knowledge of DES application.

5.1 Theoretical Implications

This study provides important contributions to research focused on the challenges of applying DES using empirical evidence collected during the early stages of production system design. First, this study provides new insight into the importance of equivocality to the challenges faced in the DES model design phase by demonstrating that the existence of multiple and conflicting interpretations limited the overall comprehension of the intricacies of the production system during design (Fowler and Rose 2004). As a consequence, the design teams faced difficulties in identifying problems during the production system design and translating these problems into DES models. Furthermore, the design teams also experienced problems in specifying an appropriate level of model abstraction when incomplete and conflicting production system knowledge existed (Mönch et al. 2011). These findings extend those of prior studies in two ways. Our results show that addressing equivocality is not a trivial issue in that it reduces the availability of critical resources necessary for the design of DES models. In addition, the findings of this study provide empirical insight into the importance of equivocality, which has been previously reported when studying the introduction of new production process or technologies, but has received limited attention otherwise in DES literature. This knowledge may be critical in identifying countermeasures that can mitigate the effects of equivocality and help avoid challenges in the application of DES in the early stages of production system design.

Second, the results of our study provide novel contributions to a widely known challenge troubling the development of DES models: the lack of data. Our findings suggest that uncertainty is a challenge that is never truly resolved in the early stages of production system design. Accordingly, this shows that uncertainty constitutes a critical challenge for the application of DES models during these early stages. Specifically, uncertainty of input data and the need to verify the DES model were the most frequent of challenges of DES application in this context. Furthermore, the challenges of uncertainty were found to be related to the absence of real-world production system from which to draw data. This was a consequence of introducing a change that was significantly different from the subject manufacturing company's current operations (Rönnberg et al. 2016). The severity of this issue was increased by the high levels of uncertainty related to the probability that certain assumptions made during design were incorrect or to the presence of entirely unknown facts that have a bearing on the designed production system (Frishammar et al. 2011). Consequently, uncertainty may not only affect the output of DES models, but can also hinder the use of DES altogether, as previously reported in the literature (Oberkampf et al. 2002; Bokrantz et al. 2018).

Third, this study demonstrates that specifying the interrelation of subsystems in a production process may be just as important as specifying accurate parameters for input values in DES models. Data from the three evaluated cases agree on the importance of establishing the interrelation of subsystems in the production system to obtain input data, determine the level of abstraction of DES models, and specify the evaluation parameters of the DES models. This study reveals that specifying the interrelation of subsystems and their representation in DES models requires close coordination between production system designers. Although this issue has been previously observed in the literature (Robinson 2008), there remains a need to identify ways to facilitate this coordination and its development during the early stages of production system design. Our data suggests that proper coordination would bring production system design teams a step closer to avoiding many known challenges of DES application.

Fourth, the results of this study highlight the importance of addressing assumptions and simplifications to mitigate the effects of uncertainty in the development of DES models. Empirical data show that addressing assumptions and simplifications is a resource-intensive activity that can determine whether a DES model is developed and deployed or discarded. The findings of this study identify the necessity of continuous work throughout the early stages of production system design to manage and revise assumptions and simplifications. Thus, one-time efforts to define assumptions and simplifications may be insufficient. Instead, manufacturing companies must develop a strategy to continuously acquire data to inform the reduction of assumptions and simplifications over time. This study showed that assumptions and simplifications are frequently handled through informal processes that are dependent on people rather than processes. This approach is both time- and resource-intensive and provides no guarantee of a successful outcome. This constitutes a novel insight demonstrating that processes focused on the reduction of uncertainty and assumptions through the acquisition of data are necessary, in addition to the conventionally accepted steps of designing, planning, and deploying DES models.

It is important to note that not all challenges in the application of DES outlined by Fowler and Rose (2004), Wang and Chatwin (2005), and Mönch *et al.* (2011) (see Table 1) were detected (see Table 5), and different levels of challenge occurrence existed between cases. However, the absence of several previously identified challenges does not indicate a disagreement with extant theory. The lack of evidence of these challenges can be explained by contextual circumstances. The absence of challenges related to representation of production system dynamics and complexity, as well as to modelling the combinatorial explosion of options in a production process, was a consequence of the choice of production system modelled and how it was modelled. The DES models used in the cases evaluated in this study required assumptions and simplifications that limited the representativeness of the system complexity and potential options. Additionally, challenges affecting simulation model maintenance were not found as the DES models in the evaluated cases were not re-used after the model results were presented.

5.2 Managerial Implications

The results of this study provide direct managerial implications that may benefit project managers, production engineers, and DES specialists of manufacturing companies who wish to use DES in the early stages of production system design. Our findings show that a lack of knowledge of DES applications is a challenge that continues to bewilder manufacturing companies and affects the design, development, and deployment of DES models. For example, empirical data showed that specifying what should be modelled and how to do so required the assistance of DES experts, and that DES specialists were required to continuously demonstrate the ways in which DES contributed to the design of the production systems (Fowler and Rose 2004). Additionally, communication of DES model results required expert interpretation, limiting the ability of project team members to make effective decisions (Heilala et al. 2010). Similarly, the low-reusability of DES models observed in this study was linked to the lack of in-house resources with DES expertise that could modify or re-use developed models at later times. Although many of these challenges could be avoided by increasing team member education regarding DES, it is reasonable to assume that dissemination of DES knowledge in manufacturing organizations is a long-term journey. A contingent, but not opposite, approach could arguably include formalized processes for DES model design, development, and deployment.

Indeed, the findings of this study demonstrate the need for structured processes to design, develop, and deploy DES models in the early stages of production system design (Flores-García et al. 2015). A structured process is explicit, widely known, and characterized by clear responsibilities (Kurkkio et al. 2011). While DES experience of team members is still necessary under a structured process, as shown by the empirical findings of this study, experienced team members may not be the only source of knowledge to determine when, how, and to which activities to apply DES in the early stages of production system design. In this way, manufacturing companies can reduce dependence on team member experience, which can be difficult to transfer and access, instead developing structured processes that facilitate team-wide access to DES knowledge. This appears to be of critical importance because the results of our study suggest that the avoidance of DES challenges is largely dependent on the experience of project managers.

Finally, the results of this study show a promising future for those companies willing to utilize DES in the early stages of production system design. Empirical data indicate that DES models were critical in supporting decisions made during the early stages of production system design. Importantly, DES models did not replace any existing decision-making support tools; instead, design team members benefited from the outcomes of DES models through analyses not available in previous production system design projects. These benefits included understanding the consequences of changes in one part of the production system and its effects on other subsystems or processes, identifying problems and testing alternatives, and evaluating the operational performance of the production system during the design phase. These findings are likely to be particularly relevant in cases involving the introduction of new production processes or technologies where limited operational information exists.

6. CONCLUSIONS

This paper analyzed the challenges of using discrete event simulation (DES) in the early stages of production system design with a focus on its application to the introduction of new production processes or technologies. Three real-time case studies were performed at a manufacturing company between 2014 and 2016 to determine the similarities and differences in the challenges of applying DES compared to those identified in extant literature. Based on the existing understanding of DES challenges, the results of this paper offer important contributions related to the early stages of production system design.

The results of this study show that equivocality affect the level of abstraction of a DES model and result in limited specification of what should be modeled and how to do so. In addition, this study suggests that uncertainty is never truly resolved in the early stages of production system design, and affects input data and understanding the interrelation of subsystems in production. The results of this study highlight the importance of addressing assumptions and simplifications to mitigate the effects of uncertainty in the development of DES models. Finally, the lack of DES know-how at the manufacturing companies jeopardized communication during DES model development and interpretation, essential phases in the successful deployment of DES models.

Limitations of this study include the choice of the case study method, as well as the selection of three case studies from a single manufacturer of heavy vehicles. While this study gave precedence to the sampled cases in formulating conclusions, it remains important to provide generalizable results that have implications beyond the context of this study. An additional limitation is the focus on multi-product assembly as a new production process in a legacy production system. Therefore, an important recommendation for future research is the investigation of additional production processes or technologies of equal novelty to validate the findings presented in this study.

The study of DES challenges related to equivocality and uncertainty in the early stages of production system design provide rich venue for future research. First, both manufacturing practice and current understanding could benefit from the identification of aspects that facilitate DES support of decision making despite uncertainty and equivocality. Second, the results of this study emphasize the importance of establishing a structured process for early-stage production system design using DES. Therefore, future research could focus on analyzing how currently available processes detailing DES model design, development, and deployment can be applied under conditions of high uncertainty and equivocality.

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