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# CHALLENGES OF DATA ACQUISITION FOR SIMULATION MODELS OF PRODUCTION SYSTEMS IN NEED OF STANDARDS

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## ABSTRACT

In this paper, we analyze the challenges in data acquisition for simulation models of production systems based on two cases from the robotics and aerospace industries. Unlike prior research, we focus not only on the challenges of data acquisition but also on how these challenges affect decisions in production systems. We examine this linkage using the concepts of strategic objectives, decision areas, and internal fit from operations management literature. Empirical findings show that for data acquisition to lead to improved production system performance it is necessary to develop standards. Standards should consider ownership of data by different functions within a manufacturing company, alignment of data to performance measurements, and the connection between data, information, and production decisions. Using these concepts, this paper proposes a set of guidelines that facilitate the standardization of data acquisition for simulation models in production systems. We conclude by discussing the managerial implications of our findings.

## 1 INTRODUCTION

Literature emphasizes the importance of data acquisition for simulation models of production systems (Choudhary et al. 2008; Jain et al. 2017), yet recent findings warrant an examination of a decision perspective that informs standardization challenges in this field. Indeed, research efforts and the development of standards focused on addressing the challenges of data acquisition for simulation models have led to a surge in the availability of data in the factory floor (Stein et al. 2018). However, very few studies provide insight into how managers use acquired data to make decisions in a production system such as Kibira et al. (2015). This problem is critical because it leaves researchers without empirical insight to inform the development of standards for data acquisition of simulation models. More importantly, managers find themselves without adequate means to make use of acquired data, a situation that is increasingly important for competitiveness (Trkman et al. 2010). Addressing this problem, the aim of this paper is to analyze the challenges in data acquisition for simulation models of production systems from a decision approach. Based on this, the paper provides insight to facilitate the standardization of data acquisition for simulation models in production systems proposing a number of guidelines. To do so, we examine the following research questions: How do the challenges in data acquisition for simulation models affect decisions in production systems? What considerations should be taken into account to address challenges in data acquisition for simulation models of production systems from a decision perspective to facilitate standardization?

This paper presents findings from two case studies in the robotics and aerospace industries. Our analysis includes a decision approach from the field of operations management (Cyert and March 1992) and extant knowledge about data acquisition for simulation models of production systems. The results of this paper offer several contributions. First, we identify the challenges encountered in the data acquisition process. This result shows that an interplay of challenges exists which affects the decisions in a production system. This finding is important because it reveals novel insight about the challenges of data acquisition which have been viewed as stand-alone occurrences (Robertson and Perera 2002; Barlas and Heavey 2016). Second, we propose a set of guidelines to facilitate the standardization of data acquisition for simulation models in the manufacturing context. These include specifying a connection between data and production decisions, determining ownership of data across different functions within a manufacturing company, and establishing the alignment of data to performance measurements. Our results show how theoretical perspectives from the field of operations management may be useful to address challenges in data acquisition for simulation models.

# 2 THEORY

## 2.1 Data Acquisition for Simulation Models of Production Systems

Simulation, including Discrete Event Simulation (DES), has been applied for decades in the manufacturing domain to support and analyze decision in production (Shao et al. 2014). DES can analyze and understand the dynamics of a production system which makes it a suitable tool when addressing real-world problems in the manufacturing domain (Bokrantz et al. 2017). The importance of DES in the analysis of production systems is increased because of ever more competitive manufacturing environments which emphasize the reduction of costs and production lead times (Skoogh et al. 2012). Data acquisition is crucial because it provides the inputs to DES models for the analysis and representation of real-world systems (Shao et al. 2014). Data acquisition is afflicted by the absence of data useful to simulation models and uncoordinated methodologies for its acquisition and is therefore frequently reported as a time-consuming activity (Perera and Liyanage 2000; Robertson and Perera 2002; Ülgen et al. 2006).

Data acquisition for simulation models can be assigned to three different categories depending on availability (Robinson 2004; Skoogh and Johansson 2008). First, data is available, fits a simulation purpose, but requires validation. Second, data is not available, is collectable, and requires the investment of resources for its acquisition. Third, data is not available and not collectable. Consequently, data should be based on expert opinion, similar production processes, or historical data.

Classifications for the sources of data acquisition include primary and secondary source of data, see Figure 1. Primary sources of data consist of measurements of a discrete event in a production system as recorded by staff. Secondary sources of data refer to data that has been collected for another purpose but can be used for the simulation model and may require further processing to be relevant. Three categories of secondary data exist and include external reference system, corporate business systems, and project-specific data. Project-specific data is for instance a forecast of the production volumes to understand a changing situation that should be simulated. Data in the corporate business system are of operational type (e.g. machining and set-up time for a machine) (Skoogh et al. 2012). This category includes Enterprise Resource Planning (ERP) systems, which are adapted to the needs of a manufacturing company, have no industry standard guide, and emphasize deterministic over stochastic data (Kelton et al. 1998). ERP systems are characterized by a lack of involvement of the simulation domain when data acquisition systems and databases are specified (Skoogh and Johansson 2008). Data from external reference systems can be data for a new machine that need to be known for the simulation. If there are still data that are needed for the simulation project, that cannot the found in these three sources, data need to be collected i.e. primary data (Skoogh et al. 2012).

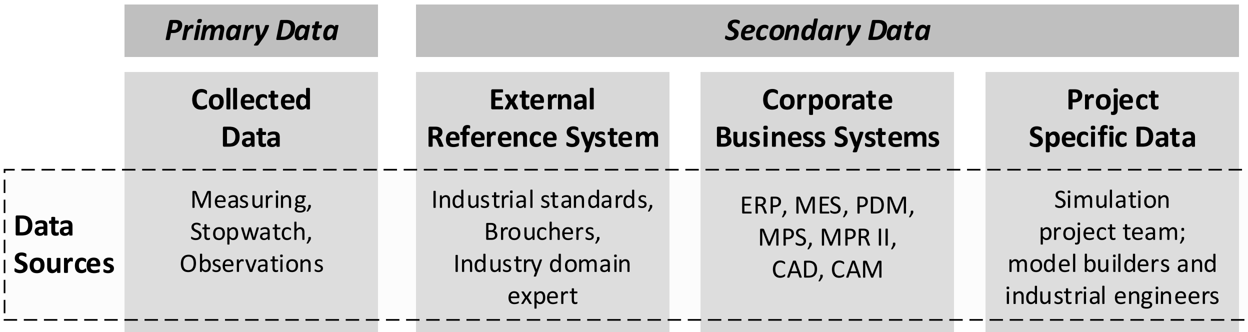


Figure 1: Categorizing data sources used for simulation projects (Skoogh et al. 2012)

## 2.2 The Need for Standardization of Data Acquisition

The need for standardization of data acquisition for simulation models is underscored by three outstanding issues. First, the dependence of DES models on input data to produce trustworthy results (Robertson and Perera 2002). Second, the effect that data, made available through its acquisition, has on the timeliness of a simulation model (Perera and Liyanage 2000). Third, a variety of non-conforming data acquisition methodologies to develop simulation models of production systems (Batini et al. 2009). Accordingly, extant literature has identified eight challenges in the acquisition of data for simulation models of production systems (Robertson and Perera 2002; Fowler and Rose 2004; Skoogh et al. 2012). These are presented in Table 1.

Table 1: Challenges of data acquisition for simulation models of production systems

| **Challenges of data acquisition** | **Description** |
|---|---|
| Accuracy | Data is not free from mistake or error. It is necessary to investigate data sources or format |
| Correctness | Lack of data standards, communication problems, or incorrect data labeling exist |
| Duplication | Two or more sources for the same event are present |
| Consistency | Different sources of data present different values |
| Timeliness | Data is no longer valid after a period of time |
| Validity | Data does not describe the behavior of the real-world system |
| Reliability | Data is not trustworthy in the eyes of stakeholders |
| Completeness | Data is partial and assumptions or additional data acquisition is necessary |

Additionally, the need for standardization of data acquisition is confronted by the data needs of modern day production systems (Esmaeilian et al. 2016). From this perspective, the challenges of data acquisition lie on acquiring data suitable for a specific task with minimal processing before its use for that task. Thus, standardization challenges of data acquisition involve the integration of data from different sources, assumptions made when collecting and measuring data, and the quality and validity of data (Kandogan et al. 2014). This situation is problematic because data acquisition has assumed that data is acquired free of errors (Bokrantz et al. 2017), a situation that contrasts with studies reporting on data acquisition practice in manufacturing (Byrne et al. 2014). Correspondingly, extant findings emphasize improvements of data acquisition from its point of origin to its point of use and the development of practical guidelines that assist manufacturing companies in data acquisition (Bokrantz et al. 2017). For the composition of different technological solutions and repeatable results, standards are the building blocks in order to succeed. Standards will also be required for the manufacturing system in order to succeed with efficient information flows and system responsiveness (Lu, Morris, and Frechette 2015).

### 2.3 From Data to Decisions in Production Systems – A Decision Approach

Perspectives from the field of operations management coincide with those of simulation on the importance of addressing the challenges of data acquisition for increased competitiveness. This argument sustains that manufacturing companies process data to generate information, and that information is subsequently processed to make a decision (Davenport 1997; Bruch and Bellgran 2013). From this perspective, data is understood as quantifiable facts about an event (Tsoukas and Vladimirou 2001). While information is interpreted as collection of data, which, when presented in a particular manner and at an appropriate time, allows a person to make a decision (Galliers 1987). Thus, manufacturing companies determine the functionalities and capabilities that lead to increased competitiveness by way of decisions. This is known as a decision approach (Cyert and March 1992). This approach regards a decision as a point of reference for the commitment of actions and resources across different departments of a manufacturing company (Mintzberg et al. 1976; Frishammar 2003). The concepts of strategic objective, decision area, and internal fit underpin a decision approach.

The strategic objective concept defines the purpose pursued by a manufacturing company and establishes that all decisions in a production system should align to the accomplishment of a common goal (Machuca et al. 2011). A strategic objective is set to prioritize a limited number of tasks that will achieve a competitive advantage through the competitive priorities of cost, quality, flexibility, and delivery (Ketokivi and Schroeder 2004). The concept of a decision area includes the set of choices that determine the capabilities of a production system to deliver a level of competitive priorities. These choices include long-term impact decisions with major capital investments and decisions of tactical nature that demand minor investments (Bellgran and Säfsten 2010). Thus, decision areas determine the constituents of a production system including the selection of process technology, capacity, facilities, vertical integration, human resources, organization, quality, production planning, new product development, and performance measurement (Hayes and Wheelwright 1984). The concept of internal fit implies that decisions made in different parts of the production system are mutually supportive and consider the interaction of choices across decision areas (da Silveira 2005). This is important because the achievement of competitive priorities in manufacturing depends upon the patter of decisions defined by its internal fit (Miltenburg 2005).

## 3 METHODOLOGY

### 3.1 Research Design

A case study method was selected to meet the purpose of this paper. The justification behind this choice of method rests on the need to investigate challenges of data acquisition in a real-life setting and develop theoretical insight explaining how to address these challenges (Negahban and Smith 2014; Bokrantz et al. 2017). These conditions are well suited for the use of a case study method (Yin 2013). The criteria for selecting a case included manufacturing companies with ongoing initiatives including the development of DES models and who considered the acquisition of data critical. The sampling of cases in this study was of polar type and included two cases (Mills et al. 2010). This choice is explained by the difference in how data is acquired from the production system, and the need to understand the challenges of standardization in data acquisition irrespective of a data acquisition methodology (Skoogh et al. 2012). Thus, Case A represents a manufacturing company where data is manually collected and Case B one in which machine data is acquired automatically. To perform the analysis of this paper, we looked into how data was acquired in these two cases during the development of simulation models for production systems. Specifically, we focused on those challenges identified as necessary for the standardization of data acquisition in Section 2. Additionally, we concentrated on understanding how data acquisition contributed to strategic decisions in what we termed considerations for standardization in data acquisition for simulation models. These choices are justified by the importance of data for production systems and simulation models to decisions in production systems (Bruch and Bellgran 2013; Barlas and Heavey 2016).

### 3.2 Data Collection and Analysis

Data was collected between December of 2017 and March of 2018. Data collection focused on two steps. First, the authors met managers and familiarized themselves with the DES initiatives. Through a series of discussions, the authors were introduced to key personnel related to these initiatives. This allowed identifying five participants who were selected on the basis of their roles, backgrounds, and responsibilities. These participants included a production, logistics, and production planning managers, a simulation expert and a production-planning engineer, further introduced in section 4. Semi-structured interviews were held with these participants. The interviews began with an open discussion about the background of the participant, and a description of their activities in relation to data acquisition. Then, the participants narrated the most important decisions required by their functions and explained how issues experienced when making these decisions were associated with challenges in data acquisition. Next, the participants described the achievement of data accuracy, correctness, duplication, consistency, timeliness, validity, reliability, and completeness. The interviews finalized with follow up questions to generate a better understanding of how data contributed to decisions in production systems. Interviews lasted 60 minutes and were recorded and transcribed by the first two authors.

The second step included understanding the role that the strategic objective, decision areas, and internal fit concepts had on the challenges of data acquisition for simulation models of production systems. After each interview, the authors discussed and categorized their first impressions according to themes that emerged from case data including background, challenges of data acquisition, critical issues, vision for a solution, importance of production decisions, and agreement about data. Based on these themes, the authors worked separately in the coding of interviews, analyzed findings within each case, and then compared findings across cases as described by Miles et al. (2013). To rule out unsubstantiated claims, the authors compared these preliminary results in a joint session. This resulted in an initial draft of a set of guidelines that facilitate the standardization of data acquisition for simulation models in production systems. These guidelines were refined through iterations between empirical findings and theory. The description of Case A and B are presented in Table 2.

Table 2: Description of Case A and B

| | **Case A** | **Case B** |
|---|---|---|
| Description | Manufacturer of satellite components and aerospace equipment | Manufacturer of industrial robots and components |
| Production type | Job shop assembly with a high proportion of manual work | Line assembly with a high proportion of manual work |
| Data acquisition | Data collected manually and stored in multiple external sources including corporate business systems and spreadsheets | Direct link and manually collected data stored in one corporate business system |
| Objective of DES initiative | Reduction of lead time in production process and identify capacity need | Reduction of lead time in production process |

## 4 RESULTS

This section provides a short background about the participants and their functions, the impact of data to decisions in production, data documenting and acquisition methodologies as well as the challenges of data acquisition.

An participant with responsibility for logistics and production development in a new role as project manager for improvement projects connected to production. The participant uses data to analyze routings as well as the lead time. Information about the lead time impacts on the holistic understanding of the production. A long lead time in customer projects has a negative effect on work in progress, tied-up capital, and storage in the production area. The view is that it will become even more important in the future to work actively with a lead time that is representing the reality of the factory floor. To generate information about lead time, data is fed to the ERP system in a varying manner depending on production unit or department in the organization. Different mindsets and ways of working are found, which impact on how data is handled and documented. Logistics and production management is troubled by a lack of clarity about which data should be considered in the lead time of a product. For instance, material handling time is not reported in the ERP system when material is received at the plant. How data is documented and fed to the system depends very much on individual's understanding and has primarily been performed manually before. It will now become more automated with a start and stop functionality in the system.

The production manager is heading one of three production units with the responsibility to make sure that the production is running. This implies to make decisions about required staffing and resources but also space needed in the workshop in order to meet the demand from customers. The participant has hold this responsibility for almost a year but has long experience at the company and from production. Lead time is an important information source to be able to plan for the expected delivery time to customer and it is measured for all processes. Cycle time data is partially recorded in the ERP system since preset values are used, and when data is acquired this is done manually The organization deals with several self-made solutions such as spreadsheets for documenting the production processes. Challenges for the data handling involve no standard way of handling data and no application or use of the data for the time being. The data that exist cannot be trusted and does not support decisions in production.

For production planning, the responsible manager and an operational planner for one of the production segments were interviewed. The production manager has years of experience in a managerial role in both the current organization and previous ones. The production-planning engineer has several years of experience at the company but is new to the current position. This production segment is a common resource for the production and receives production orders from all units. Information about the lead time is important for a reliable planning and involves data about cycle times for operations, delivery and availability of material as well as the forecast that can inform about waiting orders. Currently, data is manually registered by feeding the ERP system with data e.g. cycle time. Self-made solutions, spreadsheets, are also used to complement with necessary data. What has become common practice for the planning process is that data from the system is compared to statistics of the production process and evaluated based on the experience of personnel. This is due to data that is incomplete, incorrect and missing important components. Another major challenge is the non-existing connection between the machine software to the ERP system, which imply that data are not automatically transferred. The ERP system is neither easy to maintain nor cost efficient to update with the right data.

The simulation expert is involved in a research project with case company B where the objective is to be able to cut lead time of the product with the aid of simulation. The expert is associated to a research institute with core competence in optimization and statistics for R&D projects. The purpose of the DES model is to demonstrate the importance of having data free from issues available and to have systematic procedures for collecting and documenting data. The case company has systematic ways of documenting data and machine data are automatically collected from the machine. Based on experience, the way of documenting data at this company is considered to be performed systematically. For the simulation project, data have been collected manually with a stopwatch and following the flow. This requires a systematic way of performing it because there is always the risk of human errors involved. Challenges that are encountered with data acquisition is that is based on the ability to collect the data rather than the need for collecting. To have the holistic view of the data acquisition as well with a motivation of why data is collected is important to keep in mind.

### 4.1 Standardization Challenges in Data Acquisition

The challenges of data acquisition presented in Table 1, were discussed during the interviews. The results, with a comparison for each data challenge and case study, are presented in Table 3.

Table 3: Challenges of data acquisition found in Case A and B

| Challenges of data acquisition | Case A | Case B |
|---|---|---|
| Accuracy | Uncertainty about what times that should be used and the data is not accurate with many factors impacting. | Free from errors, machine data are automatically collected and the manual collection is performed in a systematic way. |
| Correctness | Different labeling for the same operation because of no standard way of reporting. Pre-set values can be used in ERP-system instead of feeding actual times. Data need to be adjusted and compared to statistics. | Not analyzed the data yet but it is not considered as an obstacle in this case. |
| Duplication | Multiple fields in the system are used and the same data item is stored in both ERP-system and spreadsheets. | Has not been encountered in this case. |
| Consistency | Differences between departments of how times are reported in ERP-system and different results depending on the data source. | Measurement repeatability and reliability is an issue for manual collection. |
| Timeliness | Change to the system impact on data over time. Data changes in reality but not in the system. | Is a challenge when collecting and sampling data. |
| Validity | Not describing the behavior of the system, discrepancy between reality and data in the system. | Data collected matches the actual processes and has been validated. |
| Reliability | Unrealistic data has been encountered and there is no common understanding within the organization of how to use data. Planning is always questioned by other departments. | Has not yet been evaluated, but the data collectors are trusted. |
| Completeness | Do not provide all necessary parts and assumptions need to be made with gut feeling leading the way. Estimations of the data are done to get a more accurate planning. | Has not been encountered as an issue for this project yet, but is expected to be later on. |

### 4.2 Considerations for Standardization in Data Acquisition for Simulation Models

Empirical findings from Case A and B show that having a holistic perspective was perceived as an important factor to avoid the challenges of data acquisition for simulation models. Participants understood a holistic perspective as a valid and up-to-date representation of all function of the production process informed by data. The consequences of not having a holistic perspective were stressed repeatedly during the interviews. For instance, participants identified making decisions based on gut feeling when data representing the production system was missing. The following interview excerpt exemplifies this by the production planning manager in Case A, "*lack of data in the planning process about material availability implies that man-hours are spent on a production order that cannot be started because the material is missing*." Opposite to this, the simulation expert from Case B identified data as a solution to a holistic perspective, "*data acquisition is very important for this initiative, it is a no-brainer*." However, the benefits of data acquisition were perceived as a potential cost in what became a recurrent theme during our interviews. The following passage from our interview with the project manager in Case A summarizes this opinion, "*Data acquisition is seen as a cost by manufacturing companies, and unless there is a clear value to these actions (data acquisition), it is questionable why it should be done*."

Data from Case A and B show agreement across participants about the importance of lead time to competitiveness despite the difference in data acquisition in both cases. The results of a simulation model focused on lead time were associated to that of information and managerial decisions, "*Good information is necessary to make good decisions, and this is related to production lead times… it is a measure of all* *our processes. Any improvements in the factory should preferably be seen here including capacity, space, people, work in progress and tied up capital*." Also, lead time as result of simulation was identified as an aggregation of data from different functions within a production system. Participants from both cases identified three considerations in data acquisition for simulation models. First, establishing a connection between data, information, and decisions based on a holistic perspective. Second, ownership of data across different functions. Third, alignment of data to performance measurements leading to improved decisions. These perspectives are summarized by the representative quotes of Table 4.

Table 4: Representative quotes about considerations for standardization in data acquisition

| **Case** | **Representative quote** |
| --- | --- |
| Establishing a connection between data, information, and decisions from a holistic perspective | |
| Case A | "*Not knowing what data contributes to the lead time is a consequence of a lack of a holistic perspective in the organization. Data helps solve this issue. I can understand our processes better through data. For instance the lead time from the suppliers, our system represents the purchasing time but it does not reflect on all the quality checks that go before it is made available to our production*" |
| Case B | "*The lack of a holistic perspective is a consequence of the dispute when people have different backgrounds and functions. It is natural to perceive things differently. This is an issue that reflects in our simulation*" |
| Ownership of data across different functions in the production process | |
| Case A | "*Data comes from the activities that go on at the factory floor. It is important for the operators to report data. The system cannot help us as long as we are not responsible for feeding the right data to it*" |
| Case B | "*There is a challenge in the tendency to invest a lot of technology and time into collecting all sorts of data, having huge databases, and not doing anything with it, or answering very basic questions with it"* |
| Alignment of data to performance measurements leading to improved decisions | |
| Case A | "*Data acquisition is a top-down effort which needs the interest of management to follow up. Performance measures are needed for this. We need to measure to decide on something, and measurements need data*" |
| Case B | "*That data is needed, is not visible if there are no measurements. More importantly, we need to understand why we are measuring. Because if there is no value in our measurements we cannot justify the cost of acquiring data*" |

## 5 DISCUSSION

Despite advances in the fields of simulation of production systems (Negahban and Smith 2014), knowledge about how data informs decisions in production practice remains scarce (Phadnis et al. 2017). To a background where standardization of data acquisition for simulation of production systems is increasingly relevant (Jain et al. 2017), the need for studies that analyze this challenge from a decision perspective is required. Our research helps provide novel findings that contribute to this knowledge. First, our study presents new insight regarding the challenges of standardization in data acquisition for simulation models and how these affect the decision in productions systems. In the past, the challenges of data acquisition have been identified as stand-alone occurrences (Robertson and Perera 2002; Fowler and Rose 2004; Skoogh et al. 2012). Instead, case results show that there exists an interplay between the challenges of data acquisition, a situation that, to the best of our knowledge, has not been previously reported in literature. For instance, Case A and B reveal that data consistency, accuracy, correctness, duplication, and timeliness were associated to data completeness. Furthermore, our results expose that manufacturing companies relied on assumptions to overcome incomplete data, a situation that led to two issues. First, manufacturing companies based production decisions on gut feeling. Second, incomplete data compromised data consistency, accuracy, correctness, duplication, and timeliness. Also, our results indicate that manufacturing companies mitigated the challenges of data accuracy when automatic data acquisition were employed (Case B). Oppositely, our results add to mounting evidence of how data accuracy is jeopardized by manual acquisition methodologies (Mönch et al. 2011).

Additionally, an important finding of our study relates to validity and data acquisition. Manufacturing companies perceive data acquisition as conductive to increased data validity. Participants from Case A reported challenges with data validity when data was collected manually, while in case B no problems with data validity when data was automatically acquired. The lack of a holistic perspective for the data collection was a recurring topic and has an impact on the challenges of data acquisition. This is associated with the different understandings of how data should be handled and how data is used in production decisions. Due to the difference of how data is viewed in the organizations, the reliability of data was questioned. For case A, an interesting comment identified for the reliability of data was how the participants questioned data they received, but at the same time were questioned by other functions for the data they provided.

Second, we have identified a set of guidelines to facilitate the standardization of data acquisition for simulation models in production systems based on a decision perspective. This finding is important because it indicates how data acquisition for simulation models of production systems is complemented by theoretical perspectives from the field of operations management. Specifically, we refer to the understanding of how data is not only necessary for decisions in a production setting, but how data, information, and decisions shape the competitive priorities of a manufacturing company (Frishammar 2003). To this extent, results from Case A and B show that DES models aggregated data (e.g. orders, capacity, material stock, material routing, machining time, etc.) to generate information about lead time and thereby address strategic decisions (e.g. units produced, manufacturing footprint, staff organization, tied up capital, work in progress, and delivery to customers). Importantly, our results confirm the tenuous awareness of how data from different functions are mutually supportive and necessary to address strategic decisions (Miller 1992). This is exemplified by the challenges of data acquisition in Case A, and a partial understanding of the events that contribute to lead time in Case A and B. This finding is important because prior studies suggest that challenges in the acquisition, sharing, and utilization of information generated through data moderate manufacturing competitiveness (Bruch and Bellgran 2013). Therefore, standards which help acquire, share, and utilize data across different functions seems to be crucial.

Also, our analysis revealed the need to establish the alignment of data to performance measurements. In agreement with literature focusing on the development of strategic objectives, this showed the need from manufacturing companies to define the priorities that will lead to competitiveness, establish measurements, and acquire data to determine the desired outcome (Machuca et al. 2011). Yet, our results show that no formal means on how to align data to performance measures existed, and that alignment was specified through the development of DES models. We interpret this finding as encouraging to simulation as an instrument that facilitates alignment of data to performance measurements. Also, our findings reveal that despite difference in product and production type, simulation models focused on providing the same information (lead time) which was used for equal strategic decisions in both cases (cost, manufacturing footprint, tied up capital, work in progress; delivery, delivery to customers, units' products; and flexibility, staff organization). This would suggest that future studies focused on standardization challenges of data acquisition may not only be interpreted from how, where, when, and why data is acquired. Additionally, future studies could also center on how, where, when, and why strategic decisions are aligned to data for simulation models of production systems.

Moreover, we have identified that ownership of data by different functions within a manufacturing company is a necessary consideration about the challenges of standardization in data acquisition. Our results show two dimensions to this issue. First, ownership of data as the responsibility of the staff of a specific function in a manufacturing company. Our analysis reveals that automatic data acquisition methodologies provide the first step in relation to this issue. In our study, this is highlighted by the avoidance of five of the eight challenges of data acquisition in Case B which made use of this type of data acquisition. The increase in automatic data collection suggests that efforts on this topic could contribute to a similar decline in the incidence of data acquisition challenges (Skoogh et al. 2012). Second, ownership of data as the continuous use of data in the set of choices that determine the capabilities of the functions of a production system to deliver a level of competitive priorities. To date, this issue is studied from an operations management perspective (da Silveira 2005), and to our knowledge, the importance of standards for data acquisition has not been considered. This appears to be important since our results indicate that acquisition of data does not guarantee its use to inform decision in a manufacturing context (Case B in Table 4). This paper summarizes its findings on five guidelines to facilitate standardization of data acquisition for simulation models of production systems:

1. The existence of interplay between challenges in data acquisition.
2. A holistic perspective for the data collection.
3. Decision perspective where standards should help in acquiring, sharing, and utilizing data across different functions.
4. Align the data to performance measurements.
5. Ownership of data by different functions within a manufacturing company.

## 6 CONCLUSIONS

This paper aimed to analyze the challenges in data acquisition for simulation models of production systems from a decision approach and provide insight to facilitate the standardization of data acquisition for simulation models in production systems proposing five guidelines. The results of this paper contribute with two key findings based on two cases from the aerospace and robotics industries. First, results show that an interplay of these challenges exists and that this affects the decisions in a production system. Second, a set of guidelines to facilitate the standardization of data acquisition for simulation models of production systems. Limitations of this study include the investigation of two manufacturing companies. Therefore, validation of our results against other cases and methods is a necessary next step. Additionally, this study has focused on a decision perspective based on semi-structured interviews. This study identified that a relationship between challenges of data acquisition is at play. Much remains to be explored in this area. Future studies could focus on how these challenges correlate to each other. We trust that this paper is a next step in understanding the challenges in data acquisition for simulation models of production systems motivating further standardization efforts.

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