Use of DES to develop a decision support system for lot size decision-making in manufacturing companies

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ABSTRACT
There exists a wide range of optimization models in the Operations Management (OM) community to solve complex problems such as lot sizing. However, their practical performance is often criticized due to the complexity of implementation and insufficient applicability in real-world decision processes. These theory-driven approaches are either simple to compute, but only focus on single aspects of the decision without being able to capture the practical problem comprehensively, or are complex computational models with limited practicability. We apply a Design Science Research approach to resolve this issue and show how lot size decision-making models should be designed to thoroughly support managers. Our innovative model combines Discrete Event Simulation (DES) with OM methods and is developed and tested in a case study in the metal processing industry. Results reveal that the model is suitable to provide transparency about effects and a range of efficient solutions.

1. Introduction and problem statement
Lot sizing decisions are crucial operational key planning activities in manufacturing companies to minimize changeover and inventory costs while keeping a high service level (Glock et al., 2014; Jans & Degraeve, 2007). The lot size (batch size) refers to the quantity of products or parts in one production order that are produced directly one after the other without an interruption in production. The decision for smaller or larger lot sizes has to consider the trade-off between flexibility and resource utilization. Lot sizing decisions thus are crucial to run operations competitively (Bookbinder & H’ng, 1986), but belong to one of the most complex managerial decision problems in production planning (Karimi et al., 2003).

Although research on lot sizing is not a new topic, there is still much activity in developing models to support and optimize lot size decision-making (Boctor, 2022; Larroche et al., 2021; Zhao & Zhang, 2020). This is due not least to the sustained trend of mass customization, where manufacturing companies must cope with higher product varieties and resulting smaller lot sizes (Hu, 2013). Even though it never entirely
disappeared, this research topic has been revitalized by new digital technologies and the rising data availabilities (Wu et al., 2021). Digital twins, big data and analytics are becoming dominant methodologies for decision-making in manufacturing research (Martinez et al., 2021; Sahoo, 2021).

The complexity of a lot sizing problem is dependent on the variables considered by the various models (Karimi et al., 2003). Three main lot sizing problems can be distinguished: the single-level lot sizing problem (SLSP), the multi-level lot sizing problem (MLSP) and the capacitated lot sizing problem (CLSP; Bruno et al., 2014). The characteristics influencing the complexity of the lot sizing decisions can be distinguished by features such as planning horizon (McClain & Thomas, 1977), number of production levels (Bogaschewsky et al., 2001), number of products, capacity constraints (Brahimi et al., 2017), demand type (Bookbinder & H’ng, 1986), item deterioration (Goyal & Giri, 2001) and set-up structure (Jaber & Bonney, 1999). Decision-makers are required to deal with this complexity. As demand fluctuations, number of product variants due to mass customization and the global scattering of value chain processes increase, this decision problem becomes more important. However, decision-makers are insufficiently supported, mainly due to a lack of information and transparency, a missing link between information and decision-making, and the resulting effects.

Operations Management (OM) and Decision Support Systems (DSS) literature have carried out much research to provide optimization models to support decision-making, resulting in different lot sizing techniques for identifying cost-optimal production lot sizes, such as the Economic Order Quantity model (EOQ; Harris, 1990), the Wagner–Whitin-Algorithm (Wagner & Whitin, 2004) and the Silver–Meal heuristics (SMH; Schulz, 2011; Silver & Meal, 1973). These lot sizing techniques differ from each other in their consideration of the above-mentioned features. Almost every feature combination can be found in the literature (see e.g. Brahimi et al., 2017; Drexl & Kimms, 1997; Glock et al., 2014; Goyal et al., 1993).

Most of the approaches have a single-item and single-level focus, are uncapacitated and concentrate on cost minimization, thus not sufficiently reflecting operational reality. Models that consider further features risk becoming unusable in industry practice due to their complexity (Jans & Degraeve, 2007). Furthermore, both types of approaches (simple and more complex) have in common that they still primarily focus on local cost performance criteria (inventory, set-up costs per product), and thus lack a system perspective with its reflecting impact on global operations. The more complex models also require a higher diversity and quality of information, leading to an information overload for many decision-makers.

To address these issues of information overload, complexity of solution, limited system perspective and guidance in lot sizing decision models, the purpose of this study is to contribute towards developing a more effective and user-friendly decision support system for lot size decision-making. Based on a Design Science Research approach (DSR), we apply Context–Intervention–Mechanism–Outcome (CIMO; Denyer et al., 2008) methodology to understand the lot sizing problem from a practitioner’s perspective, implement a solution to the relevant field problem, and therefore generate prescriptive, instrumental knowledge for optimized managerial decision-making.
The motivation for this research was the case of a leader in production of fine blanking parts for the automotive and construction industry. We supported the company in the optimization of lot sizes, the design of production capacities and the decision-making process. Based on that we derived the following research question together with the case company: How can managers be digitally supported to better understand and solve complex lot size decisions in taking into consideration the trade-offs between conflicting objectives?

In this paper, we contribute to literature on lot size decision-making by demonstrating how OM methods can be successfully implemented in practice, when considering application-oriented specifications from the DSS domain for the solution design. We develop a Discrete Event Simulation (DES) model, which builds on a real case study encompassing a multi-item and multistage focus with capacity constraints. We test eight different lot sizing algorithms to derive optimal lot sizes. Furthermore, we aim to contribute to the discussion around how digital technologies might change classical OM concepts, as theory still remains unaddressed. The results reveal six key findings, which serve as a foundation for future research in lot size decision-making. We use the results in the specific context of lot size decision-making to abstract from and derive findings for classical OM decision-making concepts.

To answer the research question of how models for lot size decision-making should be designed with the integration of digital technologies, this paper starts with an overview of lot sizing concepts and theory to set a theoretical basis and to reveal the shortcomings of existing approaches. This knowledge basis is used to identify the main requirements to be solved by a new model (artifact). Based on this, we introduce the CIMO approach in Section 3 followed by the model development, implementation, and evaluation in Section 4. Subsequently, Section 5 discusses the managerial and theoretical implications, limitations and points out future research activities. Section 6 concludes the paper.

2. Review of concepts for lot sizing decision-making utilizing digital technologies

2.1. Lot size decision-making and decision support requirements

The optimal determination of lot sizes in production planning is a complex decision problem encompassing demand, orders, capacities, delivery times, multiple products and process flows as well as costs (Brahimi et al., 2017). The objective of lot sizing models is to determine an optimal production plan to satisfy demand at minimal costs (Glock et al., 2014). A company that must fulfill customer demands needs to decide when and where, how much and in which sequence to produce and purchase.

Several reviews about lot sizing techniques have been published and reveal the range of existing problem solutions in this important field of operations research and management (Andriolo et al., 2014; Baciarello et al., 2013; Brahimi et al., 2017; Glock et al., 2014). The lot sizing techniques vary in their object of investigation and thus in the information needed to determine optimal lot sizes. Many of the models addressing the static lot sizing problem are single-item and single-stage uncapacitated (SLULP) approaches because of their simplicity of application (Van Hoesel & Wagelmans, 2001). Extended models and heuristics consider multiple items and levels
with capacity limits but are more complex (MLCLSP) and difficult to apply in practice (Billington et al., 1983). A performance comparison of different lot sizing methods reveals respective weaknesses and suitable application areas (Baciarello et al., 2013; Buschkühl et al., 2010; Jans & Degraeve, 2007; Van den Heuvel & Wagelmans, 2010). They mostly concentrate on minimizing costs. Other strategic objectives such as productivity or service levels remain insufficiently examined or entirely unconsidered. There is a need for hybrid optimization models combining modelling and algorithms (Jans & Degraeve, 2007).

These issues imply that DSS for lot sizing should allow for the computation of a range of trade-offs including additional targets, such as throughput, utilization, quality, and delivery rates. DSS is focused on the development of IT-based systems to substantially strengthen decision processes (Arnott & Pervan, 2016). Within DSS, the goal is to optimize the manager’s performance in decision-making processes, measured by decision time, confidence, and total cost. Decision-making styles vary from manager to manager and require different tools to enable effective decision-making. In this article, we rely on Personal Decision Support Systems (PDSS), which belongs to the subset of DSS developing problem solutions to support a specific decision task, such as lot size decision-making. Therefore, we selected four different guidance mechanisms that are relevant for managerial decision support: the form (Arnold et al., 2004), the mode (Parikh et al., 2007), the intention (Arnold et al., 2004), and the format of decision-guidance (Gregor & Benbasat, 1999; Morana et al., 2017).

Creating value from a growing real-time database is hereby the key for success for various decision-making situations (Kobbacy & Vadera, 2011). Data in diverse enterprise systems are becoming available for analysis in ever-increasing volumes and velocities (McAfee & Brynjolfsson, 2012). ‘The shared decision-making activity between a manager and a computer that is fundamental to DSS is highly compatible with the big data concept’ (Arnott & Pervan, 2016). Visualizations combined with intelligent scenario simulations drive decision-making towards a company optimal perspective and will increase the autonomy in different decisions and activities in a factory (Osterrieder et al., 2019).

To achieve this, quantitative optimization such as EOQ or Groff heuristics must be complemented with other methods that can handle and visualize diverse data types (Groff, 1979; Mickein et al., 2022). Digital technologies encompassing data capturing (e.g. IoT, Sensors, Track & Trace, etc.), data transmission and storage (e.g. 5G, edge computing) and analytics (big data, artificial intelligence) provide these features to make use of big data and support operational decision-making. The DES is flexible with incorporating different OM methods while providing an understandable and simple visualization. The next section provides an overview of such lot sizing approaches in the literature.

2.2. Characteristics of existing lot sizing methods

Determination of the optimal lot size can be a difficult problem to solve. Different models have been developed and extensively studied. These models differ in their included features and the resulting computational complexity (Jacobs & Chase, 2014). Features include computational set-up, the number of products simultaneously considered (single
or multiple items), the production system levels (single or multiple stages), capacities and different demand types. Diverse feature combinations can be found in the literature (Andriolo et al., 2014; Beck et al., 2015; Brahimi et al., 2017; Helber & Sahling, 2010).

Lot sizing models can be categorized as belonging to one of three programming types: static, periodic, and dynamic. Static lot sizing techniques define a fixed order quantity (FOQ), order the precise amount needed to fulfill the forecasted demand, known as Lot To Lot (LTL) or define an order quantity that minimizes the total holding and ordering costs (EOQ; Andriolo et al., 2014; Harris, 1990). Periodic lot sizing techniques use the demands of different periods to define lot size, such as the Fixed Order Period (e.g. FOP). Dynamic lot sizing concepts such as Silver–Meal heuristics (SMH), Part Period Balancing (PPB), Least Unit Cost (LUC) and Groff (GMR) consider the cumulated forecasted demand throughout the entire time horizon to define optimal lot sizes (Beck et al., 2015; Brahimi et al., 2017). As time goes by and the production demand changes, plans may be adapted accordingly (Beck et al., 2015; Buschkühl et al., 2010). Dynamic models require a more complex computation compared to static lot sizing techniques (Florian et al., 1980).

Single-item models encompass only one item (e.g. final product) in the production planning, whereas in multi-item production systems, several items exist (Karimi et al., 2003). The single-stage characterizes a production system where the final product is simple and raw materials are directly processed by one continuous operation into the final product, as in a casting process (Karimi et al., 2003). More complex models cover a multistage production system, in which raw materials are processed in different operational steps to produce the final product.

Furthermore, many models are uncapatitated. These models do not consider the resources in a production system such as manpower, equipment, and machines (Aggarwal & Park, 1993; Wagelmans et al., 1992). This reduces the complexity of computation and the effort to gather the needed information about the capacities (Florian et al., 1980) with the downside of incompletely capturing the decision-problem.

Extensions of these basic lot sizing models also exist, including multistage production systems (Bogaschewsky et al., 2001; Glock, 2011), productivity (Jaber & Bonney, 1999), and the determination of safety stocks (Glock & Ries, 2013). Heuristic solution procedures use the properties of the static models to find a good solution (Hindi, 1996; Kohlmorgen et al., 1999). Meta-heuristics such as tabu search (TS), simulated annealing (SA), and genetic algorithms (GA) receive more attention because of their flexibility and ability to solve complex problems (Jans & Degraeve, 2007) with (Barbarosoğlu & Özdamar, 2000) and without capacities (Dellaert et al., 2000; Kuik & Salomon, 1990).

Furthermore, existing models differentiate themselves by demand type: deterministic or stochastic. In deterministic demands models, the demand is known in advance, whereas in stochastic cases, the demand values are based on probability distributions (Brahimi et al., 2017; Karimi et al., 2003). Lot sizing techniques also differ in the considered length of demand horizons used to compute optimal lot sizes (Bookbinder & H’ng, 1986).

A common missing feature in existing models is the practical implementation of lot sizing models in decision-making processes. Models focus on cost minimization, and often neglect other strategic targets, thus failing to capture the entire managerial decision-process. Thus, while design principles are well researched, this remains an issue in
the OM literature. In addition, these models do not sufficiently cover the opportunities enabled by digital technologies, such as data availability that allows the building of new models to support and automate decisions in operations.

The presented literature indicates that a combination of DES and OM methods with the rising opportunities around digital technologies and data availability can be helpful to solve lot size decision-making problems (Martinez et al., 2021; Sahoo, 2021). To answer our research question, we deploy a solution model integrating the introduced methods in the context of a practical case, using a DSR approach. Our solution model considers the identified issues (limited system perspective, complexity of solutions, cognitive limitations, etc.) and limitation of existing research to overcome these issues. Table 1 shows a summarizing overview of these findings and provides directions for detailed definitions of the different lot sizing techniques. The applied methodology is explained in Section 3.

3. Research methodology

3.1. CIMO Logic

To develop a new body of prescriptive knowledge for lot size decision-making and to show its usefulness in a practical case, we opt for a research design that follows DSR principles. The goal of DSR is to extend organizational and human capabilities through the creation of a new artifact (Henfridsson & Bygstad, 2013).

The DSR process is based on existing theory and uses this knowledge to inform design (Gregor & Hevner, 2013). Descriptive as well as prescriptive knowledge is considered to inform the researcher about the object of investigation and the design process. Many variants of reference processes and ways to conduct a DSR exist (Dresch et al., 2014). In this research, we choose the CIMO-approach due to its strength in extending alternative applications of design proposition thinking to consider contextual specificities (Denyer et al., 2008).

First, we describe the problem in-Context (the C in CIMO), which is represented by the underperformance of existing manufacturing (e.g. utilization) due to suboptimal lot size determination and the inadequacy of managerial practices and mechanisms to address it. Next, we continue with the description of the Intervention (the I in CIMO) by the scientific team and the managers, containing the design of the decision support model by applying the discrete event simulation methodology combined with eight different analytical methods. Based on that, we develop a Mechanism (the M in CIMO) to support managers in their decision-making process concerning the lot size determination in production planning. The Outcome (the O in CIMO), and thus the observable improvement of this decision-making, is subsequently described. In this paper we use simulation experiments and qualitative expert discussions as evaluation methods. The emphasis in this paper is on knowledge transfer and process transformation rather than the efficiency gains due to the application of scientific methods.

3.2. Data overview

In order to understand the case company’s problem and solution requirements, several semi-structured interviews and workshops were conducted. Information about product specifications, production processes (working plans), machine characteristics and
Table 1. Review of lot sizing approaches.

| Fixed order quantity (FOQ) | Lot for lot (discrete order quantity) (LTL) | Economic order quantity (EOQ) | Fixed order period (FOP) | Wagner–Within algorithm | Silver–Meal heuristics (SMH) | Part period balancing (PPB) | Least unit cost (LUC) | Groff (GMR) | Capacitated lot sizing problem (CLSP) | Multi-level capacitated lot sizing problem (MLCLSP) |
|----------------------------|---------------------------------------------|------------------------------|-------------------------|-------------------------|----------------------------|-----------------------------|----------------------|------------|--------------------------------------|-----------------------------------------------|
| Jacobs and Chase (2014)    | Jacobs and Chase (2014)                      | Harris (1990); Andriolo et al. (2014), Glock et al. (2014) | Jacobs and Chase (2014) | Wagner and Whitin (2004); Jans and Degraeve (2007) | Silver and Meal (1973); Schulz (2011) | Baciarello et al. (2013); Van den Heuvel and Wagelmans (2010) | Baciarello et al. (2013); Brahimi et al. (2017) | Groff (1979); Beck et al. (2015) | Dixon & Silver (1981); Bruno et al. (2014); Wu et al. (2021) | Billington (1983); Helber and Sahling (2010); Mickein et al., 2022; Zhao & Zhang, 2020 |

| Problem type | SLULSP | SLULSP | SLULSP | SLULSP | SLULSP | SLULSP | SLULSP | SLULSP | CLSP | MLCLSP | MLCLSP |
|--------------|-------|-------|-------|-------|-------|-------|-------|-------|------|-------|-------|
| Considers inventory costs | x | | | | | | | | | | |
| Considers order or set-up costs | | | | | | | | | | | |
| Considers service level | | | | | | | | | | | |
| Considers capacity constraints | | | | | | | | | | | |
| Considers multiple products | | | | | | | | | | | |
| Considers multi-level production | | | | | | | | | | | |

(Continued)
| Fixed order quantity (FOQ) | Lot for lot (discrete order quantity) (LTL) | Economic order quantity (EOQ) | Fixed order period (FOP) | Wagner–Within algorithm | Silver–Meal heuristics (SMH) | Part period balancing (PPB) | Least unit cost (LUC) | Groff (GMR) | Capacitated lot sizing problem (CLSP) | Multi-level capacitated lot sizing problem (MLCLSP) |
|--------------------------|---------------------------------------------|------------------------------|-------------------------|-------------------------|-------------------------------|----------------------------|----------------------|-------------|-------------------------------------|---------------------------------------------|
|                          |                                             |                              |                         |                         |                               |                            |                      |             | x                                    | x                                           |
| Integrates different objectives into a single decision |                              |                              |                         |                         |                               |                            |                      |             | x                                    | x                                           |
| Visualizes trade-offs and effects of decisions and between objectives |                              |                              |                         |                         |                               |                            |                      |             | x                                    |                                             |
| Analytical/ statistical approaches |                              |                              |                         |                         |                               |                            |                      |             | x                                    | x                                           |
| Dynamic simulations | x                                           | x                            | x                       | x                       | x                             | x                          | x                    |             | x                                    | x                                           |

SL, single-Level; ML, multi-level; U, uncapacitated; C, capacitated; LSP, lot sizing problem.
Table 2. Overview of data case company.

| Step                                           | Purpose                                                                 | Data item                                                                 | Source                                      |
|------------------------------------------------|-------------------------------------------------------------------------|---------------------------------------------------------------------------|---------------------------------------------|
| Understanding of problem and scope of researcher involvement | Overview of the current situation, identify the problem, define the objective (KPIs) and decisions to make | Three interviews with problem owner, discussion of current problems such as delay in delivery, low throughout rate | Supply Chain Manager, Head of Operations, CEO, COO |
| Design of the model                            | Data collection to understand the decision-making process, production processes and sequences for the different products | Receiving data and explanations from problem owner, continuous communication about model design | ERP system, Supply Chain Manager and Head of Operations |
| To model the customer demand pattern           | To calculate on-time-delivery (OTD)                                      | Sales data: during the last 3 years                                        | ERP system                                 |
| To model the material flow                     | To calculate costs                                                       | Costs: resource hourly rate, product yearly inventory cost                 | ERP system                                 |
| To calculate costs                             | To model system capacity                                                 | Resource capacity: machine amount, working schedule                        | ERP system                                 |
| Application of the model                       | Comparison of previous state and improved state, discussion about solution and the performance (KPIs) of solution   | Current production planning method and current lot-sizes                   | ERP system and Head of Operations           |
| Evaluation and refinement                      | Receive feedback from problem owner about our solution approach. Evaluate the solution regarding decision-support and outcome. | Final interview with problem owner | Supply Chain and Operations Manager        |

capacities, costs, and sales for the last three years were collected and analysed in detail to understand production and the related planning. We combined quantitative data sourced from IT systems with qualitative knowledge from the experts from the case company to generate transparency about production flows, planning activities, decision-making and the corresponding performance. Interviewees included the purchasing and supply chain manager together with the head of operations. A data overview is provided in Table 2.

Evaluation and generalization are central to a DSR approach. In this study we follow the guidelines of O’Keefe (2014). To demonstrate the utility and validity of the presented solution, jointly with the case company, we evaluated the construction and testing and analysed the intervention results. To further validate the usefulness of the solution and to enable a generalization of the specifications to other contexts, we conducted interviews with four top operation managers in international companies from diverse industries (Venable et al., 2012). An overview about these interviews is provided in Table 3.

Table 3. Overview of interviews outside the case company.

| Company | Position                                | Industry          | Size (employees) | Duration (min) |
|---------|-----------------------------------------|-------------------|-----------------|----------------|
| Company A | Head of Operational Excellence & Projects | Glass production | ca. 16,000      | 90             |
| Company B | Head of Production                      | Spring production | ca. 300         | 45             |
| Company B | Head of Operational Excellence & Projects | Spring production | ca. 300         | 60             |
| Company C | Lean Manager                            | Measuring Equipment | ca. 500         | 120            |
4. Deploying CIMO-logic and evaluation

4.1. Context

The case company is a technology leader in the production of fine blanking parts for the automotive and construction industries. It produces 12 main products with 28 production processes (e.g. fine blanking, pressing, heating, surface mounting, grinding, polishing and final assembly) with around 100 employees in production and planning. Each product goes though the production process sequences following a specific operations plan. Demand arrives at the beginning of each month. The yearly planned demand is known 6 months ahead; monthly real demand is normally known 3–5 weeks ahead. Demand can also vary due to short notice changes by customers. The production planning is organized as follows. No safety stock is planned. Rather, when a new order leads to negative inventory, production is triggered. Batch production results in a new inventory level, from which customer orders are fulfilled, until a new order leads to another negative inventory level.

Recently, the company has faced several challenges, such as high-cost pressure and short delivery times, which have endangered profitability. Constant cost optimization programs helped the company to survive. The delivery situation recently worsened due to strong demand variations driven by the global corona crisis. Management had little transparency about production and delivery performance due to constant reprioritization of orders. These constant changes to the operation plans drove the company to split and overlap orders, resulting in partial shipping to customers. The ERP System could not properly handle all these changes due to many manual and off-system actions. The company’s data quality of the actual production situation worsened daily. This ultimately created significant delivery issues with customers.

Based on semi-structured interviews with operations managers, the COO and the CEO together with data analyses, reasons for poor performance have been revealed and locations for optimization identified. Large lot sizes generated the need for reprioritization of orders including respective measures to partially meet customer delivery needs. Improvement in capacity management including order sequencing became critical as transparency was missing. To optimize the decision process for lot sizes and improve resulting KPIs (e.g. throughput, on-time delivery), tools other than the static ERP system were needed to provide analytical capabilities, at the same time remaining transparent and usable.

4.2. Intervention

4.2.1. Design requirements from the case study

Our role was to develop and implement a decision support system based on scientific methods for optimizing lot size decision-making in production planning. The target was to design an assistant system in close collaboration with the company (the problem owner) that could be handed over and applied after our collaboration.

The main requirement from the company was that the solution model encompass the ability to generate a digital copy of their production process flows. It must include all relevant quantitative information, such as demand, capacities, inventory costs, resource hourly costs, processing time and set-up time. It was important for the company that the solution provides a solid basis for discussion and collaboration.
between different functional departments. Therefore, the solution must be able to visualize causes and effects to help stakeholders better understand problem and the results of their decisions.

4.2.2. Design requirements and empirical justification
Based on the introduced knowledge about lot sizing concepts, as a first step we must collect requirements for our DSS. These design requirements (DRs) are based on considerations in OM and DSS and the expert interviews with our case company. Both domains look at the same problem from different perspectives. OM focuses on modelling real-life problems as closely as possible and delivering feasible and optimal solutions. Approaches should consider quantitative and qualitative data, be multi-objective and provide trade-offs between conflicting goals. DSS on the other hand focuses on the application, the decision-making process itself. Researchers in this domain provide insights and mechanisms on how to guide decision-makers, and on the interfaces between the tools and the managers. A summary of the derived design requirements from OM and DSS literature can be found in Table 4. The different design requirements have been validated with the case company and with the interview partners of the other selected companies facing similar challenges. Figure 1 illustrates how each design requirement is addressed in the artefact’s design principles.

4.3. Mechanism
4.3.1. Choice of methods
Our solution model has at its core a Discrete Event Simulation (DES) method and combines it with established OM lot sizing methods to fulfil the derived design requirements stated previously. This solution model allows the user to optimize lot size for different strategic objectives. Results and effects are presented in a 3D-animation including performance evaluation of different strategies.

We chose DES as our solution method, as it models complex environments or systems where events occur in sequence. DES is one of the most frequently applied simulation techniques for manufacturing processes (Negahban & Smith, 2014). DES allows users to perform analyses of system characteristics, identify bottlenecks of process flow and compare the performance of various decisions before the system is actually built or modified.

In this study, we selected eight lot sizing techniques that are established in the literature. As our focus is not the lot sizing technique itself, but the decision-making process, other lot sizing techniques could be implemented as well.

This approach allows us to integrate different OM methods to implement a multi-objective optimization for a complex problem, in this case, lot size decision-making with simultaneous production of simple and clear effect and performance visualizations for stakeholders. These visualizations serve as a basis for discussing the range of different lot sizing strategies. Figure 2 shows our solution approach, including the way the methods are applied.
Table 4. Design requirements from OM and DSS.

| Domain | Derived design requirements (DR) | Supporting literature | Empirical validation |
|--------|---------------------------------|-----------------------|---------------------|
| From Operations Management (OM) literature | DR1: Model the problem as real as possible | Brahimi et al. (2017), Drexel & Kimms, 1997 | 'Information about demand patterns, trends, risks, capacities, products and process flows as well as order status need to be considered' – Head of Production, Springs |
| | DR2: Consider multiple objectives and information sources | Florian et al. 1980, Aggarwal and Park 1993 | 'We need to see the effects on different KPIs to decide on the optimal lot size, not just the costs perspective' – Head of Production, Springs |
| | DR3: Identify feasible and optimal solutions compute trade-offs between conflicting goals | Glock et al. 2014 | 'We need to consider real-time data for capacities, order status, processing times to derive optimal solutions' – Head of Operational Excellence, Glass |
| From Decision Support Systems (DSS) literature | DR4: Consider a broader system perspective and show the value of respective lot sizes to make informed lot size decisions | Form of guidance (Morana et al., 2017) | 'We have to get away from lot size discussions only focused on inventory and set-up costs, we have to establish a broader, more holistic decision perspective,' 'MRP systems are limited to single-products and single-stage considerations.' – Head of Production, Springs |
| | DR5: Decrease the complexity of lot size determination for managers | Intention of guidance (Arnold et al., 2004) | 'We have to integrate more information, to facilitate better decision-making and have to make it understandable at the same time' – Lean Manager, Measuring equipment |
| | DR6: Provide an understandable visualization of effects and interdependencies to all stakeholders | Format of guidance (Gregor & Benbasat, 1999) | 'The challenge is to show a complex problem in simple way, so that stakeholders can make use of it' – Head of Production, Springs |
| | DR7: Foster a cross-functional decision-making discussion to decide on the final option | Participative guidance (Morana et al., 2017) | 'If we are able to visualize a broader system perspective, this will allow us to integrate other operational decisions such as make or buy, product allocations, etc.' – Head of Production, Springs |
| | DR8: Enable a learning form decision | Dynamic guidance (Morana et al., 2017) | 'Transparency about effects of decisions, will bring learning and cross-functional collaboration on another level' – Head of Operational Excellence & Projects, Glass |

4.3.2. Model design and application

First, we choose and collect necessary information inputs. As we know from existing lot sizing techniques, included features dictate which specific information about products (e.g. bill of materials, process sequences, sequencing rules, buffers, etc.) and costs (set-up, holding and processing for each single product) are required. The information was gathered from the ERP system and complemented with semi-structured interviews with the company’s operations manager, as described in Section 3.2.

Figure 3 provides an overview of the decision support system for lot sizes of the case company including the simulation of the production process: inputs, process map, decisions, and outputs. The whole process includes three departments: sales, inventory management and production. As shown in the processes map, first, customer demand
arrives monthly and is entered into the demand database (demand queue). Then inventory levels are checked to identify whether products required by the demand are available and can be delivered immediately. If yes, the products are delivered to customers and the demand is filled. If not, the demand stays in the demand queue, and production planning and production processes are triggered. Production planning implements a certain lot size technique, considering the projected inventory level and relevant costs, to determine the lot sizes. Thirdly, when the production process of a new batch is completed, it enters the inventory. The corresponding on-hand inventory levels and projected inventory levels are updated. Pending demands are checked to see what can be filled thanks to the arrival of the new batch. The material and information flows, such as demand arrival, production, and delivery, are modelled as discrete sequences of events. The queue levels of demand orders, materials and final products are simultaneously modelled.
In the sales department, 3 years’ historical sales data and the targeted lead time are used as input data. We consider six different demand patterns using information from historical demand: (a) historical data; (b) constant demand; (c) normally distributed demand; (d) uniformly distributed demand; (e) demand with seasonality; and (f) demand with high fluctuation. As outputs, the total demand and pending demand are computed. KPIs such as customer satisfaction and throughput (hourly delivered amount) are also calculated.

In the inventory management department, yearly inventory costs for all products are inputs. As outputs, the on-hand inventory levels, projected inventory levels and hourly inventory costs are calculated.
In the production department, inputs are production process information: operations sequences for the 12 types of products, processing time, set-up time, resource hourly rate, resource capacity for the 28 processes, and current lot-sizes. All machines run two-shifts (18 hours) per working day operation. The monthly demand, inventory cost, set-up cost, and original lot size for each product are presented in Table 6. For each process,

- The processing time depends on the respective specific processes and products.
- The set-up time depends on the processes but not on products.
- The FIFO rule is followed in choosing the next batch.
- For a given batch, a processing step is always completed before the next step is started.

The decision-maker sets the strategic objectives, which vary according to the company’s global strategy. According to the strategic objectives, we define the corresponding KPIs and acceptance criteria together with the management team. In our study, the following four KPIs are considered to be important:

1. Hourly costs: production and inventory costs;
2. Resource utilization: the utilization of each machine is (set-up time + process time)/(set-up time + process time + idle time);
3. Throughput: hourly produced and hourly delivered amounts (for the whole plant) are the corresponding total amount divided by the time simulated;
4. Customer satisfaction: Fill rate that is ‘delivered amount/demanded amount’, and OTD rate that is ‘on time amount delivered/amount delivered’.

Based on the various data inputs and interdependencies between the different functional departments and related processes, we combine the simulation with existing OM methods to support lot size decision-making. Different lot size techniques are implemented in the simulation model. When a decision-maker decides on a specific technique, the production decisions (lot sizes and lots amounts) and the resulting KPIs, such as hourly production costs, resource utilization and throughput (hourly produced amount) and customer satisfaction, are calculated.

We have selected eight lot size techniques, which are commonly introduced in literature (see also Section 2), require fair computational effort and are simple to understand. We classify the strategies in two groups: I. Non-cost-oriented strategies: Fixed order quantity (FOQ) and Lot for lot (Discrete order quantity) (LTL). II. Cost-oriented strategies: Economic order quantity (EOQ), Fixed order period (FOP), Silver–Meal heuristics (SMH), Part period balancing (PPB), Least unit cost (LUC), Groff (GMR). When implementing static lot sizing techniques such as Fixed Order Quantity (FOQ), it is possible that the decision-maker sets the order quantity manually. In our simulation we implemented the following lot sizes: current lot size, monthly average demand, half, twice, three times and four times current lot size. When implementing the LTL technique, we consider a lot size equal to the exact amount that matches the current net demand or for 0, 1, or 2 periods later. When implementing other lot sizing techniques, the system calculates the lot size according to the appropriate formula. Denote the
quantity to be produced by \( Q \), yearly demand by \( D \), demand of month \( t \) by \( d_t \), set-up cost by \( A \), yearly holding cost by \( H \), and number of periods covered by \( n \). The sum of the production set-up cost and the holding cost of products for the next \( n \) periods is

\[
C(n) = A + H \sum_{t=1}^{n} (t-1)d_t,
\]

(1)

\[
EOQ : Q = \sqrt{\frac{2AD}{H}},
\]

(2)

FOP: Fixed order period is given by \( n \) and it is calculated by the formula “\( \sqrt{\frac{2AD}{H}} D^{*12} \)”;

\[
SMR : k(n+1) > k(n), k(n) = \frac{C(n)}{n};
\]

(3)

\[
PPB : \sum_{t=1}^{n+1} (t-1)d_t \geq A;
\]

(4)

\[
LUC : \frac{C(n+1)}{\sum_{t=1}^{n+1} d_t} \geq \frac{C(n)}{\sum_{t=1}^{n} d_t};
\]

(5)

\[
GMR : HA/(n(n+1)).
\]

(6)

In the last step, we run the model for a sufficient length of time and with replications if uncertainties exist. The performance regarding the achievement of the strategic objectives of different scenarios are measured and compared. Based on this, the decision-maker can choose the most suitable scenario for actual implementation.

We use the program SIMIO (version 12) to build the DES model, which models the above-mentioned data, processes, and strategies. Compared to reality, our simulation model contains some simplifications. Our case company agreed with these changes. We model the processes without considering machine and material failures and walking time between resources. One of the 28 processes is an external process heat-treatment, which is modeled as having infinite capacity and always delivering on time. The model was randomly paused during several runs and each component was checked to ensure consistency with the flow diagrams. Model validation was conducted to compare with the case company’s real performance.

By running experiments with different parameter settings in a time length of 2.5 years, the decision-makers receive an overview of the performances from different strategies and can choose the one that performs the best with regard to the self-chosen KPIs. Selected experiment results are summarized in Tables 5 and 6. Further performance results for other demand patterns can be provided by the authors upon request.
4.3.3. Results from the application

We calculate a total of 15 different scenarios including all 12 product types of our case company. In our simulation experiments, we consider six different demand patterns from actual demand (historical data, constant demand, normal distribution, uniform distribution, with seasonality, with high fluctuations).

Overall, scenario 1.3 (fixed order quantity with 0.5*current lot size) has the highest throughput (hourly delivered) rate, fill rate and OTD rate. At the same time, it has the lowest bottleneck resource utilization rate, and relatively low hourly cost and inventory levels. Scenario 1.1 (with current lot size) has similar performance. According to the targets of our case company, scenario 1.3 is the most suitable scenario to address the existing issues such as low OTD, throughput and customer satisfaction.

It is worth mentioning that, as shown in Table 6, the lot sizes calculated by classic strategy EOQ are much larger (c.a. 10 times) than the best performed lot sizes (FOQ: Q/2). Comparing scenario 1.3 with scenarios 3–8 in Table 5, we can see that the classic lot sizing strategies have significant worse performances: much higher costs, inventory and bottleneck resource utilization, at the same much lower OTD. This underlines the effectiveness of our decision support system.

Figure 4 shows a performance example produced by our simulation model. The first 12 rows contain states of inventory levels and production planning for the 12 different products, while the second 12 rows list the states of throughput and customer satisfaction. Other KPIs such as costs and resource utilization are similarly displayed by our model.

With our decision support system, we helped the company to increase its on-time-delivery rate by 17%, thus increasing delivery reliability, enhancing company reputation, and increasing customer loyalty, and consequently, contributing to an increase in demand. The inventory level reduced by 20%, which reduced working capital. Overall, we estimate an EBIT improvement of 3%.

Table 5. Lot sizing strategies performance in the case company.

| Sc. | Strategy-lot size | Hourly cost (CHF) | Utilization rate | Hourly throughput (product units) | Customer satisfaction |
|-----|-------------------|-------------------|------------------|-----------------------------------|----------------------|
|     |                   | Total            | Average          | Bottleneck                        | Produced  | Delivered | Fill rate | OTD rate |
| 1.1 | FOQ: Q            | 241.0            | 0.5              | 14%                               | 2,523.5   | 2,526.0   | 100%      | 80%      |
| 1.2 | FOQ: Monthly average | 241.7            | 0.7              | 15%                               | 2,499.9   | 2,496.9   | 99%       | 57%      |
| 1.3 | FOQ: 0.5* Q       | 241.1            | 0.4              | 13%                               | 2,511.2   | 2,526.6   | 100%      | 97%      |
| 1.4 | FOQ: 2* Q         | 243.2            | 0.7              | 15%                               | 2,521.1   | 2,487.4   | 98%       | 43%      |
| 1.5 | FOQ: 3* Q         | 244.9            | 0.8              | 15%                               | 2,519.6   | 2,480.0   | 98%       | 35%      |
| 1.6 | FOQ: 4* Q         | 245.4            | 1.0              | 15%                               | 2,573.4   | 2,501.2   | 99%       | 42%      |
| 2.1 | LTL 0             | 242.6            | 0.4              | 15%                               | 2,496.9   | 2,496.9   | 99%       | 45%      |
| 2.2 | LTL 1             | 238.9            | 0.9              | 15%                               | 2,471.7   | 2,442.8   | 97%       | 22%      |
| 2.3 | LTL 2             | 238.8            | 1.0              | 15%                               | 2,424.9   | 2,368.9   | 94%       | 21%      |
| 3   | EOQ               | 479.4            | 11.4             | 28%                               | 5,291.6   | 5,256.6   | 100%      | 81%      |
| 4   | FOP               | 625.5            | 8.3              | 37%                               | 3,780.4   | 3,237.2   | 92%       | 60%      |
| 5   | SMH               | 632.9            | 9.5              | 37%                               | 4,087.9   | 2,448.4   | 97%       | 59%      |
| 6   | PPB               | 629.6            | 9.3              | 37%                               | 4,073.5   | 2,448.4   | 97%       | 62%      |
| 7   | LUC               | 639.9            | 9.7              | 37%                               | 4,359.4   | 2,467.1   | 98%       | 66%      |
| 8   | GMR               | 631.0            | 9.4              | 37%                               | 4,105.2   | 2,448.4   | 97%       | 60%      |
4.3.4. Outcome and evaluation

The DES provides transparency about the effects of different lot sizing techniques on performance factors. Managers are equipped to visualize effects, trade-offs, change assumptions and calculations, discuss alternatives, and eventually select the lot size best suited to their strategy. Evaluation in DSR is a central and essential step in conducting rigorous DSR (Venable et al., 2012). It is used to provide evidence that the newly designed artifact achieves the purpose for which it was designed (March & Smith, 1995). We consider the evaluation criteria from Venable et al. (2012). To test these, we use simulation experiments and a semi-structured interview to evaluate our model and the formalized knowledge.

The case company interview was conducted with an expert in production planning, who has worked for several manufacturing companies in their planning departments. Thus, considerable familiarity with topics around scheduling, lot sizing and IT systems was assured. The expert discussions took place during the design phase of the model to

| Product number | Monthly demand mean | Monthly demand STD | Yearly inventory costs (CHF/Pcs) | Set-up costs (CHF) | FOQ: Q | FOQ: Q/2 | EOQ |
|----------------|---------------------|--------------------|----------------------------------|-------------------|--------|---------|------|
| 1              | 334,124             | 163,156            | 0.007219                         | 363.0             | 120,000| 60,000  | 635,012|
| 2              | 328,426             | 124,883            | 0.007219                         | 341.0             | 120,000| 60,000  | 610,199|
| 3              | 133,276             | 124,551            | 0.004125                         | 363.0             | 120,000| 90,000  | 684,932|
| 4              | 206,572             | 111,435            | 0.007219                         | 341.0             | 120,000| 60,000  | 499,303|
| 5              | 205,092             | 90,024             | 0.007219                         | 341.0             | 120,000| 60,000  | 482,200|
| 6              | 201,789             | 71,641             | 0.014438                         | 341.0             | 100,000| 50,000  | 338,210|
| 7              | 34,960              | 41,460             | 0.009625                         | 284.9             | 72,000 | 36,000  | 157,593|
| 8              | 108,001             | 75,968             | 0.002406                         | 581.9             | 200,000| 100,000 | 791,724|
| 9              | 100,968             | 58,652             | 0.001444                         | 581.9             | 200,000| 100,000 | 1,397,117|
| 10             | 70,571              | 43,162             | 0.007219                         | 363.0             | 60,000 | 30,000  | 291,838|
| 11             | 71,089              | 40,875             | 0.007219                         | 363.0             | 60,000 | 30,000  | 292,907|
| 12             | 51,737              | 36,456             | 0.009625                         | 308.0             | 36,000 | 18,000  | 199,334|

Figure 4. Example of KPIs displayed in the simulation model.
gather the requirements and to reflect and evaluate design elements before the final model is used by the company to investigate if the purpose can be achieved. The results are presented below.

(1) Define data inputs: The expert from the company sees the various data inputs as important sources to establish a holistic perspective. Although today there are still holes in the data due to missing connectivity or data layer, to build the model it is worthwhile gathering and integrating the most important data fields for the lot size decision, such as machine data, process data, capacities, set-up times and costs. ‘There should be an adequate effort benefit ratio for the data generation. Digital technologies will further lower the transaction costs in the future.’ This supports our design principles DP1 and DP4.

(2) Set strategic options: This is a feature that allows a user to select specific objectives in addition to costs, such as delivery reliability. ‘This design feature is important for the expert to foster strategic discussions, which haven’t taken place in the past.’ This supports our design principle DP1.

(3) Process model visualization: Visualization is seen as the most important feature of the model to create acceptance and to enable fact-based discussions. The classical MRP 1 and 2 are usually not accessible enough to create foundational system understanding and do not show the effects of certain decisions. ‘In production there often exist a high variety and level of competences (from apprenticeship to PhD), where a formula-based model is not the adequate way to create a common understanding and beliefs, to influence behaviour and decision-making.’ The formulas are seen as black boxes and do not foster a real system understanding. This leads to the fact that in many cases an individual is not aware of the consequences of its decision for the system (in this case the entire company). Through this simulation model, the consequences become visible. This supports our design principle DP2 and DP5.

(4) Analytic techniques and performance: To have different options for optimization is always welcome, but individuals need to see and feel the effects in operations. ‘There will be a capacity problem at machine B, or this will lead to a lower utilization at machines C, D, E, and we will have longer waiting times for the orders 15, 16, 18.’ The development of scenarios fosters a system understanding and drives decision-making towards a more system-oriented perspective. This supports our design principle DP3.

(5) Linkage to related decisions: This is an important feature of the model, as it can be a ‘game changer’ for certain other decision types. One example the expert explained to us is related to long-term resource planning, which is always done when a new customer request comes in. In this planning process, a rough calculation to investigate the ability to fulfil the customer request is conducted. Operational lot sizes and customer lot sizes are not considered at this point in time, which lead to the problem that, in some cases, the rough planning is operationally infeasible. If a lot size perspective can be integrated in the early customer request process, the company can considerably benefit from and reduce the number of not feasible customer requests. Besides the integration of lot size in this perspective, there are also further beneficial relations to other decisions, such
as make or buy and customer lot sizes. The expert told us that the combination of the three different perspectives such as customer lot size, purchasing lot size and the internal operational lot size would help to support the identification of global optima. This supports our design principle DP1.

5. Discussion and theoretical implications

The literature review revealed the lack of practical acceptance of existing OM lot sizing approaches in decision-making (see Section 2, Table 1). Our intervention-oriented research showed that managers can profit from applying design methods from theory to enable structure and objectivity. The data gathered during the design and evaluation phase (Tables 2–4 and Section 4.3.5) and the interviews in and outside the case company confirm the equivalent importance of decision-process oriented and problem-focused requirements. One of the key success factors is the visualization of results to foster acceptance and facilitate discussions between stakeholders (Arnold et al., 2004), while considering a broader system perspective around the specific practical problem (Morana et al., 2017). These aspects were lacking in existing OM approaches and have been improved by our intervention. Based on our DSR approach (Denyer et al., 2008) we showed with our case company how prescriptive knowledge derived from literature can be successfully conveyed to managers as practical knowledge.

This study contributes to theory by addressing the identified research issues in OM (Table 1) and therefore providing six key implications enabled by the combination of DES with OM methods and digital technologies (Figure 5).

(1) System boundaries: Most OM approaches focus on simplified problems, as the system boundaries were limited for analytical techniques due to complexity. Based on our digital model approach, we demonstrate the extension of these boundaries. System boundaries change from a single-item/single-stage perspective to a perspective considering multiple items and stages.

(2) Strategic objectives: While a majority of lot sizing approaches have a pure cost focus and neglect other competitive priorities (Table 1), our solution considers multiple objectives (Florian et al., 1980). The objective of an optimal lot size changes from a pure cost perspective to a broader strategic priority perspective (e.g. customer satisfaction).

(3) Integral part of other dependent decisions: Although our solution represents a digital copy of the real world, the lot size decision becomes an integral part of other operational decisions (e.g. product allocation, scheduling and purchasing decision processes) to foster the achievement of global company goals. These factors influence the lot size substantially (Morana et al., 2017).

(4) Cognitive levels, learning and trust: With our solution we show how digital technologies enable individuals to overcome cognitive limitations regarding information processing for informed decisions. The visualization of process and material flows, interdependencies, and input–output relations foster the imaging of the impact of management decisions (Arnold et al., 2004). This also creates a source for continuous learning and increases trust in the quality of developed theoretical models.
5(5) Complexity reduction: Information exploitation increases while modelling and computational complexity decreases. The visualization of the real world together with analytical problem-solving techniques reduce the perceived complexity due to increased transparency (Gregor & Benbasat, 1999).

(6) Future orientation: Whereas most of the existing analytical models for lot size determination are based only on historical data, the digital copy of the physical processes (digital twin) enables the company to continuously integrate changes in demand and utilization to make better predictions of the future. This results in an increasing resilience level for the company, as this capability enables the company to adapt production systems faster than ever before.

These study results are limited to lot sizing problems in manufacturing companies. Design principles and implications for other operational problems which are enabled by digital technologies need to be further examined. The effectiveness of the model and subsequent generalisation of findings cannot be proven by large data sets, as the deployed methodology is focussed on a specific problem. Additionally, the low number of interviews to validate the solution also presents a limitation. Future research needs to rethink the operational models, as the system perspective will become more dominant in operational decision-models. This might have an impact on key performance indicator systems, concrete analytical techniques and decision-making processes and related activities. Our model can be further developed towards a digital twin to continuously make use of data and optimize model accuracy and thus decision-making foundations.

6. Conclusion

The purpose of this study was to develop a more effective and user-friendly tool to manage complex lot size decision-making problems. We developed an innovative decision-model based on DES combined with OM methods. This model supports managerial
solution for lot sizes depending on the strategic objectives by empowering managers to calculate different lot sizing strategies and get transparency about related performance outcomes and effects through visualizations. It enlarges the pure cost point of view to a wider set of performance criteria’s (e.g. on-time delivery, throughput). Stakeholders can see trade-offs, discuss potential scenarios, and select the preferred solution based on full facts. This model allowed our case company to improve delivery performance while increasing OEE at the same time. Five design principles were introduced to support the development of similar models for even other operational decision-making situations in manufacturing companies. We abstracted from the lot sizing case to generalize 6 key implications for the design of OM models driven by digital technologies, like i.a. the change from a pure cost to a broader strategic priority perspective, the switch from a past-oriented to a more future-oriented decision-making through data and the visualizations to overcome cognitive limitations of humans.

**Disclosure statement**

No potential conflict of interest was reported by the author(s).

**Data availability statement**

Due to the nature of this research, participants of this study did not agree for their data to be shared publicly, so supporting data is not available.

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