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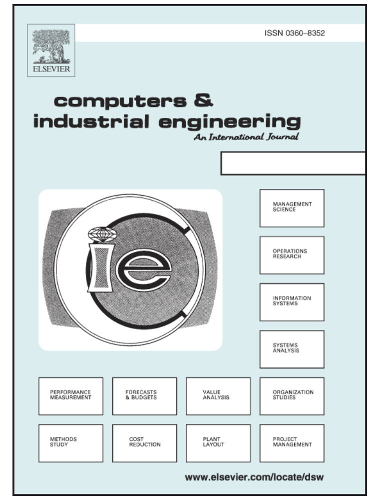

Model Simplification in Manufacturing Simulation - Review and Framework

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ABSTRACT

Simulation models are meant to support industrial engineers in understanding complex problems and provide useful insights facilitating their solution. Models achieve this by reducing focus to system elements that matter. Surprisingly, despite its relevance, simulation model simplification is still very much a green field. This is mirrored in existing literature and course materials. In this article we seek to foster development of the field by proposing a framework for simulation model simplification addressing the manufacturing domain, thereby building on an extensive literature review. The framework structures the field by providing a unifying view on simulation model simplification, in terms of its key activities, i.e., reducing and preventing model complexity, and support offered in performing these. Apart from its role as a focal point for future research, the framework is meant to benefit practitioners and educators, by giving them access to research findings, and enabling and legitimatizing development of educational materials and their uptake.

KEY WORDS

Simulation, Model simplification, Manufacturing systems

1 INTRODUCTION

Many decisions on manufacturing systems design rely on the use of discrete event simulation models (Negahban and Smith, 2014). A prime reason for their popularity is their flexibility in modeling and visualizing the various elements of industrial systems. Exploiting such flexibility, however, sets specific demands on the skills of the industrial engineer and the methods and tools at his/her disposal in simplifying the model relative to the system under study. To reduce modeling efforts, foster model understanding and safeguard computational efficiency of the model, ideally, only system elements that matter for answering to the modeling objectives are included in the model (Ward, 1989).

Surprisingly, despite being a fundamental part of modeling and simulation (Salt, 1993; Shannon, 1998; Henriksen, 2008), simulation model simplification is still very much a green field (Sevinc, 1991; Chwif and Paul, 2000; Brooks and Tobias 2000; Robinson, 2006; Van der Zee et al., 2011; Ahmed et al., 2016). Relatively few contributions have been made over the past decades. Those available make up a fragmented landscape, suggesting the lack of a (unified) view on the field. This is apparent in, for example, alternative choices of terminology, and researchers being unaware of contributions already made. In turn, text books reflect state of the art by restricting their guidance on simulation model simplification to a few rules of thumb, or not addressing it all.

In this article we seek to foster development of the field by proposing a research framework for simulation model simplification addressing the manufacturing domain, thereby building on an extensive literature review. The framework relates model simplification to simulation study set-up and the modeling process by identifying and detailing two main activities, i.e., reducing and preventing model complexity. Whereas the first activity addresses steps to take to arrive at a simplified model – starting from a more complex model, the latter activity is meant to avoid the need for model simplification by adjusting modeling objectives, (staff) resources provided, and choice of modeling methodology.

By proposing a research framework we aim to (i) structure the field by highlighting distinctive features of simulation model simplification in terms of key activities and support in executing these, (ii) recollect existing contributions for the field, where such an overview is not available, and (iii) identify main research avenues. Apart from researchers both practitioners and educators may find the framework useful as it outlines major lines of research in the field.

The article is structured as follows. Section 2 discusses the method and base for the literature review. Descriptive analysis of articles resulting from the literature search is provided in Section 3. In Section 4 the research framework is proposed and related to existing literature. Section 5 assesses contributions made by the framework by considering implications for research and practice. Concluding remarks are summarized in Section 6.

2 RESEARCH METHOD - LITERATURE REVIEW

2.1 Basic terminology

To prepare the groundwork for the literature review key terms are defined. Model simplification is defined as the reduction of inappropriate model complexity. Here "inappropriate" is related to model conformance with modeling objectives and the variance in the data available to the modeler (Innis and Rexstad, 1983). Simulation refers to discrete event simulation: "The modeling of a system as it evolves over time by a representation in which the state variables change instantaneously at separate points in time" (Law, 2015). The process of simulation modeling is characterized by four main activities, i.e., conceptual modeling, model coding, experimentation, and implementation (Robinson, 2014). Respective activities are performed within the context of a simulation study, being characterized by the client, stakeholders, problem faced, modeling objectives, modeling methodology, and resources in terms of a project team, hardware, software, budget, and lead time.

2.2 Delimitations and search process

To clarify the boundaries of the literature review we make the following notes:

(1) This analysis aimed at articles in peer-reviewed scientific journals and conferences in English as they appeared until 2017. Inclusion of conference articles is motivated by the fact that many authors consider the field to be green, see Section 1. In this way we

attempt to record progress for the field which has not yet been captured in journal articles. Conference articles that were extended towards journal articles were excluded.

(2) Articles which only focused at comparing the use of simulation vs. analytical tools for decision support were excluded. We consider simplifications within the context of a simulation model, and do not address the overarching debate on the appropriateness of operational research methods for addressing specific types of problems.

(3) The domain of interest is in the use of simulation for modeling and analyzing operations systems in manufacturing. Operations systems facilitate the material flow cycle, in terms of supply, production, and distribution. The domain covers a wide choice of systems, ranging from simple job shops to supply chains.

The search for related publications was mainly conducted as a structured keyword search on major databases. The following keywords were used in combination: simulation and model abstraction, simulation and model reduction, simulation and model simplification, simulation and model enrichment, simulation and model complexity, simulation model* and abstract*, simulation model* and reduc*, simulation model* and simpl*, simulation model* and enrich*, simulation model* and complex*, simulation model* and redundan*. In accordance with the delimitations mentioned above we followed two avenues in our search process. Firstly, searches of the Web of Science and Scopus aimed at articles in peer-reviewed scientific journals in English. Secondly, IEEE Xplore was searched for articles presented at the Winter Simulation Conference, being the premier international scientific forum for the simulation field. Relevance of the approach for a good coverage of the field was confirmed by the search outcomes. Content-wise articles resulting from both searches often complemented each other. Many contributions presented at the conference did not appear in journal articles yet. Reading the articles found in aforementioned searches, cited references were used as a secondary resource. Apart from additional journal articles this resulted in a few articles originating from conferences other than the Winter Simulation Conference.

3 DESCRIPTIVE ANALYSIS OF ARTICLES

3.1 Source characteristics

Our searches resulted in 82 articles with 41, and 41 of them being published as journal articles and conference articles respectively. Figure 1 illustrates the distribution of the articles over the publication years. It shows how numbers of articles published increase over the years, indicating a somewhat growing popularity of the field. Journal articles are about equally divided among (Industrial) Engineering journals (22) and OR journals (19). The latter category hosts many journals dedicated to the simulation field such as Simulation, and the Journal of Simulation. The rising interest in decision support for semiconductor manufacturing, see above, is marked by several articles being published in IEEE Transactions on Semiconductor Manufacturing (5). Given article numbers, no journal or journals seem(s) to stand out as being the primary outlet(s) for the field.

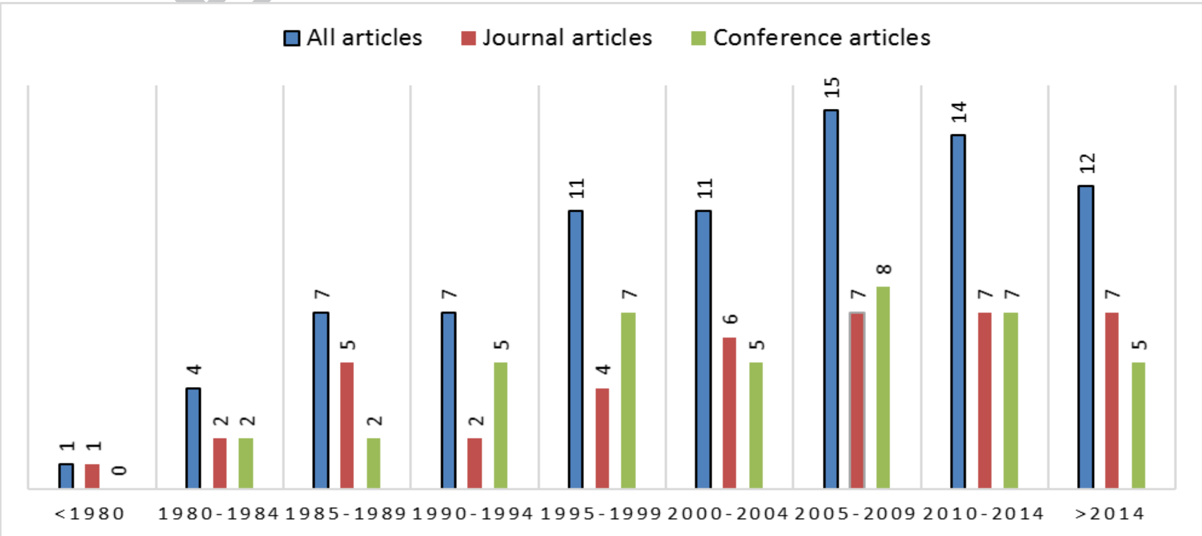

Figure 1 Distribution of the articles by the publication year

3.2 System characteristics – domain, level and use

Most of the articles (45) address the general case of manufacturing systems, i.e., they do not start from specific assumptions about system characteristics. Among those articles that do differentiate a strong focus on semiconductor manufacturing is apparent (19 out of 37). The complexity of manufacturing systems in this domain representing large capital investments, is a likely explanation for the interest shown (Jain et al., 1999; Fowler and Rose, 2004; Fowler et al. 2015). Remainder articles address a large variety of manufacturing domains.

Level refers to the scope of the system under study. Here we differentiate between work centers, manufacturing sites, and supply chains. Typically, the choice of level sets specific demands on the need for, the nature and extent of model simplifications. Most articles favor use of simplification methods for modeling work centers (14) or manufacturing sites (19). Supply chains are hardly addressed (4). The latter finding is confirmed by observations from semiconductor manufacturing, suggesting supply chain simulation to be a rather new area of application (Fowler et al., 2015).

Apart from system scope also model use appears to be a denominator of interest shown in simulation model simplification. Six articles show how model simplification may facilitate simulation-based scheduling, by allowing it to deal with a short horizon for decision making.

3.3 Modeling activities supported

Modeling activities considered in the review are conceptual modeling, model coding and experimentation, linking to the set-up of the conceptual model, the coded model and the experimental frame respectively. With no exception all articles in our study link model simplification to conceptual modeling. Given the high impact of conceptual modeling decisions on remainder modeling activities and – ultimately – study success (Robinson, 2006), this is hardly a surprise. Relatively few articles discuss simplification of the coded model (9) and experimental frame (6).

4 TOWARDS A FRAMEWORK FOR SIMULATION MODEL SIMPLIFICATION

By proposing a framework we seek to structure the field, where such structuring is currently largely lacking. In doing the literature review we found no attempts to structure the field going far beyond listings of methods, good practices or rules of thumb. Moreover, to our knowledge, no literature review has been published so far.

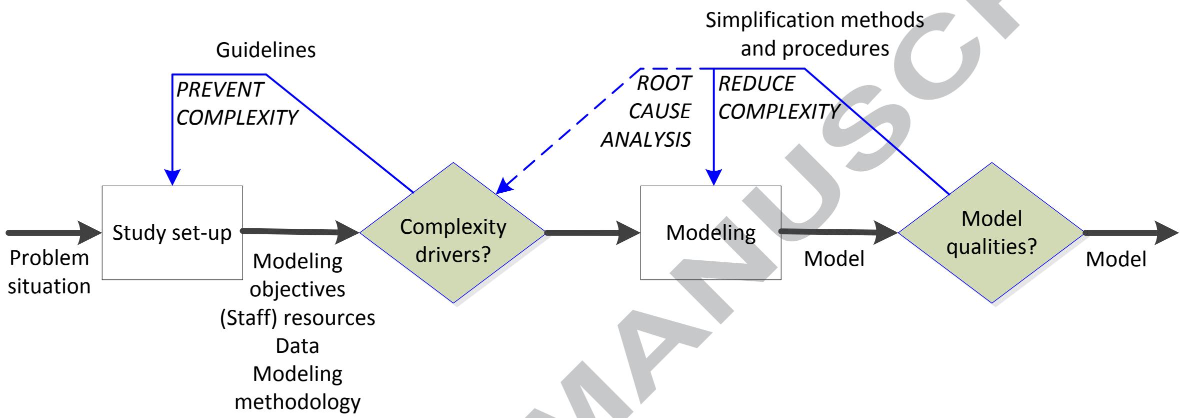

Figure 2 A framework for simulation model simplification

Essentially, the framework links simplification to two main activities, i.e., reducing and preventing model complexity, see Figure 2. The first activity addresses steps to take to arrive at a simplified model – starting from a more complex model. The majority of articles in our review seek to support this activity by developing and/or testing methods and procedures for (i) tracing inappropriate model complexity, and (ii) model modification aiming to realize a reduction of model complexity. Need for and success of model reduction build on an assessment of model conformance to modeling objectives in terms of essential model qualities, especially validity, utility and feasibility (Section 4.1). A smaller group of authors shows an interest in the drivers of inappropriate model complexity, thereby hinting at the need for prevention by a careful set-up of the study through adherence to guidelines (Section 4.2). Both aforementioned activities may be related, as successful model reduction may require reconsidering study set-up. A root-cause analysis is meant to establish and underpin the need to do so (Section 4.3). Main focus of the framework is on modeling support for simplifying the conceptual model, entailing model content, inputs and outputs. As such it reflects state of the art for the field, being the net result of most research efforts being directed towards conceptual modeling rather than the development of the coded model or experimental frame, see Section 3.3. In Section 4.4 we consider extensions of the framework addressing simplification of the latter types of models.

4.1 Model complexity reduction

4.1.1 Improving model qualities – assessing costs and benefits of model simplification

Clearly, model simplification is not an end in itself but is meant to improve model qualities that determine its conformance to modeling objectives (Kotiadis and Robinson, 2008; Robinson, 2008a). Essentially, model simplification should facilitate an increase of model utility and feasibility, not being at the expense of its validity (Robinson, 2008a). Model utility stresses the way a model's ease of use, flexibility, visualization, and run speed contribute to its usefulness. Requirements set on time, resources and data determine feasibility of the proposed model set-up and use. Whether model simplification does not hurt its validity, i.e., model accuracy, should be decided upon based on judgement and/or tests by computer models (Edmonds and Moss, 2004; Harrison et al. 2007; Kotiadis and Robinson, 2008; Robinson, 2014).

Many authors suggest benefits of simplification, thereby detailing its added value for model qualities, see Table 1. In turn, benefits identified reveal those outcomes of the study set-up that may be involved in assessing model scope and detail. For example, a reduced model may benefit model feasibility by requiring less input data, thereby decreasing the modeler's efforts, and lessening resource use, as observed by project management. Likewise, it may be considered whether excess model detail is hindering its interpretation by model users.

Table 1 Benefits of simpler models for various stakeholders

Role	Tasks	Benefits of simpler models	References
Project manager	Manage process	Project resources • Less expensive • Less time involved • Less use of resources • Involves less efforts of project manager Project content • Helpful in specifying modeling objectives • Helpful in acquiring more projects • Avoids solutions that are too advanced being implemented	 • Innis and Rexstad (1983), Yin and Zhou (1989) • Yin and Zhou (1989), Chwif et al. (2000) • Chwif et al. (2000) • Chwif et al. (2000) • Rexstad and Innis (1985) • Ward (1989), Salt (1993) • Musselman (1994)
Modeler	Model development	Data requirements • Less input data required Model building • Facilitates more flexible modeling • Easier to develop and maintain • Avoids solutions that are too advanced being implemented Model validation and verification • Easier to validate, verify • Higher accessibility of assumptions • Clear exposure of flaws; avoid errors • More accurate Modeling methodology • Facilitates evolutionary path for the modeling process	 • Innis and Rexstad (1983), Yin and Zhou (1989), Salt (1993), Sinreich and Marmor (2004), Fletcher et al. (2007) • Innis and Rexstad (1983), Yin and Zhou (1989), Salt (1993), Musselman (1994), Chwif et al. (2000) • Rexstad (1985), Fishwick (1988), Ward (1989), Chwif et al. (2000), Brooks and Tobias (1996, 2000), Salt (1993) • Musselman (1994) • Chwif et al. (2000), Rexstad and Innis (1985) • Ward (1989) • Musselman (1994), Rexstad and Innis (1985), Brooks and Tobias 1996) • Musselman (1994) • Fishwick (1988)
Model user	Do and analyze experiments	Analysis • Easier to interpret • Higher accessibility of assumptions • Easier to use • Enhances insight Experimenting • Speeds up experiments • Allows exploratory use of model • Sensitivity analysis is more practicable	 • Innis and Rexstad (1983), Fishwick (1988), Yin and Zhou (1989), Brooks and Tobias (1996, 2000), Chwif et al. (2000), Sinreich and Marmor (2004) • Ward (1989) • Fripp (1985), Henriksen (2008), Sinreich and Marmor (2004) • Fripp (1985), Brooks and Tobias (2000), Musselman (1994), Anderson and Morrice (1999), Fletcher et al. (2007) • Fishwick (1988), Sevinc (1991), Brooks and Tobias (1996, 2000), Salt (1993), Rank et al. (2016) • Salt (1993), Fletcher et al. (2007) • Ward (1989), Brooks and Tobias (2000)
Client	Owns problem, recipient of results, funds study	Project resources • Less expensive Project content • Helpful in specifying modeling objectives • Avoids solutions that are too advanced being implemented	 • Innis and Rexstad (1983) • Rexstad and Innis (1985) • Musselman (1994)
Domain expert	Provide data	Data requirements • Less input data required	 • Innis and Rexstad (1983), Ward (1989), Salt (1993), Sinreich and Marmor (2004), Fletcher et al. 2007
Third party expert	Provide software support and/or modeling expertise	Software • Applicability of software may increase Model building • Easier to develop and maintain	 • Henriksen (2008) • Rexstad (1985), Ward (1989), Chwif et al. (2000), Brooks and Tobias (1996, 2000), Salt (1993)
Management	Benefit from the study	Implementation of results • Quicker results facilitating speedier decision making, allowing more time for alternative actions and implementation • Results being less specific, allowing managers to incorporate their own knowledge and preferences • Recommendations are easier to sell • Improve fit with strategic nature of problem	 • Ward (1989), Brooks and Tobias (2000), Fletcher et al. (2007) • Ward (1989), Brooks and Tobias (2000) • Ward (1989) • Ward (1989)

Relevance of stakeholder perspectives in assessing benefits of model simplification (Maier et al., 2017) has been reflected in Table 1 by differentiating among various roles in a simulation study. Roles are specified according to Robinson (2014) and Ormerod (2001). While some observed benefits may relate to a specific role, others may be shared among roles. For example, both modeler and domain expert may take advantage of the fact that data requirements may be less. However, simplifications may also imply a trade-off. For example, increasing model speed – by simplifying the model by leaving out detail – may not always improve model understanding among stakeholders. Or even stronger, efforts towards increasing model understanding by simplifying the model may not always be successful, as stakeholder backgrounds may differ (Ward, 1989; Salt, 1993). Furthermore, the need for simplification may differ over the modeling cycle. For example, during the verification phase, a model that is easy to code and debug is desirable, whereas during the experimentation phase, a fast implementation is preferred (Schruben and Yücesan, 1993).

Benefits of a simplification are conditional on its impact on model validity. Many authors suggest the existence of a certain range in which a reduction of model complexity in terms of its scope and detail due to simplifications does not/hardly impact its validity (Figure 3), also compare Benjamin et al. (1998), Chwif et al. (2000), Astrup et al. (2008), and Robinson (2008a). The “choice of range” will be determined by the modeling objectives and the nature of the answers that are to be provided. Nice illustrations of the choice of range can be found outside the manufacturing domain, in the health scene. Fletcher et al. (2007) developed a generic model for simulating emergency departments (EDs) throughout England, as a part of a campaign of the National Health Service (NHS) to improve ED performance. They found that in case basic insights in system workings would be asked for the generic model would suffice. However, in case impact of local decisions has to be accounted for the model has to be refined. Starting from the observation that the implementation of many health policies may be extremely expensive, Davies et al. (2003) stress the relevance of tailoring model detail towards factors that will make a substantial difference to the results and conclusions of the simulation study. In specific cases, simplifications may even increase model validity (Figure 3, right hand side), by removing model complexity not or insufficiently supported by data or information (Innis and Rexstad, 1983; Brooks and Tobias, 2000; Robinson, 2008a). Clearly removing too much complexity hurts model validity, compare Figure 3 (left hand side).

Usually, model simplification comes at a cost. Costs relate to the efforts put in developing, implementing and validating a simplification (Rexstad and Innis, 1985; Brooks and Tobias, 1996; Frantz, 1997; Davies et al., 2003). Moreover, simplification may be a risky undertaking, as efforts put in may not result in an acceptable simplified model (Brooks, 1999). Also detailed models may still be required to ascertain model credibility (Brooks, 1999). Not surprisingly, several authors point out that decisions on model simplification require a cost-benefit analysis (Innis and Rexstad, 1983; Barlow, 2009), ideally building on clear modeling objectives (Chwif et al., 2000). Expectedly, larger and more complex models will require greater analysis detail – as stakes tend to be higher.

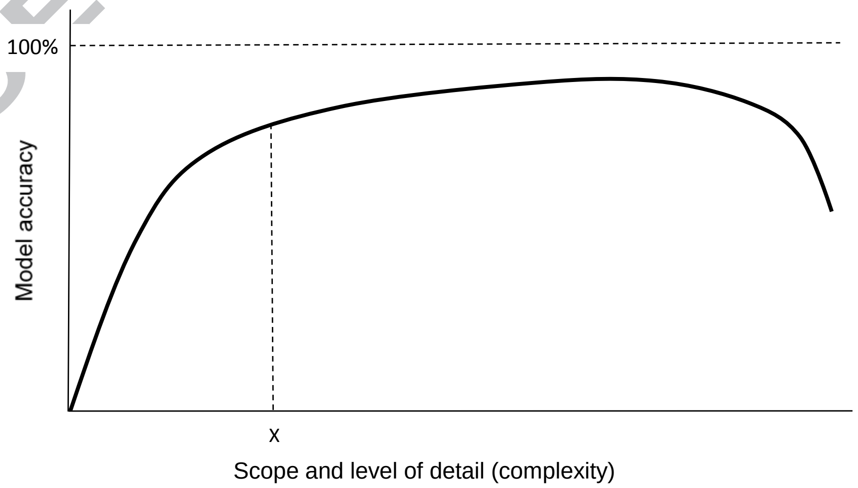

Figure 3 Simulation complexity and model accuracy - similar to Robinson (2008a)

Several authors clarify how benefits may not outweigh costs. Rexstad and Innis (1985) found how in some cases a simpler model may take longer to develop, due to the presence of many alternative simplifications, and/or their development and testing being laborsome. Spiegel et al. (2005) demonstrate that even for simple problems model simplification may not be easy, due to undocumented assumptions. What if simplification is not easily attained? Under these circumstances, model transparency is still possible building on good communications of modelers – speaking the language of the problem domain – with the model users, being supported by, for example, manual simulations or structured walkthroughs of the model (Salt, 1993).

4.1.2 Methods for tracing inappropriate model complexity

How to trace model components that are eligible for simplification, i.e., are of no significant relevance in capturing the causal connection between model inputs and outputs (Law et al., 1993; Benjamin et al., 1998; Robinson, 2008b). Basically, eligible components qualify by allowing for their omission, aggregation or substitution (Pegden et al., 1990; Rank et al., 2016). Omission of model components builds on the assumption that system elements represented by them have no significant influence on system performance. Aggregating model components into a single component that approximates joint behavior, is another way of reducing the number of model components. Substitution entails replacing complex model components with simpler ones that approximate behavior of the former. Note that aggregation and substitution are related, with the latter being the result of repeated aggregation (Rank et al., 2016).

Various checklists have been put forward suggesting rules supporting the selection of model components for possible simplification. Essentially, rules identify components by studying their behavior. Often mentioned examples are shown in Table 2 (Robinson, 1994; Robinson, 2014; Rank et al., 2016).

Table 2 Rules for selecting model components for possible simplification

Rule
• Exclude resources that are always available. • Group products being processed batch wise. • Represent similar products by a single product type. • Do not distinguish between products showing similarities in part routing and resource use. • Exclude infrequent events. • Exclude non-critical materials. • Do not distinguish between shift patterns suggesting similar operations during shifts. • Exclude rules governing entity flow addressing rare situations. • Substitute model components representing resources for which utilization is low, queue length is small, or waiting or lead times are short with delays.

Whereas rules mentioned in Table 2 address the general case of operations systems in manufacturing, other authors provide domain specific guidance. For example, Morrison (2011) suggests considering the possibility to ignore wafer transport robots in a fab-level simulation. Likewise, Jiminez et al. (2008) propose a method for classifying semiconductor wafer fab models by the level of capacity detail and the level of detail of automated handling systems, as deemed required given the modeling objectives. Further evidence on the relevance of recollecting and developing domain specific guidance on model simplification is also found outside manufacturing, in related fields of interest. Starting from the benefits associated with model re-use, Monks et al. (2017) recollect, propose and evaluate a set of simplification rules dedicated to acute stroke care chains.

While checklists start from observations on model behavior, principles of aggregation work the other way around, by first typifying various notions of aggregation and next applying them to the model. Frantz (1995, 1997) distinguishes between four principles of aggregation, i.e., state aggregation, temporal aggregation, entity aggregation, and function aggregation. According to the principle of state aggregation, states whose distinctions are not relevant considering modeling objectives may be combined. For example, if exact routing of an automated guided vehicle (AGV) transporting goods within a manufacturing system is not relevant for decision making, routes taken and routing logic may be left out of the model. Temporal aggregation seeks to improve computational efficiency by seeking a reduction of the number of events, for example, by assuming that events that occur close in time to be simultaneous. Entity aggregation assumes a higher level entity to represent a collection of lower level entities. Reasons for entity aggregations may be found in both function and structure of the entities. For example, parallel identical machines may be modeled by a single machine with correspondingly shorter processing times, but executing functions similar to the machines being represented. Also, hierarchical structures, like workstations or departments being composed of multiple resources may be represented as a single entity. In a similar way, the notion of a product class may be exploited to refer to a group of products for which mutual differences are not relevant given modeling objectives, see, for example, Piplani et al. (2004). Finally, function aggregation seeks to combine resource activities. For example, instead of decomposing a maintenance job in several individual activities they may be represented by a compound activity, i.e., the maintenance job.

In principle, component selection for model simplification may further underpinned by dynamic analysis, assuming the presence of a coded model (Webster, 1984). This allows selected components to be assessed for their contributions to overall system performance and – interpreting these – impact on model validity. Components for which a low impact on model validity is confirmed are considered for model complexity reduction, also see Section 4.1.3. Alternatively, analysis may be skipped if sufficient trust has been built (Law, 1991; Robinson, 2014) or performed using simpler or alternative means, such as, rough cut calculations, analytic approximations for estimating effects of selected components on system performance and/or domain expert judgement. Research by Hood (1990), who puts some common simplifications for simulating semiconductor manufacturing lines to test, and Jain et al. (1999), who study criticality of detailed modeling in semiconductor supply chain simulation, show how validation of simplifications should not be taken lightly.

Several authors suggest the notion of complexity metrics in trying to facilitate an a-priori evaluation of a simulation model specification given some criterion. For example, model characteristics like the quantity of components (for example, number of machines), the quantity of connections (for example, part routings), and the quantity of calculations required in determining which connection to take from each component may set demands on computational resources (Yücesan and Schruben, 1998; Brooks and Tobias, 2000; Jacobson and Yücesan, 1999). Hence, they may influence model utility in terms of speed of experiments. Likewise, Wallace (1987) proposes the term psychological complexity to capture the complexity of model understanding among users. Although some progress is made in this area, it seems to be still very much in its infancy. Chwif et al. (2000), and Yavari and Roeder (2012) underpin this situation by their finding that no standard measures of complexity are widely accepted. Chwif et al. (2006) offer some explanation for this by clarifying how the definition of suchlike measures may be dependent on the choice of a proper model representation technique - making model complexity “tangible” by identifying model elements in a structured way. For an entry and initial results in this area see Zeigler (1976), Brooks and Tobias (1996), Zeigler et al. (2000), Chwif et al. (2006), and Yavari and Roeder (2012).

Other reasons for simplifications of model components may concern their weak underpinning by data or information (Law, 1991), also compare Section 4.1.1 (Figure 3, right hand side). Identifying suchlike components typically requires scrutinizing model assumptions, and model scope and detail. Rule sets (Robinson, 2014) and input distributions (Yavari and Roeder, 2012) present two important examples.

4.1.3 Methods for developing simplifications

How to simplify model components? Two main avenues may be considered, i.e., modifying model component behavior, by leaving out or adjusting its detail or changing component form starting from the principle of black-box modeling (Pidd, 2004). According to the latter principle (parts of) a real system may be represented as a "black box" that can be observed and for which we can relate its inputs to its outputs.

Choice of model detail may be guided by generic model structures. For example, Rank et al. (2015) propose an adjustable base model addressing automated material handling systems of semiconductor fabrication plants. Likewise, Duarte et al. (2007), and Pehrsson et al. (2015) suggest to model manufacturing plants and supply chains by a simplified model, concerning a few standard components. Morrison (2011) proposes deterministic multi-class flow line models for representing semiconductor manufacturing equipment such as multi cluster or clustered photolithography tools being part of an overall fab simulation. Extensions of his work are discussed in Park et al. (2017). A next step may be to combine the notion of generic model structures with automatic model generation (Bergmann and Strassburger 2010). This would require the definition of a model generation algorithm that builds models from selecting, configuring and structuring the components, relying on available data sources (Huang et al. 2016). Various data sources may be considered, for example, technical data describing the production system, organizational data capturing system planning and control, and system load data (Bergmann and Strassburger 2010). In addition, techniques like data and process mining and machine learning may be adopted for interpreting data (Van der Aalst 2012, Akhavian and Behzadan 2013, Bergmann et al. 2016). For example, process mining may be helpful in supporting model simplification of complex manufacturing systems, by distilling main product categories by identifying common routings. Hence, the number of product types modeled may be reduced, also compare Table 2 ("Represent similar products by a single product type").

Multiresolution modeling seeks to improve computational efficiencies of large models by allowing highly detailed parts to be combined with parts of lower detail within a single model

(Vasudevan and Devikar, 2011). Gains are associated by those parts of lower detail – referring to system elements with a perceived low impact on model validity. By means of a case example concerning automotive final assembly Vasudevan and Devikar (2011) clarify how developments during a project life cycle, for example, new solution directions, may require the addition of more detail to the model. Under these circumstances, they suggest not to change the abstraction level of the whole model. Instead it is advocated to restrict additional detail to selected areas. Fishwick (1988) proposes a taxonomy of process abstraction methods in an effort to characterize the fundamental concepts of traversing levels of detail. The notion of dynamic multiresolution models adds the possibility of changing level of selected model parts detail during simulation (Celik et al., 2010; Huber and Dangelmaier, 2011). Huber and Dangelmaier (2009) propose a method for mapping simulation state between models of different level of detail. Celik et al. (2010) propose Dynamic-Data-Driven Application Systems (DDDAS) as a new modeling and control paradigm which adaptively adjusts the detail of a simulation model. The need for adapting model detail is established by using an abnormality detection algorithm that detects deviations of system status that violate thresholds set.

Frantz (1995) mentions how the input/output relationships for a model component may be captured by look-up tables, probability distributions, linear function interpolations, and metamodeling. Further examples are provided by Thomas and Charpentier (2005), Thomas and Thomas (2011), Thomas et al. (2011, 2014, 2015) who consider representing non-bottleneck machines by neural networks and regression trees. The use of probability distributions received significant attention in semiconductor manufacturing. To simplify the complex models often found for this field, probability distributions are employed to represent subsystems (aggregates of semiconductor resources) or non-bottleneck machines as delays. Proposed probability distributions account for the fact that delays may be influenced by the work-in-process, and possibilities of parts overtaking each other – due to the re-entrant nature of semiconductor manufacturing (Rose, 2000; Rose, 2007; Etman et al., 2011; Veeger et al., 2011; Kabak et al., 2012; Ewen et al. 2017). For modeling non-bottleneck resources several authors advocate use of fixed time delays, see, for example, Hung and Leachman (1999) and Johnson et al. (2005). Some of the aforementioned work also made an entry in related fields. For example, Jansen et al. (2012) explored use of probability distributions proposed for semiconductor manufacturing for modeling resources at a Magnetic Resonance Imaging (MRI) department.

4.1.4 Simplification procedures

Simplification procedures seek to contribute to a comprehensive approach towards model complexity reduction by embedding methods for tracing inappropriate complexity (Section 4.1.2) and developing simplifications (Section 4.1.3) in a step-wise procedure. For example, starting from a detailed manufacturing model, Johnson et al. (2005) propose a simple procedure that (i) establishes a list of machines ordered according to their utilization, (ii) selects those machines with a low utilization from the list and replaces them with constant delays, and (iii) validates the resulting reduced model by comparing its outputs with those found for the detailed model. Similar examples, employing different methods and different manufacturing settings, are given by Brooks and Tobias (2000), Völker and Gmilkowsky (2003), Huber and Dangelmaier (2009), and Zhou et al. (2016).

Apart from their choices of underlying methods and focus on specific manufacturing settings, simplification procedures differ for their algorithmic and/or tool-based support. Use of data flow analysis and expert systems for tracing inappropriate model complexity is advocated by Nance et al. (1999). Chwif et al. 2006 propose a “backtracking” reduction algorithm that traces those model elements that are not connected to model outputs. Likewise Chiang (2010) proposes the use of evolutionary algorithms in order to choose among a great many alternative model simplifications. Other possibilities for tool-based support are linked to the notion of automatic model generation, see Section 4.1.3. Chwif et al. (2006) clarify how the use of algorithmic and tool-based support requires the use of a proper model representation technique. Sevinc (1990) studies possibilities for the automation of model simplification from a theory–based angle, using a weakened definition of homomorphism for simulation models as a formal basis.

4.2 Preventing model complexity

The efforts that may be involved in model reduction – as indicated in the previous section – present a clear case for the need for preventing inappropriate complexity. Avoiding model complexity builds on the modeler's awareness of its drivers, and his/her appropriate response once detected. Table 3 shows various drivers, being categorized according to the outcomes of the study set-up, i.e., modeling objectives, (staff) resources available or provided, access to data, and choice of modeling methodology. Checking outcomes of simulation study set-up for respective drivers may be considered as an initial guideline. We found little evidence on more elaborate guidelines informing the modeler on how to act once relevance of specific drivers has been established.

Many authors indicate that poorly understood, conflicting, or too many modeling objectives may significantly contribute to model complexity. This starts from the observation that under these circumstances the modeler may easily be tempted to draw the bounds of the model too wide, hoping to cover whatever the model user is interested in (Salt, 1993). Nance et al. (1999) point out how model development objectives in terms of model portability, extensibility and re-usability may increase model complexity. For example, model re-use may be facilitated by generic – but more elaborate – model components. Pace (2000) nuances the role of modeling objectives as complexity drivers by suggesting modeling objectives and model development to be a "chicken–egg" pair. According to him they may each stimulate and derive from the other, thereby possibly making an iterative and interactive formulation of modeling objectives with the model development beneficial. Urenda Moris et al. (2008) clarify how such a situation may be encountered in the early development phases of an industrial project. Given a clear lack of information and data, models relying on appropriate simplifications are less accurate, but may contribute to system understanding. In turn, these early insights obtained may be helpful in clarifying modeling objectives.

Table 3 Drivers of inappropriate model complexity

Factor	Driver	References
Modeling objectives	• Various model development objectives	• Nance et al. (1999), Ahmed et al. (2016)
	• Unclear modeling objectives	• Innis and Rexstad (1983), Yin and Zhou (1989), Salt (1993), Law (1991), Nance et al. (1999), Chwif et al. (1998, 2000), Yavari and Roeder (2012), Rank et al. (2016)
	• Misfit between model nature and modeling objectives	• Henriksen (1998)
	• Problem size	• Morris (1967), Salt (1993), Chwif et al. (2000)
	• Number of model inputs	• Innis and Rexstad (1983), Kim et al. (2003), Yavari and Roeder (2012), Ahmed et al. (2016)
	• Number of model outputs	• Innis and Rexstad (1983), Yavari and Roeder (2012), Ahmed et al. (2016)
	• Choice of input space	• Frantz (1995)
Modeler	Educational background	
	• Limited application domain knowledge	• Innis and Rexstad (1983), Yin and Zhou (1989), Law (1991), Nance et al. (1999), Chwif et al. (2000), Rank et al. (2016), Nance et al. (1999)
	• Limited training or experience in modeling	• Law (1991), Salt (1993), Jain et al. (2001), Chwif et al. (2000), Fowler and Rose 2004, Ahmed et al. (2016), Rank et al. (2016)
	• Unfamiliarity with simulation software	• Yin and Zhou (1989), Chwif et al. (2000), Rank et al. (2016)
	• Poor modeling practices	• Innis and Rexstad (1983), Yin and Zhou (1989), Chwif et al. (2000), Yavari and Roeder (2012)
	Personality	
	• Preference for impracticably difficult tasks	• Salt (1993)
	• Show off: complex models are impressive references of the modeler's skills and work	• Salt (1993,) Chwif et al. (2000), Rank et al. (2016)
	• Joy of creating intricate programs	• Salt (1993)
	Pitfalls	
	• Considering details as inherently good for increasing realism	• Henriksen (1989), Salt (1993), Chwif et al. (2000)
	• Being unsure about what to include	• Chwif et al. (2000), Vasudevan and Devikar (2011)
	• Adding complexity is easy	• Salt (1993)
	• Difficult to get rid of a complex model	• Salt (1993), Rank et al. (2016)
	Stakeholder involvement	
	• Lack of communication with stakeholders	• Law (1993)
	• Project team size	• Ahmed et al. (2016)
Simulation software	• Default attribute assignments	• Nance et al. (1999)
	• Library choice of building blocks	• Jain et al. (2001), Vasudevan and Devikar (2011)
	• Choice of event list algorithm	• Henriksen (1983)
Diagramming techniques for model specification	• Low abstraction levels employed in capturing a real world manufacturing system	• Liu and Lijima (2015)
Computer hardware	• Increasing computational power	• Salt (1993), Brooks and Tobias (1999), Jain (1999), Chwif et al. (2000), Rank et al. (2016)
Data	• Availability of detailed data	• Henriksen (1989), Law et al. (1993), Jain et al. (2001), Ahmed et al. (2016)
Methodology	• Excess attributes	• Nance et al. (1999)
	• Manual simulation approaches	• Lucko et al. (2010)

Another explanation for model complexity may be in the fit between model nature and modeling objectives (Henriksen, 1989). For example, would a "toy model" be more appropriate than a "realistic model". Or, alternatively, should an "abstract" model be preferred over a "detailed" model? See Henriksen (1989) for further examples on alternative choices of model nature, and the way respective choices set requirements to the model.

Not surprisingly, also size of the underlying problem may contribute to model complexity. Problem size may be at a debate if it can be split into simpler problems (Morris, 1967; Courtois, 1985; Salt, 1993; Chwif et al., 2000). Likewise, the presence of many model inputs may act as an indicator of excess model detail (Innis and Rexstad, 1983; Kim et al., 2003; Yavari and Roeder, 2012; Ahmed et al., 2016). Ideally, some a-priori prove of their relevance is provided building on good reasoning and/or quantitative approximations. Note that, in some cases, implementation of model inputs may imply a modeling exercise of its own. Frantz (1995) hints at the relevance of acknowledging input space, i.e., the conditions under which the system is going to be studied. For example, is it necessary to put a system to the test for fluctuating workloads or is it allowed to focus on its behavior for a single high workload level only. The latter case may allow for model simplifications such as leaving out scheduling logic or approximating queueing behavior.

Most drivers of model complexity are associated with the modeler. We consider four subcategories of drivers, i.e., those that relate to the modeler's educational background and, personality, possible pitfalls that may be encountered by him/her, and his/her interaction with stakeholders. Novice modelers may easily tempted to solve modeling issues by adding detail, because they are not aware of alternative lean modeling solutions or coding tricks, not familiar with the domain, or do not (fully) understand potential benefits of simpler models. Note that the likeliness of modelers encountering pitfalls may be related with their modeling training and experience. For example, it may take some time to find out that more detail does not necessarily improve model accuracy (Henriksen, 1989; Chwif et al., 2000). Salt (1993) clarifies how various aspects of a modeler's personality may impact on model complexity. This may refer to the modeler's enthusiasm in developing more fancy models, and/or a belief that more complex models are more impressive, i.e., give a better account of modeling competences and the amount of work done, or may more easily convince the client. Finally, Law (1993) and Ahmed (2016) indicate how model complexity may be a net consequence of a lack of stakeholder interaction.

Choice and availability of supportive modeling tools and methodology may present other challenges for the modeler. Increasing computational power may easily add to model complexity, simply because it is there (Chwif et al., 2000). On the other hand, choice of modeling formalisms and methodology may guide the modeler in including (too) much detail by building on generic building blocks meant to address a large class of systems (Nance et al., 1999; Jain et al., 2001; Vasudevan and Devikar, 2011; Liu and Lijima, 2015). Likewise, availability of detailed input data may make the modeler tempted to choose the scope and level of detail for the model accordingly (Henriksen, 1989). Lucko et al. (2010) clarify how the great flexibility entailed by manual simulation generation approaches vs. domain specific (semi)automated simulation generation approaches together with a modeler's lack of domain knowledge may add to model detail.

Many researchers suggest to prevent model complexity by advocating an evolutionary development of the model, i.e., start with an (overly) simple model and next add detail incrementally until the model is considered valid for its purpose (Pidd, 1999; Sánchez, 2006; Robinson, 2008a). By being (somewhat) in control of modeling steps such an approach may be helpful – although it comes at the cost of an initial set of simplifications relative to the (would be) system under study (Brooks and Tobias, 2000). Also it does not deny relevance of the above complexity drivers.

4.3 Linking activities – Root cause analysis

In previous sections we discussed the two main activities associated with model simplification. Both activities may be linked in case successful model reduction requires reconsidering study set-up. For example, if the need for model reduction is a net effect of poor modeling skills, training of the modeler may be required to improve his/her modeling skills and – next – the model. In the latter case a root-cause analysis may be appropriate which links observations on the model and its development to possible complexity drivers, compare Table 3.

So far, researchers did not acknowledge the need for a root-cause analysis questioning outcomes of the study set-up as a prerequisite for successful model reduction. A likely reason is in their focus on developing methods for model complexity reduction, rather than questioning model development so far. Starting from main categories of complexity drivers shown in Table 3 many indicators can be defined that may be helpful in establishing the need for such a root-cause analysis. Examples include unclear modeling objectives, poor modeling or coding, large detailed models, lack of communication among stakeholders, and a high number of model inputs, state variables and outputs. In turn, complexity metrics may be associated with these indicators, see Section 4.1.2. Clearly, more research is required supporting questions on when and how to do a root-cause analysis. Concerning the latter question, Vasudevan and Devikar (2011) suggest the use of simple lean techniques like the "5 whys" in analyzing the need for model detail.

4.4 Framework extensions – coded model and experimental frame

Main focus of our framework is on modeling support for simplifying the conceptual model. In this section we explore extensions of the framework towards development of the coded model and experimental frame. Our exploration is restricted to its support for model reduction, compare Section 4.1. It is likely that findings on preventing inappropriate model complexity will also apply to the coded model and experimental frame. However, further research is required to support this thesis, and refine findings given model specifics.

Support for simplifying coded models may be related to development, choice and good use of simulation software. Henriksen (2008) discusses technical requirements for simulation software development that may contribute to a reduction of model complexity by enhancing model development and use. Starting from examples he highlights demands to be put on meaning and availability of language constructs, openness of source code, model extensibility, and model interfacing. Yuan and Ponsignon (2014) develop a dedicated library of building blocks targeting supply chains in semiconductor manufacturing aiming to reduce modeling efforts. Rank et al. (2015) propose a high-level base model for simulating automated material handling systems in wafer fabs, aiming to speed up model execution – as a net effect of reducing model detail.

Innis and Rexstad (1983) clarify how an appropriate choice of simulation software may contribute to model simplification by requiring less code, as the language facilitates an easy mapping of the real-world system on model components, and exploits system properties in model analysis. Recent work on (semi)automated model generation builds on this finding by suggesting the development and use of a library of domain specific model components, allowing for the construction of models using a model generation algorithm (Lucko et al. 2009, Lucko et al. 2010, Huang et al. 2016, Bergmann et al. 2017).

Once a choice has been made for a specific simulation software package, it is up to the modeler to make good use of it. This refers to code readability, debugging, and execution speed (Innis and Rexstad, 1983; Frantz, 1997; Brooks and Tobias, 2000). Wallace (1987), Yücesan and Schruben (1998), and Popovics and Monostori (2016) provide metrics which may be helpful in assessing algorithmic and computational complexity of the coded model. Akpan and Shanker (2017) consider the realized benefits and costs associated with modeling and simulation in 3D and virtual reality through a descriptive meta-analysis of evidence from research and practice.

Various authors suggest to simplify the experimental frame by leaving out model inputs or restricting their range (Kim et al., 2003; Yavari and Roeder, 2012). Rank et al. (2016) clarify the need to legitimatize the choice of input factors and their range by static deterministic estimates of system performance. Assuming presence of a coded model, McGraw and MacDonald (2000) suggest alternative experimental designs, like extremum experimentation, factorial experimentation, and input sensitization as means for tracing inputs that may be omitted. Furthermore, Innis and Rexstad (1983), and Fowler et al. (2004) advocate the use of variance reduction techniques to reduce run lengths, and – hence – computational efforts.

5 DISCUSSION

In the previous section, we have described a framework for simulation model simplification, thereby building on an extensive literature review. We elaborate on the contributions to research and practice, and highlight some potential research directions.

5.1 Contributions to research

The first research contribution is in formulating a framework that incorporates and structures existing knowledge on simulation model simplification for the manufacturing domain. It organizes research contributions in terms of methods, good practices and insights by relating them to two main activities, i.e., reduction and prevention of inappropriate model complexity, and linking these activities to simulation study set-up and the modeling process respectively. Reduction of model complexity entails cost-benefit analysis of model simplification, tracing of inappropriate model complexity, and development and validation of model simplifications. Prevention of inappropriate model complexity is linked to the notion of complexity drivers, concerning the definition of modeling objectives, modeler's skills, available hardware and software tools, choice of modeling methodology and access to data. Both activities may be coupled if successful model reduction may benefit from reconsidering study set-up – as indicated by a root-cause analysis.

The second research contribution of the framework is in serving as a starting point for future research by allowing for the identification of patterns of research development, current research avenues, and research gaps. Early research contributions paved the way by clarifying relevance of the field in terms of the benefits of simplification, compare Table 1. They allowed for further contributions to theory, concerning insights on drivers of complexity (compare Table 3) and simplification methods that are helpful in tracing inappropriate complexity, and development and validation of model simplifications. As far as simplification methods are concerned two research avenues emerged. A first avenue concerns the development of (automated) simplification procedures, i.e., comprehensive methods that address both tracing of inappropriate model complexity, and development of model simplifications. In most cases research on model simplification assumes a manual approach towards modeling – being still the dominant approach. Alternatively, emergence of automated simulation generation approaches sets a new perspective for providing guidance on model simplification by seeking to exploit re-use of domain specific knowledge in terms of elementary buildings blocks and their construction. In addition, techniques like, for example, data and process mining and machine learning may be helpful in tracing and developing simplifications by interpreting manufacturing data. A second avenue is associated with contributions concerning domain related simplification methods. Main examples concern simplification methods proposed and validated for use in semiconductor manufacturing simulation. We observed how, so far, main focus in research has been on simplification of the conceptual model, rather than the coded model and experimental frame.

A likely explanation is in the impact of the conceptual model – acting as a precursor for the coded model and experimental frame – on modeling efforts and study success.

Despite its age, spanning many decades, the field is still rather green. Among others, this may be clarified by a relatively low number of journal articles addressing it. Clearly, this does not deny the relevance of contributions made, and the highly relevant body of knowledge – as captured in the framework – that emerged from these. At the same time many opportunities for future research may be mentioned addressing observed gaps. Without pretending to offer a complete list, we mention the following themes: method-based support for doing cost-benefit analysis for model simplification, developing standardized metrics for assessing model complexity, validation of model simplifications, theory building enabling automation of model simplification, simplification of model representation, guidelines for preventing inappropriate model complexity, lean techniques for root-cause analysis seeking to explain model complexity from study set-up, and domain-based simplification procedures – also outside semiconductor manufacturing. Clearly, building on the framework, more opportunities may be mentioned, thereby serving the development of research agenda's and fostering the academic debate. In addressing aforementioned issues there is a great need for validating research findings by empirical research. So far, we found how insights provided on cost and benefits of simplification, complexity drivers and proposed methods often lack a rigorous validation.

The third contribution of the research framework may be in acting as a vehicle for research itself. The framework may be used as a starting point for addressing other domains, especially the (health) service industry. Starting from observations on case examples in literature we found how several simplification methods originating from the manufacturing scene made an entry in the service industry. Methods suggesting to group patients sharing similar needs, or simplifying low-utilized (staff) resources are much encountered, see for example Virtue et al. (2011), Huggins et al. (2014), Tako et al. (2014). Similar examples may be found in finance, where simulation models are simplified by reducing routing options of products (Anderson et al. 1999). We also encountered few examples in service industry being of relevance for the manufacturing domain, thereby underlining the benefits of cross fertilization. Apart from suchlike evidence, research seems to have hardly touched the service industry. Furthermore, we mention the framework's possible use for addressing other types of simulation like agent-based simulation and system dynamics.

5.2 Contributions to practice

The relevance of model simplification for practical use of simulation in the manufacturing domain is undenied. Moreover, the ever increasing complexity of manufacturing systems suggests an increasing importance of model simplification in targeting and being responsive to management problems. Progress made in simulation software and computer hardware will not likely change this situation in the near future (Chwif et al., 2006). A main problem faced by practitioners concerning model simplification is a lack of overview on what research on model simplification is available, thereby hindering their access to relevant means of support. Furthermore, we observe a missing link, as educational materials for training their skills in employing simplification methods are hardly available. Hence, practitioners are more or less left on their own creativity in addressing model simplification.

The framework contributes to solving issues faced by practitioners by providing an overview of current research. By organizing it according to the framework it is meant to (i) facilitate an easy linkage of decisions to be made in study set-up and the way they may impact model complexity, and (ii) offer modeling support by categorizing simplification methods according to their roles for tracing inappropriate complexity and developing modeling simplifications. In turn, by organizing the field we strive to benefit educators and their students by providing an initial basis for the development of course materials.

6 CONCLUSION

In summary, this article proposes a framework for simulation model simplification. Building on an extensive literature review, our study contributes to literature in several ways. Firstly, it structures the field by providing a unifying view on simulation model simplification, in terms of its key activities and support offered in performing these. In doing so it clarifies the way model simplification relates to study set-up and the modeling process. Apart from its relevance as a starting point for future research, the structuring of the field implies direct benefits for practitioners and educators, by giving them access to research findings, and enabling and legitimatizing development of educational materials and their uptake. Secondly, the framework facilitates development of research agenda's and fosters academic debate by allowing for the identification of patterns of research development, current research avenues, and research gaps.

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Model Simplification in Manufacturing Simulation - Review and Framework

HIGHLIGHTS

- Simulation is a popular tool among industrial engineers.
- Simulation use for manufacturing systems design builds on model simplifications.
- Simulation model simplification is an underdeveloped field.
- We propose a research framework building on an extensive literature review.
- Reducing and preventing model complexity are identified as key modeling activities.