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APPROACHES FOR SIMULATION MODEL SIMPLIFICATION

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ABSTRACT

Simplification is considered a fundamental part of modelling and simulation. Model simplification is instrumental in creating models that are useful – by focusing on system elements that matter, and feasible – by reducing study efforts. Despite its widely acknowledged relevance simulation model simplification may still be considered an underdeveloped field. This is mirrored in existing literature, and course books. While the former shows a fragmented landscape in addressing the issue, the latter often offer little guidance for the (future) analyst. To foster further development of the field we assess current progress by providing a literature review. Issues addressed by the review concern: (i) definition and scope of model simplification, (ii) reasons for model simplification, (iii) drivers of inappropriate model complexity, and (iv) approaches for model simplification. The review is meant to provide a useful overview of the work undertaken in this field, aiming to benefit educators, practitioners and researchers.

1 INTRODUCTION

Simplification is considered a fundamental part of modelling and simulation (Salt 1993, Shannon 1998). Most management problems addressed by simulation models can be characterized as complex and difficult to analyze. Simulation models are meant to support managers in understanding these problems and provide useful insights facilitating problem solution. Models achieve this by presenting problems in a structured, rational manner, with an associated reduction in complexity relative to the real-life situation (Ward 1989).

Essentially, by simplifying a simulation model the analyst aims to increase a model's utility and feasibility, while safeguarding its validity and credibility. Simulation model simplification impacts its utility by influencing its ease of use, flexibility, visualization, and run speed, as well as its feasibility in terms of time, resource and data needs (Robinson 2014). As such, proper simplifications are highly important for simulation study success. Moreover, the ever increasing complexity of operations systems like supply chains, transportation networks, health pathways and advanced manufacturing systems suggest an even higher importance of model simplification in targeting and being responsive to their problems. Progress made in simulation software and computer hardware will not likely change this situation in the near future (Chwif et al. 2006).

Importance of simulation model simplification for simulation study success makes guidance for the analyst in identifying and implementing appropriate model simplifications a relevant issue. Unfortunately, it appears to be at the bottom of the research agenda, being identified as a green field (Sevinc 1991, Chwif et al. 2000, Brooks and Tobias 2000, Robinson 2006, Van der Zee et al. 2011). This is mirrored in existing literature and text books. While the former shows a fragmented landscape in addressing the issue, the latter often restricts their guidance to rules of thumb or does not address the issue at all. Clearly, this lack of guidance for (future) analysts may hurt both efficiency and quality of their work.

To foster further development of the field, being motivated by an earlier panel session (Van der Zee et al. 2010) and personal observations in class, we assess its current progress by conducting a literature review. The review brings research contributions together by addressing four issues:

- Definition and scope of model simplification
- Reasons for model simplification
- Drivers of inappropriate model complexity
- Approaches for model simplification

The review is meant to provide a useful overview of the work being undertaken in this field. Essentially, it may benefit various parties involved in simulation modelling of operations systems. Educators (and their students or trainees) may benefit from the way the review structures the field by answering key questions concerning terminology, scope, raison d'être, and simplification approaches. Practitioners may be accommodated by identifying and categorizing approaches currently available for addressing model simplification. Last but not least, researchers may be supported by providing a source of references, and a starting point for building their own research agenda.

The paper is structured as follows. Sections 2-5 address issues identified above. Section 6 discusses main findings of the review. Finally, Section 7 summarizes main conclusions.

2 SIMULATION MODEL SIMPLIFICATION – DEFINITION AND SCOPE

To sketch the nature and the contours of the field, in this section, we discuss basic terminology and its scope. Firstly, a consensual name for this subject has yet to be defined (Chwif 2006). Commonly used terms are model reduction (Chwif et al. 2006), model abstraction (Sevinc 1991, Frantz 1995, McGraw and MacDonald 2000), and model simplification (Brooks 2000, Robinson 2008a, Barlow 2009, Huber and Dangelmaier 2009). We prefer the term *model simplification*, because of its frequent use in literature, and its clarity in stressing the underlying purpose, i.e., complexity reduction.

Simplification is the removal of *inappropriate complexity* (Innis and Rexstad 1983), also referred to as representational redundancy (Nance et al. 1999). Innis and Rexstad link the notion of "inappropriate" to model conformance with modelling objectives and the variance in the data available to the modeler. This definition also implies the existence of "appropriate" complexity, i.e., complexity that inherently appears in the model because the model mimics the system to some degree (Yavari and Roeder 2012). Many authors stress the importance of model complexity being in agreement with modelling objectives, see for example, Henriksen (1989), Yin and Zhou (1989), Law et al. (1993), Chwif et al. (2000). Robinson (2008a, 2014) details model conformance to modelling objectives by stressing the increase of model *utility* and *feasibility* that should be facilitated by model simplification, not being at the expense of its *validity* and *credibility*. 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 model validity and credibility may be decided upon based on judgement or tests by computer models (Robinson 2014). By clarifying how simplification is meant to influence key model qualities, i.e., validity, credibility, utility and feasibility, Robinson aligns many partial insights from other authors – who typically link simplification to a subset of these qualities.

Despite various attempts, a practical overall definition of *complexity* for simulation models still has to be developed (Chwif et al. 2000, Yavari and Roeder 2012). In a recent literature overview Yavari and Roeder (2012) indicate how model complexity may be related to concepts such as size, validity, understandability, and fidelity. Many authors tend to relate complexity to quantity and choice of model elements. For example, Brooks and Tobias (2000) suggest to relate complexity of simulation models of manufacturing systems to 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. Robinson (2008a) relates model complexity to model scope and detail, i.e., quantity of model components and their attributes. To enable a model's complexity to be reduced by applying a *simplification approach* it should be represented into a proper *model representation technique* (Chwif et al. 2006). Model representation techniques make model complexity "tangible" by identifying model elements in a structured way. See Brooks and Tobias (1996), Chwif et al. (2000), and Yavari and Roeder (2012) for a somewhat more elaborate discussion on complexity definitions and complexity measurement.

Various simplification approaches have been developed over the years, see Section 5. Essentially, they reduce model complexity by *omission*, *aggregation* or by *substitution* (Pegden et al. 1990, Rank et al. 2016). Omission of elements builds on the assumption that they have no significant influence on system outcomes. Aggregating elements of a subsystem into a single element, that approximates joint behavior such that model accuracy is not being hurt, is another way of reducing the number of model elements. Substitution entails replacing complex model elements with simpler ones that approximate behavior of the former.

Model simplicity may be helpful in model understanding, however this is not guaranteed, as user backgrounds may differ (Ward 1989, Salt 1993). Therefore Ward (1989) suggests to make a difference between a model's *constructive simplicity (complexity)* and its *transparency*. Transparency refers to the model user's perception, and depends on, for example, his/her familiarity with modeling methods, interest in the problem, and the degree to which the analyst explains the model. Constructive simplicity is a feature of the model, and can, in principle, be measured (Salt 1993), also see the above discussion on complexity definitions and measurement. Note that there is a subtle link between model transparency, and model credibility, according to which a user's model understanding is an important denominator of his/her acceptance of the model and its outcomes (Robinson 2008a).

Most authors (implicitly) link the use of simplification approaches to the specification of the conceptual model content, being an abstraction of some real world or would be operations system. However, some authors widen scope of simplification approaches towards other phases in a simulation study by suggesting to, for example:

- Re-assess the problem definition underlying the modelling objectives by seeking possibilities to split underlying problems into smaller problems that require smaller models (Morris 1967, Salt 1993), or study reduced sets of model inputs and outputs (Yavari and Roeder 2012).
- Consider coding tricks for speeding up the simulation coded model (Innis and Rexstad 1983, Brooks and Tobias 2000, Rank et al. 2015).
- Apply variance reduction techniques or efficient experimental designs to reduce efforts put in performing experiments (Innis and Rexstad 1983).
- Foster model re-use by using simpler models, thereby convincing users to perceive simulation studies as short term and rather low risk activities (Salt 1993)

Furthermore model simplification may be linked to its visualization and means for interaction (Robinson 2008b, Akpan and Brooks 2014). As far as application of simplification approaches is concerned experienced users tend to focus more on the conceptual modelling phase, resulting in simpler models (Chwif et al. 2000).

3 WHY (NOT) SIMPLIFY?

Many (lists of) reasons are supplied in literature that may underpin decisions to simplify a simulation model. Typically, respective lists link to the interests of the various stakeholders involved in the simulation study. Unfortunately, most authors do not consider alternative stakeholder perspectives in putting benefits forward, by, for example, focusing on a single type stakeholder, or not linking benefits to stakeholder groups. Furthermore, the reader is often not informed on the costs of model simplification.

Table 1: Benefits of simpler models for various stakeholders

Role	Tasks	Benefits of simpler models	References
Project manager	Manage process	• Less expensive • Less time involved • Less use of resources • Involves less efforts of project manager • Helpful in specifying modelling objectives • Helpful in acquiring more projects	• 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)
Modeller	Model development	• Less input data required • Facilitates more flexible modelling • Easier to develop and maintain • Easier to validate • Higher accessibility of assumptions • Clear exposure of flaws; avoid errors • More accurate • Avoids solutions that are too advanced being implemented	• Innis and Rexstad (1983), Yin and Zhou (1989), Salt (1993) • Innis and Rexstad (1983), Yin and Zhou (1989), Salt (1993), Musselman (1994), Chwif et al. (2000) • Ward (1989), Brooks and Tobias (2000), Salt (1993) • Chwif et al. (2000), Rexstad and Innis (1985) • Ward (1989) • Musselman (1994), Rexstad and Innis (1985) • Musselman (1994) • Musselman (1994)
Model user	Do and analyze experiments	• Easier to interpret • Higher accessibility of assumptions • Sensitivity analysis is more practicable • Easier to use • Enhances insight • Speeds up experiments • Allows exploratory use of model	• Innis and Rexstad (1983), Yin and Zhou (1989), Brooks and Tobias (2000), Chwif et al. (2000) • Ward (1989) • Ward (1989), Brooks and Tobias (2000) • Fripp (1985) • Fripp (1985), Brooks and Tobias (2000), Musselman (1994) • Sevinc (1991), Brooks and Tobias (2000), Salt (1993) • Salt (1993)
Client	Owns problem, recipient of results, funds study	• Less expensive • Helpful in specifying modelling objectives • Avoids solutions that are too advanced being implemented	• Innis and Rexstad (1983) • Rexstad and Innis (1985) • Musselman (1994)
Domain expert	Provide data	• Less input data required	• Innis and Rexstad (1983), Ward (1989), Salt (1993)
Management	Benefit from the study	• 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) • Ward (1989), Brooks and Tobias (2000) • Ward (1989) • Ward (1989)

Table 1 categorizes benefits of simplification mentioned in literature by linking them to the main beneficiaries, in terms of roles that may be considered in a simulation study (Robinson 2014). Roles that are assumed to benefit most from model simplification are selected from the list provided by Robinson. Note that some benefits may be linked to multiple roles.

Several authors point out that decisions on model simplification require a cost-benefit analysis. Such an analysis should start by establishing benefits aimed for (Innis and Rexstad 1983, Barlow 2009), thereby building on clear modelling objectives (Chwif et al. 2000). Costs of simplification are related to the efforts required in developing simpler models. For example, Rexstad and Innis (1985) and Brooks and Tobias (2000) clarify how in some cases a simpler model may take longer to develop, as there may be a large number of ways in which a model can be simplified or because development and testing of simplifications is laborsome. Natrajan et al. (1997) clarify how simplification may easily hurt model consistency. Spiegel et al. (2005) demonstrate that even for simple problems model simplification may not be easy, due to undocumented assumptions. Rank et al. (2016) go beyond aforementioned authors by considering the use of simulation model vs. an analytic model. They suggest that in specific cases development of a comprehensive analytical model is more expensive than a complex simulation model. What if costs are too high? Salt (1993) suggests that in case simplification is not easily attained, model transparency is still possible building on good communications with the users – that may be supported by, for example, manual simulations or structured walkthroughs of the model.

Robinson (2006, 2008a) clarifies how there may be a certain parameter range in which simplification may be considered beneficial. Putting simplification to some extreme may reduce (specific) benefits associated with simplification, possibly up to a level that makes the model less suited for its purpose. For example, Pritsker (1986) states how simple models may not be able to accommodate changes of modelling objectives. Schruben and Yucesan (1993) suggest that reducing a model's computational complexity (for fostering model execution speed) does not necessarily contribute to its understanding, ease of coding and debugging. Note that Schruben and Yucesan highlight the interests of two stakeholders, the modeler and the model user, see above. Likewise, Davies et al. (2005) point at the fact that simple models require more elaborate assumptions. Also there is the danger of missing important problem facets.

4 DRIVERS OF (INAPPROPRIATE) MODEL COMPLEXITY

How to avoid inappropriate model complexity? After all, it may be better to prevent models becoming (too) complex, instead of repairing, i.e., simplifying, them afterwards. For this reason it is good to be aware of possible drivers of model complexity. A surprising number of contributors to model complexity may be mentioned, see Table 2. We categorize drivers by linking them to main study elements, i.e., the study objectives, the modeller, simulation software, computer hard ware, data, and choice of simulation methodology.

Many authors indicate that poorly understood modelling objectives are main contributors to model complexity. This starts from the observation that under these circumstances the modeller 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.

Most drivers of model complexity are associated with the modeller. We consider three subcategories of drivers, those that link to his/her educational background or personality, and possible pitfalls that may be encountered by him/her. Novice modellers may easily solve modelling issues by adding detail, because they are, for example, not aware of alternative lean modelling solutions or coding tricks, not familiar with the domain, or do not (fully) understand potential benefits of simpler models. Note how the likeliness of modellers encountering pitfalls may be related with their modelling 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 modeller's personality may impact on model complexity. This may refer to his/her enthusiasm in developing fancy models, but also his/her belief that more complex models are more impressive, i.e., give a better account of his/her modelling competences and the amount of work done, or may more easily convince the client.

Finally, we mention a number of technical drivers of model complexity. Increasing computational power may easily add to model complexity, simply because it is there (Chwif et al. 2000). Likewise, availability of detailed input data may make the modeller tempted to choose the scope and level of detail for the model accordingly (Henriksen 1989). Furthermore, Nance et al. (1999) clarify how simulation software and methodologies may force more complex models, by building on generic building blocks meant to address a large class of systems.

5 APPROACHES FOR DEVELOPING SIMPLE(R) MODELS

Unfortunately, no generally accepted guidelines exist to help a simulation modeller determine which elements of a system should be represented in a simulation or what level of fidelity is required for their representation (Pace 2000). In this section we provide an overview of the various approaches for model simplification that have been proposed over the years. We distinguish among general guidelines for effective simplification, simplification methods, simplification procedures, and domain specific approaches.

5.1 General Guidelines for Effective Simplification

General guidelines consider prerequisites for effective simplification.

Table 2: Drivers of inappropriate model complexity

Factor	Driver	References
Study objectives	• Various model development objectives • Unclear modelling objectives	• Nance et al. (1999) • Innis and Rexstad (1983), Yin and Zhou (1989), Salt (1993), Nance et al. (1999), Chwif et al. (2000), Yavari and Roeder (2012), Rank et al. (2016)
Modeller	Educational background • Limited application domain knowledge • Limited experience in modelling • Unfamiliarity with simulation software • Poor modelling practices	 • Yin and Zhou (1989), Nance et al. (1999), Chwif et al. (2000), Rank et al. (2016), Nance et al. (1999) • Salt (1993), Chwif et al. (2000), Rank et al. (2016) • Yin and Zhou (1989), Chwif et al. (2000), Rank et al. (2016) • Innis and Rexstad (1983), Yin and Zhou (1989), Chwif et al. (2000), Yavari and Roeder (2012)
	Personality • Preference for impracticably difficult tasks • Show off: complex models are impressive references of the modelers' skills and work • Joy of creating intricate programs	 • Salt (1993) • Salt (1993,) Chwif et al. (2000), Rank et al. (2016) • Salt (1993)
	Pitfalls • Considering details as inherently good for increasing realism • Being unsure about what to include • Adding complexity is easy • Difficult to get rid of a complex model	 • Henriksen (1989), Salt (1993), Chwif et al. (2000) • Chwif et al. (2000) • Salt (1993) • Salt (1993)
Simulation software	• Default attribute assignments	• Nance et al. (1999)
Computer hardware	• Increasing computational power	• Salt (1993), Chwif et al. (2000), Rank et al. (2016)
Data	• Availability of detailed data	• Henriksen (1989), Law et al. (1993)
Methodology	• Excess attributes	• Nance et al. (1999)

5.1.1 Split Problems

By using simulation the analyst seeks to address and solve problems that are by their nature complex (Salt 1993). How to manage such complexity? Salt (1993), Morris (1967) and Chwif et al. (2000) suggest to (re)assess problems by considering the need and possibilities to split a problem into smaller problems, which may be easier to solve by building on simpler models.

5.1.2 Clarify Modelling Objectives

Many authors consider the definition of clear modelling objectives a prerequisite for effective simplification, see Section 4. Components of modelling objectives are clarified by Robinson (2008b). He mentions three components: (i) achievement: what the clients hope to achieve, for example reduce logistic costs, improve logistic service, increase system understanding, (ii) performance: target sets, for example, reduce costs by 20%, shorten lead times by 10 days, and (iii) constraints set in solution finding, for example budget, design options, available space. Pace (2000) points out that the development of the model and the modelling objectives are a classic "chicken–egg" pair. They each stimulate and derive from the other. This suggests the existence of an iterative process, in which simplifications are instrumental in clarifying modelling objectives and vice versa. Clearly, it is up to the analyst to manage the process and safeguard its efficiency by controlling (the number of) iterations.

5.1.3 Determine and Trade-off Costs and Benefits of Simplification

In many cases costs of simplification may be significant. Hence each decision on model simplification should be supported by a cost-benefit analysis up to some appropriate level of detail. See Section 3 for a more elaborate discussion on this.

5.1.4 Trace Potential Simplifications

How to efficiently trace model simplifications that may matter? In order to identify models that are candidates for simplification, Innis and Rexstad (1983) suggest to start by roughly characterizing main study elements:

- Modelling objectives (compare Section 5.1.2): unclear objectives hint at possibilities for simplification.
- Model characteristics: poor coding, high/low connectivity of model elements, a high number of parameters, state variables, and outputs and the randomness of the system may hint at inappropriate complexity.
- Modeller skills: a limited system knowledge may suggest room for model simplification.

Pace (2000) suggests to exclude extraneous simulation elements: model components should be directly related to items in simulation requirements, assessment issues, real world items, or standard decomposition paradigms. Law et al. (1993), and Robinson (2008b) somewhat refine these exclusion rules by requiring model components to be of significant relevance in capturing the causal connection between the model inputs and outputs. Rank et al. (2016) clarify the need to legitimatize the use of simulation and 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 model components or inputs that may be omitted.

5.1.5 Involve Stakeholders

Obviously, simulation success builds on a joint model understanding among the main stakeholders for the study. Therefore Law et al. (1993) advise a continuous communication of the modeller with the stakeholders to ensure that both understand the modelling assumptions and decisions made and their impacts.

5.2 Simplification Methods

Simplification methods sketch alternative ways model complexity may be reduced by omission, aggregation or by substitution (Pegden et al. 1990, Rank et al. 2016), see Section 2. Many methods have been proposed over the years. Taken together they serve as checklists which may be employed by the analyst both as a first aid or as a follow-up of initial tracing activities (see Section 5.1.4), in realizing model simplifications.

Simplification methods may be categorized according to simplification scope, i.e., the modelling phase targeted, compare Section 2. For example, Innis and Rexstad (1983), provide a set of 17 methods spanning all main study phases. So far, however, the main focus in research has been on the (conceptual) modelling phase. Frantz (1995) provides a taxonomy of simplification methods drawn from the modelling and simulation community and the artificial intelligence community. According to his taxonomy simplification methods are categorized according to whether they address model scope, model behavior or model form. According to Frantz (1995) simplification of model scope may also include model inputs. Simplification methods addressing model behavior target the inner workings of the model by aggregating some aspect of the model like state, time, entities and functions. Simplification of model form refers to modifications of the input-output relationships of the model or the model components. Robinson (2014) provides an overview of often proposed methods of simplification in conceptual modelling, thereby building on previous works (Zeigler 1976, Innis and Rexstad 1983, Yin and Zhou 1989 and Robinson 1994). He mentions black-box modelling, grouping entities, replacing components with random variables, excluding infrequent events, reducing the rule set and splitting models as important examples of simplification methods. Whereas Frantz (1995) and Robinson (2014) focus on simplification of model content, Henriksen (1998) considers the fit between model perspective and modelling objectives and/or system characteristics. For example, considering modelling objectives and system characteristics, would a “toy model” be more appropriate than a “realistic model”. Or, alternatively, should we prefer an “abstract” over a “detailed” model? See his work for further examples.

5.3 Simplification Procedures

Simplification procedures go beyond simplification methods by detailing a step-wise sequence according to which (multiple) simplification methods may be applied to a model. Both manual and automated procedures are proposed. Typically, simplification procedures set demands on the representational technique used in model content specification.

An early example of a simplification procedure is provided by Innis and Rexstad (1983). Basically, they suggest a prioritization of the use of their proposed simplification methods (see Section 5.2), once legitimatized by the positive answers to three key questions: (i) “Is the model non-linear?”, (ii) “Are modelling objectives clear?”, and (iii) “Should indeed the model be an abstraction of reality, i.e., no duplication?”. Application of simplification methods follows study phases. First model content is considered, next its coding, and finally experimental design.

Several automated procedures are proposed. Sevinc (1990, 1991) relates model simplification to the use of DEVS (Discrete Event Systems, Zeigler 1976). Nance et al. (1999) consider elimination of redundancy by using data flow analysis and expert systems. The latter build on an understanding of the domain in which simulation is being used, and the use of simulation as a problem-solving technique. Chwif et al. 2006 propose a “backtracking” reduction algorithm that traces those model elements that are not connected to model outputs. Another angle is taken by Kotiadis and Robinson (2008) who consider the use of problem structuring techniques in abstracting the conceptual model.

5.4 Domain Specific Approaches

Whereas aforementioned approaches address the general class of operations systems, domain specific approaches target a specific field of interest. So far, the main research focus has been on manufacturing systems.

Brooks and Tobias (2000) propose an eight step procedure for simplifying manufacturing models. General steps suggest the use of coding tricks, tracing non-appropriate model complexity by checking model components’ relevance in linking model inputs and outputs (see Section 5.1.4) and considering possibilities for replacing part of a model with a simpler sub-model (like a random variable or a regression model). Furthermore, the approach allows for a simulation model to be replaced by an analytical model (if model accuracy permits this). Domain specific steps concern the identification of non-bottleneck machines (that can be removed). Huber et al. (2009) build on the work of Brooks and Tobias (2000) in proposing a two-stage automated simplification procedure. The initial stage entails an iterative method for simplifying the original model up to some pre-defined level of complexity (using a specific complexity metric). Next, accuracy of the simplified model is put to the test by comparing its outcomes with the outcomes of the original model. Urenda et al. (2008) suggest to consider possibilities for processing time aggregation and abstraction for product variants in the early phases of manufacturing systems development.

Thomas (2003) and Thomas et al. (2005, 2011, 2015) consider model simplification for simulation-based scheduling. Industrial examples studied indicate a need for reactive scheduling, such that existing schedules may be quickly updated for new information on job progress. To speed up model responses respective authors propose to replace model components representing non-bottleneck machines by, for example, neural networks and/or regression trees.

Most contributions to (the validation of) model simplification methods are related to semiconductor manufacturing. Semiconductor manufacturing systems are considered highly complex due to the presence of, for example, many alternative machines, tools, routings (that may allow for re-entries), and the presence of machine failures. High system complexities faced in this industry make model simplification an intrinsic issue. A relatively large group of researchers propose, employ and debate (for example, Rose 2000) simplification methods in doing simulation-based research on logistic issues. Usually, common simplification methods are employed (See Section 5.2), that may be somewhat adjusted to the domain or even study context. For example, machines may be replaced by delay elements (Sprenger and Rose 2011). However, one still has to choose among the right type of distribution and decide upon its parameters. Many more approaches that apply aggregation and substitution methods for complexity reduction can be mentioned for semiconductor manufacturing. See Rank et al. (2016) for an entry in this field.

6 DISCUSSION

Findings from our review confirm that simulation model simplification is still very much an immature field. This is underpinned by the relatively low number of publications, and the fact that contributions are rather fragmented, thereby hardly acting as building blocks, and there are many open issues. Note that this does not deny the relevance of the individual contributions. Does this imply that no progress has been made? Certainly not. This can be clarified by a short sketch of main advances. Early contributions paved the way by defining and clarifying relevance of the field (compare Sections 2,3). They allowed for further contributions to theory in later years, concerning insights on complexity drivers (compare Section 4) and the creation of simplification approaches (Section 5). As far as simplification approaches are concerned two trends may be witnessed. The one trend marks a shift of attention from the development of simplification methods towards (automated) simplification procedures. The other trend concerns the development of domain related simplification approaches. Main examples concern simplification approaches proposed and validated for use in semiconductor manufacturing simulation.

How to proceed? By our literature review we aim to assess progress of the field. The need for structuring of the field is apparent in the many "fragments" that constitute the field, see above. In turn, being aware of accomplishments is meant to benefit key stakeholders, i.e., educators, practitioners, researchers. By somewhat organizing the field by addressing its relevance, main issues and key references we hope to contribute to the development of course materials, where these are largely absent now. Practitioners may benefit from the overview of simplification approaches. Last but not least, the review is meant to foster the set-up of research agendas and academic debate. As the field is rather green, many research issues may be put forward. Starting from observations made on the outcomes of our review we mention some examples: definition of simulation model complexity metrics, embedding simplification methods in conceptual modelling (frameworks), domain specific simplification methods, requirements on the set-up of simplification procedures (Chwif et al. 2006), validation of model simplification, and cost-benefit analysis in simulation model simplification.

7 CONCLUDING REMARKS

Clearly, analysts' efforts put in model simplification rely for a major part on their own creativity. In turn, such creativity builds on their professionalism in terms of their awareness of the relevance of model simplification for the success of the study, and the means available enabling model simplification. This professionalism is addressed by the article by supplying a literature review on approaches for simulation model simplification. The review considers four main issues: (i) definition and scope of model simplification, (ii) reasons for model simplification, (iii) drivers of inappropriate model complexity, and (iv) approaches for model simplification. Although the review provides answers to the questions posed, it is also concluded that simulation model simplification is still very much a green field. Nevertheless, accomplishments made so far may enable and legitimize development of educational materials and uptake by practitioners. At the same time, it clarifies issues that are candidate topics for the field's research agenda. Finally, to stress need of urgency: "We do have some techniques for reducing complexity, but we need more, because complexity is growing faster than our ability to deal with it" (Henriksen 2008).

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