Framework for Simulation-Based Decision Making in Semiconductor Value Chains

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Abstract. Simulation is an important industrial engineering tool in many semiconductor wafer fabrication facilities. In this paper, we are interested in obtaining an understanding of the capabilities of simulation to support various planning and control functions in semiconductor value chains. This research effort is challenging since it requires knowledge of the different planning and control functions and the related decision-making approaches. It seems also to be difficult to generate supply chain simulation models from scratch or reuse existing simulation models of an appropriate level of detail. In this paper, we discuss the major design issues for a framework to guide decision-makers in semiconductor supply chains towards choosing an appropriate simulation-based decision support.

Keywords: Semiconductor supply chains · Production planning and control · Simulation-based decision making

1 Motivation

The process of manufacturing integrated circuits is one of the most complex technological achievements of the 20th century (Doering and Nishi 2007; Mönch et al. 2013; Mönch et al. 2018). The capital-intensive nature of the semiconductor industry leads to production facilities that run consistently at high utilization levels. The reentrant process flows in the production facilities cause complex competition for scarce capacity. The increasing level of automation reduces the ability to use humans to buffer the equipment. The sheer size of the facilities and value chains involved, the pervasive presence of different kinds of uncertainties and the rapid pace of change result in an environment that is challenging for current planning and control approaches and the related information and decision support systems (Chien et al. 2011).

Different simulation paradigms, such as discrete-event simulation (Fowler et al. 2015), agent-based simulation (Bonabeau 2002; Klügl and Bazzan 2012; Achter et al. 2017), or system dynamics (Sterman 2000) can be used at the different planning and control levels in semiconductor value chains. However, while simulation is often applied for representing the execution level of semiconductor value chains, simulation is only rarely used to make planning decisions (Fowler et al. 2015; Mönch et al. 2018).

There are several reasons for this observation. First of all, building fab- or even value chain-wide simulation models from scratch is very time-consuming and error-prone. Although data availability has improved to a large extent over the last decade, it is still difficult to gather and process data for specific purposes related to building simulation models, for instance, for modeling machine breakdowns in a correct way. Secondly, although simulation appears at a first glance to be a tool that can be easily used, successful simulation projects require experience in modeling and statistics and also deep domain knowledge. Using simulation for making planning and control decisions often requires many simulation replications due to multiple scenarios for what-if analysis or for simulation-based optimization approaches. Therefore, it is likely that a simulation application will create a large computational burden.

There is a need to systematically investigate the improvement potential on the value chain level when simulation is used to support planning and control decisions. Important examples are simulation-based optimization (Forstner and Mönch 2013) and using simulation within what-if analysis scenarios for designing and running semiconductor value chains (Gonçalves et al. 2005; Lin et al. 2018). This requires that simulation models for semiconductor value chains are either fully automatically generated on demand using data in information systems of the value chain or that appropriate simulation testbeds are available.

This paper is organized as follows. The researched problem is described in the next section. This includes an introduction to the notion of frameworks due to (Porter 1991). First results are presented in Sect. 3. Moreover, conclusions are discussed and future research directions are identified in Sect. 4.

2 Description

2.1 Initial Situation and Framework Notion

We strive for a better understanding of planning and control situations where simulation-based decision support leads to improved decision making compared to conventional, non-simulation-based approaches. Our goal is to design a framework that supports decision-makers in semiconductor value chains to choose an appropriate type of simulation-based decision support.

According to (Porter 1991), a framework will be designed with the goal to support a certain point of view on a given class of problems. Frameworks offer a broad, comprehensive problem description together with structuring instruments that are more suited to deal with the complexity in companies than models that are based on various assumptions. Frameworks identify the relevant variables and the questions which a user must answer to come to conclusions tailored for a specific situation (Porter 1991).

2.2 Overall Approach

Based on the framework idea, this research effort is divided into the following steps:

1. In an analysis phase, we identify relevant variables that have an impact on the success of a simulation-based decision support in semiconductor value chains.

2. In a second phase, questions are derived that have to be answered to select an appropriate simulation-based decision support. This leads to the framework.
3. In a third phase, the framework will be tested by means of use cases related to the simulation-based support of decision-making activities in semiconductor value chains.
4. Based on the results of the third phase, repeating the first three phases might be desirable.

The overall approach is depicted in Fig. 1. We can clearly observe the iterative nature of the overall approach.

Fig. 1. Iterative phase model of the overall approach

3 Results

3.1 Towards a Framework for Simulation-Based Decision-Making

The main variables are the simulation paradigm and the type of the related simulation models to be applied and the type of the planning tasks. Different simulation model types can be differentiated (Mönch et al. 2018), namely

- agent-based simulation models
- system dynamics models
- detailed discrete-event simulation models
- reduced discrete-event simulation models
- hybrid models that combine different of the aforementioned approaches.

Agent-based simulation models allow for modeling the behavior of a human decision-maker since software agents are software entities that proactively make decisions to fulfill their design goals. Agent-based simulation can be used to study the emergent behavior of the different entities in a system.

System dynamics models allow for capturing the nonlinear behavior of systems based on flows, stocks, feedback loops, and time delays (cf. Sterman 2000). System dynamics models are generally deterministic in nature. They only allow for estimating the average system performance. Moreover, they have an aggregated structure and are based on the continuous time simulation paradigm. Therefore, running system dynamics models results in shorter computing times than performing simulations with discrete-event simulation models for manufacturing systems of the same size.

Discrete-event simulation models allow for a high-fidelity representation of the base system and process of a manufacturing system or a value chain. However, simulation studies based on such models tend to be time-consuming due to the many details included in such simulation models. Various approaches exist to reduce the level of detail, for instance, modeling only bottleneck resources in detail and replacing the operations on non-bottleneck resources by delays (Ewen et al. 2017, van der Zee 2019).

Hybrid approaches, also known as multi-model approaches, are proposed to combine the advantages of the different simulation paradigms and to mitigate the corresponding limitations. For instance, it is possible to use discrete-event simulation to represent the base system and process, while system dynamics is used to represent the planning model (cf. Venkateswaran and Son 2005). However, the management of the different models within a hybrid approach is a nontrivial exercise.

The simulation paradigm is influenced by the following independent variables:

- characteristics of the decision-making processes to be supported
- required level of detail
- data availability in operational and strategic information systems of the value chain
- time available for decision making.

If the decisions are not fully automatically made by algorithms, i.e. if human decision-makers are involved, the agent-based simulation paradigm is appropriate since it is possible to model the behavior of the human decision-makers to some extent. If the required level of detail is low and the time available for decision-making is also low then system dynamics is often more appropriate than other simulation paradigms. This is also true if the data availability is low. In the remaining situations discrete-event simulation is appropriate.

The planning and control tasks to be supported can be derived from the supply chain planning matrix for semiconductor value chains. The planning matrix is shown in Fig. 2.

Fig. 2. Supply chain planning matrix for semiconductor value chains (Mönch et al. 2018)

We see that short-term, mid-term, and long-term decisions are supported, i.e., the vertical axis shows the time frame. The horizontal axis of the matrix represents material flow across the business functions. The different planning functions, represented by rectangles, produce decisions that form the input for other planning functions.

The following activities can be supported by simulation:

1. using simulation in a repeated manner within metaheuristic-based optimization approaches to evaluate the objective function (simulation-based optimization)
2. using simulation to estimate parameters of planning models, this leads to a multi-model approach that iterates between an optimization model with prescribed parameter values and a simulation model that estimates parameter values based on the optimization results
3. execution of single plans under uncertainty
4. execution of plans in a rolling horizon setting
5. using simulation to model the planning and control process itself
6. using simulation to model the stochastic behavior of external factors.

The first three approaches can be applied in a static and stochastic setting, while the fourth approach can be used in a dynamic and stochastic setting. Moreover, the first and the second approach can be used to derive plans, for instance, production plans or schedules, while the third and fourth approach requires a plan as an input. Note that the third approach is implicitly embedded into the first and the second approach, but it can also be used in a standalone manner. Moreover, the first and second approach can be

combined with the fourth approach when the quality of the derived plans in a dynamic and stochastic setting is of interest.

The fifth approach is useful if several entities are involved in the planning and control process, mainly when human decision makers are involved. In this situation, it might be useful to study the interaction of the different entities. Clearly, a dynamic and stochastic setting is considered. Finally, it might be interesting to model the behavior of external factors such as demand by simulation.

The framework equips each planning function in Fig. 2 with appropriate simulation paradigms and with meaningful simulation activities. Therefore, the decision-maker can ask the following questions:

1. What type of conventional non-simulation based planning or control approach is applied?
2. Why is it likely that a simulation-based approach outperforms the conventional approach?
3. What is the time horizon of the considered planning function?
4. What time is available for decision making?
5. What is the required level of detail when decisions are made?
6. Is the required data for building the required simulation model available in a digitalized and structured form?
7. Which effort is required to build a corresponding simulation model from scratch?
8. Is an automated or semi-automated simulation model generation possible?
9. Which effort is required to maintain and update already existing simulation models?

Some preliminary results and findings of this process are summarized in Table 1.

Demand planning is challenging in semiconductor value chains (cf. Uzsoy et al. 2018). Fully automated planning approaches rarely exist. Therefore, it is interesting to model the planning process itself. The planning capabilities of planners together with the interactions of the different decision-makers can be studied (cf. Hauke et al. 2018). Agent-based simulation is appropriate for this setting.

There are also examples known where the interaction of customers is modeled. An agent-based simulation model to predict the sales of microprocessors in the high-end gaming market, focusing on the decision of a customer to purchase a more powerful computer is proposed by (Adriaansen et al. 2013). A software agent who makes purchasing decisions based on a customer-specific internal logic is used to represent each individual customer.

Production planning and scheduling/dispatching are mainly short-term by nature (see Fig. 2). Therefore, a fairly high level of detail is needed. The time for decision making is typically short, ranging from a few seconds to compute a schedule until an hour for production plans. The data availability is typically given due to existing Manufacturing Execution Systems (MES) and Enterprise Resource Planning (ERP) systems that can be found in most companies. Therefore, it is possible and appropriate to work with discrete-event simulation models. In some situations it might be interesting to study the emergent behavior of lots when they compete for the scarce resources in wafer fabs. In this situation, agent-based modeling and simulation is appropriate. A related example can be found in (Mönch 2006).

Table 1. Application framework

Planning function	Simulation paradigm	Simulation activities
Demand planning	Agent-based simulation	<ul style="list-style-type: none"> • Using simulation to model the planning process itself • Using simulation to model external factors (i.e., the demand)
Production planning	Discrete-event simulation	<ul style="list-style-type: none"> • Simulation-based optimization • Using simulation to estimate parameter values of planning models • Execution of single plans under uncertainty • Execution of plans in a rolling horizon setting
Scheduling and dispatching	Discrete-event simulation/ agent-based simulation	<ul style="list-style-type: none"> • Simulation-based optimization • Using simulation to estimate parameter values of scheduling approaches • Execution of single schedules under uncertainty • Execution of schedules in a rolling horizon setting • Using simulation to model the scheduling and dispatching process itself

3.2 Examples from Production Planning

The framework is exemplified by the production planning function depicted by a blue-rimmed rectangle in Fig. 2. Since production planning activities are short-term by nature, the discrete-simulation paradigm, either based on a detailed or a reduced simulation model, is a reasonable simulation approach as justified in Subsect. 3.1.

Examples for the first four simulation activities are known, for instance, the execution of production plans in a large-scale wafer fab simulation model is used by (Kacar et al. 2013), (Liu et al. 2011) apply simulation-based optimization to compute production plans, iterative simulation and linear programming are applied by (Hung and Leachman 1996), and production planning formulations for a single wafer fab based on linear programming are assessed in a rolling horizon manner by (Ziarnetzky et al. 2018).

Linear programming-based production planning formulations for production and engineering activities are assessed by (Ziarnetzky and Mönch 2016, Ziarnetzky et al. 2017) in a rolling horizon setting. Process improvement activities by engineering lots are crucial for semiconductor wafer fabrication facilities to stay competitive in the semiconductor market (Mönch et al. 2013). Production and engineering lots compete for the same equipment with scarce capacity. Two production planning formulations for a simplified semiconductor value chain are discussed. The first formulation assumes reduced available capacity for production, while the second one directly incorporates

engineering activities. Additional capacity is considered in this integrated formulation because of learning effects that represent process improvements. The integrated formulation outperforms the conventional formulation in a rolling horizon setting with respect to profit.

4 Discussion/Implications

In this research, we are interested in obtaining a fairly complete understanding of the capabilities of simulation to support various planning and control functions in semiconductor value chains. This research effort is challenging since, on the one hand, it requires knowledge of the different planning and control functions and the related decision-making approaches. On the other hand, it seems to be challenging to generate supply chain simulation models from scratch or reuse existing simulation models of an appropriate level of detail.

While the research described in this paper is an ongoing effort, there are several directions for future research. First of all, it is required to complete the framework by investigating the remaining planning functions in Fig. 2. Moreover, rigorous case studies are required to support the third step of the framework building process. Based on the insights from the case studies, several iterations of the framework building process are possible to improve the framework. The development of a rich simulation testbed for semiconductor value chains is a necessary requirement for performing the case studies.

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