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A REVIEW OF SIMULATION-OPTIMIZATION METHODS WITH APPLICATIONS TO SEMICONDUCTOR OPERATIONAL PROBLEMS

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ABSTRACT

Recent advances in simulation optimization (SO) research and explosive growth in computing power have made it possible to optimize complex manufacturing system problems. Semiconductor manufacturing is known as one of the most complex manufacturing systems. Based on a review of literature in the field of semiconductor manufacturing operational and planning problems, there is little reference to SO methods, an approach that has many advantages over other solution approaches. In this paper, we first distinguish between different users of SO then consider different approaches of SO applied to semiconductor and other manufacturing problems. The article then describes the main operational and planning issues in semiconductor manufacturing drawing actively from a Bosch fab, which could be addressed using SO. Finally, we attempt to provide insights on how SO can be applied to these problems.

1 INTRODUCTION

This paper is concerned with the application of SO in semiconductor manufacturing problems. Discrete Event Simulation (DES) is arguably one of the most widely accepted and used Operations Research (OR) methodologies (Tako and Robinson 2010; Shannon 1998). SO is defined as the integration of simulation with optimization to find good or optimal solutions (Figueira and Almada-Lobo 2014). Other approaches can be used instead of SO, such as stochastic programming, fuzzy programming, and stochastic dynamic programming. The accuracy and detail of these models are however much lower when compared to SO approaches. With today's and future projected computing power increasing, this article reviews SO approaches and their application to semiconductor problems which are extremely challenging due to the size and scale of problems (Liu et al. 2011). This article presents a brief classification of SO approaches with focus on applications to semiconductor manufacturing.

In addition, this article will present different challenges, drawing from the Productive4.0 project (Productive 4.0 2018). The main objective of Productive4.0 is to improve the digitization of the European industry significantly by means of electronics and Information and Communications Technology (ICT). The main goal of Industry 4.0 is digitization and our goal in Productive4.0 is to examine digitization of semiconductor manufacturing and its supply chain to improve system efficiency. Therefore, our focus is on simulation and more specifically systems simulation to examine how this can be applied to the semiconductor sector. Within manufacturing and supply chains there are different decision-making, namely strategic, tactical and operational (Stevenson 2017). In addition there are different expertise of users of any developed decision support systems (DSS) (Dagkakis et al. 2016). Due to the complexity of semiconductor manufacturing, simulation has been widely used, but mainly by simulation experts. Here we wish to examine how simulation can be combined with optimization and applied to semiconductor manufacturing

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to allow the development of tools that can capture the variability within semiconductor manufacturing and be used by personnel with lower levels of expertise within the tactical and operational level. The focus in this paper is on the front-end of semiconductor manufacturing.

The article is organized as follows. In section 2, we present a brief overview of SO applications, and note that there are few current applications in semiconductor manufacturing. In section 3 we provide an overview of some of the challenges found in Bosch's front-end manufacturing systems, highlighting the large scale, complexity and variability in both the processes and demand found in these systems. Because of these challenges there has been limited use of quantitative tools at the tactical and operational level in these systems, due to their simplifying assumptions (Shanthikumar et al. 2007). Section 4 presents a discussion of the application of SO within semiconductor front-end manufacturing while section 5 summarizes the conclusions from the paper.

2 LITERATURE REVIEW: SIMULATION OPTIMIZATION IN MANUFACTURING

This section reviews the literature on different implementations of SO in manufacturing systems. A number of different classifications have been presented considering different approaches in SO. Some reviews focused on just optimization parameters like objective functions or solution spaces such as Fu (1994) who addressed the difference between gradient-based methods, including perturbation analysis, likelihood ratio method, and frequency domain experimentation. Shanthikumar and Sargent (1983) considered different modeling approaches in SO methods. They organized their review by categorizing into analytic and simulation based models. Fu (2002) focused on desirable features in a good implementation of optimization for commercial simulation software. His categorization investigates different research based on features like generality, transparency to the user and high dimensionality. Recently a comprehensive taxonomy on hybrid simulation optimization methods was presented by Figueira and Almada-Lobo (2014). In their study, how simulation and optimization integrated was discussed. They divided their review in three major streams of research:

- Solution Evaluation (SE): Developing a comprehensive simulation model to represent the system and use that model to evaluate the performance of various solutions.
- Analytical Model Enhancement (AME): Enhancing the analytical model using simulation results.
- Solution Generation (SG) approaches: Using simulation not to verify the advantage of one solution over another, but simply to compute some variables and hence be part of the whole solution generation.

The most recent review of SO proposed by Amaran et al. (2014) emphasizes the application of different algorithms in simulation optimization. They structured their review based on different simulation optimization algorithms in seven categories (ranking and selection, metaheuristics, response surface, gradient-based methods, direct search, model-based methods and Lipschitzian optimization). Furthermore, they presented six domains for SO applications as follows:

- Operations: Buffer location, nurse scheduling, inventory management, health care and queueing networks.
- Manufacturing: PCB production, engine manufacturing, production planning, Kanban sizing and manufacturing cell design.
- Medicine and Biology: Protein engineering, cardiovascular surgery.
- Engineering: Welded beam design, solid waste management, pollution source identication.
- Computer science and networks: Server assignment, wireless sensor networks, circuit design.
- Transportation and logistics: Traffic control and simulation, metro/transit travel times, air traffic control.

While articles on SO applications in semiconductor manufacturing systems exist, the aim here is to highlight its applicability to this topic. This is because problems in semiconductor manufacturing are difficult to solve using quantitative methods, due to their complexity, high level of variability and they are typically large scale problems (Hsieh et al. 2001). We therefore present a review of SO methods in semiconductor manufacturing to add this category to the application domain. The article uses the categorizations proposed by (Amaran et al. 2014) and (Figueira and Almada-Lobo 2014) to address SO articles published in this area. We propose a new categorization scheme considering both the domain of application and SO characteristics shown in Table 1.

Table 1: Classification of applications in manufacturing categorized using Solution Evaluation (SE), Analytical Model Enhancement (AME) and Solution Generation (SG) (Figueira and Almada-Lobo 2014).

Domain of Application	Application	SE	AME	SG
Operations	Inventory Planning	Keskin et al. (2010), Güller et al. (2015)	-	Chu et al. (2015)
	Assembly Line Design	Kuo and Yang (2011)	-	-
	Production Planning	Yang et al. (2007), Gansterer et al. (2014)	-	-
Manufacturing	Remanufacturing System	-	-	Li et al. (2009)
	Dairy Production	-	-	Armenzoni et al. (2016)
	Process Industries	-	-	Noguera and Watson (2006)
	Process Industries	-	-	Noguera and Watson (2006)
	Semiconductor Manufacturing	Hsieh et al. (2001), Bang and Kim (2010)	Liu et al. (2011)	Klemmt et al. (2008), Liu et al. (2011), Ziarnetzky and Mönch (2016)

Various studies investigated SO in manufacturing systems. For example, inventory planning are challenging issues in the management of shop floors. Chu et al. (2015) addressed a multi-echelon inventory-planning problem in manufacturing under uncertainties. They propose a simulation-based optimization framework for optimizing distribution inventory systems where each facility is operated with the (r,Q) inventory policy. The objective is to minimize the inventory cost while maintaining acceptable service levels quantified by fill rates. They considered an agent-based simulation model to address inventory of the system and then to use simulation to determine the efficiency function in their optimization model. Keskin et al. (2010) study a generalized vendor selection problem that integrates vendor selection and inventory replenishment decisions of a firm. In addition to vendor-specific procurement and management costs, they consider inventory replenishment, holding, and backorder costs explicitly to meet stationary stochastic demand faced by the firm. They build a discrete-event simulation model to evaluate the objective function of the problem that works in concert with a scatter search-based metaheuristic optimization approach to search the solution space. More recent research concerned with inventory planning in manufacturing systems was proposed by (Güller et al. 2015). They addressed a way of using a simulation-based optimization approach to determine the optimal inventory control parameters of a multi-echelon production-inventory system under a stochastic environment. They used a Multi-objective Particle Swarm Optimization (MOPSO) algorithm to determine the appropriate inventory control parameters to minimize the total inventory cost and maximize the service level utilizing an object-oriented framework for developing the simulation model to evaluate the control parameters generated by the MOPSO.

Production planning and scheduling problems have been considered by researchers using SO. One of the first reported research on the application of SO to production planning of manufacturing systems was by Kleijnen (1993). They presented a case study concerning a DSS for production planning in metal tube manufacturing. Yang et al. (2004) propose a Tabu-search DES SO method which solves the flow shop with multiple processors (FSMP) scheduling problem in a multilayer ceramic capacitor manufacturing system. Yang et al. (2007) addressed an evolutionary-simulation optimization approach in solving a multi-constant work-in-process (multi-CONWIP) pull strategy problem. They consider a case study to illustrate the performance of the applied methodology. Both the single-loop CONWIP and the just-in-time (JIT) control strategies are a special case of the proposed multi-CONWIP strategy. Kuo and Yang (2011) propose a simulation optimization method which employs a particle swarm optimization (PSO) algorithm with mutation based on similarity to address managerial parameters in a production system. They applied their method to an assembly line design problem. Li et al. (2009) present a hybrid genetic algorithm for optimization of a dedicated re-manufacturing system with simulation. Based on the simulation model, a genetic algorithm is developed to optimize the production planning and control policies for dedicated re-manufacturing. Gansterer et al. (2014) present a hierarchical production planning system in a make-to-order environment. A challenging task in this context is to determine good production parameter settings in order to benefit from established planning methods. They present a framework for hierarchical production planning which they use to identify settings for three planning parameters, named planned lead times, safety stock, and lot size. Within a discrete-event simulation model which mimics the production system they propose a mathematical optimization model for replicating the decision problem. Another research area in production planning which plays a key role to achieve an efficient production systems is capacity planning. Uribe et al. (2003) applied a two stage SO approach to address a capacity allocation planning problem for discrete manufacturing sites under an uncertain demand stream. The most recent research in application of SO to production planning and scheduling problems presented by Yuan et al. (2017). In their research a genetic algorithm based optimization model is built from improving initial population and selection process and an elite mechanism is presented in the iteration. They integrated their optimization model with a DES model to solve the flow shop scheduling problem.

An alternative application domain is Armenzoni et al. (2016) which propose a method to optimize a dairy milking process. The ultimate goal of their analysis is to reduce the time required for milking operations, through the development of a discrete-event simulation to reproduce the main processes of milking and movement of animals. Another type of manufacturing system problems which is considered to solve by SO is plant design and facility location problems. More details on plant design problems solved using SO can be find in Noguera and Watson (2006).

2.1 Applications: Semiconductor Manufacturing

Re-entrant process flows, large scale systems, complexity, high level of variability, stringent production control requirements and fast-changing technology and business environments are the main reasons why applying simulation models to a front-end fab is challenging. One of the first research done in front-end semiconductor manufacturing using SO proposed was by Hsieh et al. (2001) who investigated an ordinal optimization (OO) based simulation method to solve scheduling problems in a semiconductor manufacturing fab. Their method consists of six steps:

1. A fab model database.
2. A discrete-event simulator.
3. A library of scheduling rule options.
4. A library of performance indexes.
5. An ordinal comparator for ranking the performance measures.
6. An optimal computing budget allocation (OCBA) technique for further enhancing the simulation efficiency.

To evaluate their method they solved some benchmark problems proposed by Lu et al. (1994). Another scheduling problem in semiconductor manufacturing solved using SO presented was by Klemmt et al. (2008). They described a multi optimization approach for operative scheduling of a special oven process machine group in a front-end fab. In their research, a mixed integer programming and simulation-based optimization approach to scheduling batch processes are presented and compared with a rule-based dispatching approach. Liu et al. (2011) attempted to develop a capacity planning approach using SO that addresses the uncertainty in product demand (including the uncertainty in product mix) and takes the cycle time performance measure into consideration. They tried to answer research gaps proposed by Geng and Jiang (2009). Bang and Kim (2010) considered a production planning and scheduling problem in a semiconductor wafer fabrication facility. They propose a two-level hierarchical production planning (HPP) method that employs an iterative procedure for production planning and operations scheduling. In their method, production plans are obtained with a linear programming model in the aggregate level, and schedules at the machines are obtained with a priority-rule-based scheduling method and evaluated with discrete-event simulation in the dis-aggregate level.

Liu et al. (2011) research concerned the problem in semiconductor manufacturing production planning, which can be loosely defined as the problem of finding a release schedule of jobs into the facility over time so that the actual outputs over time satisfy, as closely as possible, the predetermined requirements. They adapt a genetic algorithm to search for a set of release plans that are near-Pareto optimal and a simulation model to evaluate results. Ziarnetzky and Mönch (2016) present recent research that considered SO in a semiconductor manufacturing system which addressed an integrated problem from front-end to back-end of the manufacturing system. They considered a simplified semiconductor manufacturing that consists of a single front-end facility and back-end facility. They present a production planning formulation that is based on clearing functions. In their study, the minimum utilization of expensive bottleneck machines in the front-end facility is a parameter of the model. At the same time, the less expensive capacity of the back-end facility is increased to reduce the cycle time in the backend facility. They proposed a simulated annealing method to determine appropriate minimum utilization levels for the front-end bottleneck machines and appropriate capacity expansion levels for the back-end.

Semiconductor manufacturing operations are faced with a wide range of uncertainties. Therefore, managers in strategical, tactical and operational levels of semiconductor manufacturing decisions must use expected values without including uncertainties or try to incorporate them (Aytug et al. 2005). Different studies have considered the role of uncertainties in semiconductor manufacturing decision making. Aytug et al. (2005) presented a review on executing production schedules in the presence of unforeseen disruptions in the semiconductor manufacturing shop floor. Barahona et al. (2005) proposed a stochastic programming approach to capacity planning under demand uncertainty in semiconductor manufacturing. They considered in their model multiple demand scenarios together with associated probabilities to identify a set of tools that is an appropriate compromise for all different scenarios. Several articles consider capacity planning that include uncertainties like Hood et al. (2003), Bermon and Hood (1999) and Chien et al. (2012), simplifying the uncertainties in their models to reduce complexity.

A small number of articles deal with these complex problems by using queuing models. Brown et al. (2010) developed and implemented the Enterprise Production Planning and Optimization System (EPOS), a queuing network model for capacity planning. Their approach extends earlier queuing network models by adding the ability to model product-specific batch service and batch arrivals and multi-chamber process equipment. Another queuing model is presented by Hanschke and Zisgen (2011) which uses a decomposition method for ordinary single class open queuing networks, extending the model to incorporate batch processing.

Supply chain operation uncertainties have also been modeled in semiconductor manufacturing. Kempf et al. (2013) provided research that focused on Intel's supply chain to address optimizing capital investment decisions. A good review in this field is Mönch et al. (2017) which describes research in the field of supply chain uncertainties related to semiconductor manufacturing. Dobson and Karmarkar (2011) discussed in a chapter different uncertainties in production planning (an aspect of supply chains). There are two useful reviews in this area provided by Mönch et al. (2011) and Mönch et al. (2013). In both articles they outline different challenges related to uncertainties in the semiconductor production planning area.

Based on this review it is clear that although SO methods have a broad range of applications in manufacturing systems with the flexibility of these methods to deal with stochastic environments and uncertainties which are mentioned above, there are limited applications within semiconductor manufacturing of SO, as shown above, due to the complexity and variability of semiconductor systems and the limiting assumptions of quantitative models together with the advancements of computing power, SO could be more widely used within these systems.

3 CHALLENGES IN BOSCH FRONT END SEMICONDUCTOR MANUFACTURING

Semiconductor microchips must be produced in one of the most complex production systems. Due to several manufacturing requirements, such as clean room manufacturing, semiconductor production is extremely cost intensive. This is the reason semiconductor production equipment require high utilization. The clean room conditions due to the small sizes of the microchips make the production floor itself highly expensive. Semiconductor microchips with around 1000 different production steps and re-entrant loops in a job shop production system face lead times of one month and more. Additionally, in recent years product portfolios are rapidly increasing with product demands experiencing high variability. To maximize and stabilize utilization of expensive equipment semiconductor production is organized in job shop systems rather than in product dedicated flow shop systems. On the one hand, this enables planners to balance utilization by sharing capacities across different products, which increases material flow complexity increasing the complexity of decisions. Within semiconductor manufacturing nearly in all equipment, a real-time material dispatching decision is necessary to decide about the sequence of lots processed on the equipment. Thereby global dispatching policies ensure material flows and priorities considering customer demands, to meet customer due dates. Additionally, local dispatching policies helps to ensure maximization utilization of specific equipment. In semiconductor industries equipment performance can be summarized in the following four equipment models (Kohn 2014):

- Single wafer equipment,
- Batch equipment,
- Parallel equipment,
- Cluster equipment.

These different equipment models set various loading requirements for maximization of utilization. Additionally, almost in every equipment model setup times have to be reduced and throughput maximized. Thereby, static policies cannot cope with any variability in inventory distribution, process times, equipment availability, process availability, worker availability and changes to demand. Too much expensive buffering of material, time, capacity or capability is necessary to compensate static plans that do not integrate variability of the different influencing random variables. This is the reason that in the past there was and still is large effort to develop different DES models for semiconductor production systems to predict future situations to support dispatching and control. Additionally, different optimization problems in semiconductor manufacturing already have been addressed with some simulation-based optimization approaches (see section 2). This section presents a number of semiconductor front-end optimization problems that could be addressed with simulation-based optimization. The necessity of simulation-based optimization in semiconductor manufacturing is due to the stochasticity that exists in these production systems. Nearly every production parameter such as process times, equipment availability, worker availability, product yield is stochastic. Actual simulation systems consider these random variables, however there is a need to combine these to create tools for tactical and operational problems for different users within the production system.

3.1 Capacity and Process Flexibilization (Equipment and Process Availability)

In dynamic industries such as semiconductor manufacturing, industry equipment availability together with changing demand creates high volatility. In a job shop production like semiconductor manufacturing, a machine can be qualified for n different processes (process flexibilization). Considering high stochasticity of machine availability this offers still a risk if the machine breaks unexpectedly. This risk can be reduced with capacity flexibilization by transferring the n different processes to m machines. Of course, the flexibilization of capacities induces costs. This leads to the following managerial question: Considering given costs for capacity flexibilization and the stochasticity of machine availability what would be the efficient number of qualified machines (m)? While Chien et al. (2013) propose a two-stage stochastic programming demand fulfillment model to optimize inter-fab capacity allocation the efficient factor of flexibilization of existing machines can still not be answered sufficiently for semiconductor job shop production systems. Several other papers on optimization of capacity expansion scenarios are published (e.g. (Kim and Uzsoy 2008; Wang et al. 2007; Liu et al. 2011)). While capacity expansion problems in semiconductor manufacturing are addressed quite broadly there still is a lack of publications tackling capacity flexibilization to be used by a wider set of users within semiconductor manufacturing which could be achieved using SO applications. An example in the semiconductor supply chains is Bard et al. (1999) who address toolset configuration with different algorithms like simulated annealing, two greedy algorithms and an exact method for the system design phase.

3.2 Operator Availability in Semiconductor Manufacturing

In deterministic systems necessary operator availability can be calculated exactly. Due to stochasticity of the production and demand, the expected necessary operator availability is often insufficient. This issue is poorly tackled in the literature for semiconductor manufacturing systems. Wu and Fu (2005) propose a linear programming approach for the general staffing problem to minimize operator staffing costs. Similar to this publication most solve the assignment problem taking qualification of workers as given (i.e., (Campbell 2011; Chen and Dabbas 2002; Pollitt and Matthews 1998)). Campbell (2011) indirectly addresses the operator availability problem with the development of a two-stage stochastic program. The results of the worker assignment show the value of cross-trained workers which increases in environments with high demand uncertainty. Iravani et al. (2005) develop an algorithm for evaluation of system responsiveness to environment volatility, while considering operator cross-training. Nembhard et al. (2005) model and financially evaluate a cross-training policy with a dynamic investment in workforce flexibility. Generally, cross-training of workers has to be fostered if demand uncertainty increases. More research is required in solving the optimization problem of demand and system volatility related to the degree of worker generalization in a semiconductor environment, as qualification of an operator for a system, costs time and money.

3.3 Parallel Machine Loading (Throughput Maximization with the Parallel Loading of Equipment)

Each process has stochastic process times on the relevant process chambers of equipment. According to the actual machine setup and the inventory waiting for the process, the sequence of parallel machine loading can be optimized according to the maximization of parallel machine throughput. Therefore, a schedule has to be developed for the different process chambers of the equipment. Jiang et al. (2015) model a preemptive scheduling problem of parallel machines with deterministic process times with classical heuristics. Gan et al. (2012) use a branch and price algorithm for the scheduling problem with parallel process chambers and a common handling server. Wang et al. (2013) tackle the problem with a genetic algorithm minimizing the makespan of the remote server to assign jobs on the parallel single servers. All papers treat parallel machines as multiple units consisting of a common server, assigning jobs to the parallel single server machines or process chambers. The target function destines maximization of throughput of the parallel equipment or minimization of makespan. The preconditions are maximum utilization of the common server and of the single parallel chambers. The single chambers can only be occupied once at the same time. For example, a wet bench has several parallel batches with different acids. The machine can be loaded in parallel. Additionally, in each batch, a batch of maximal two lots of the same type can be processed at the same time. According to the inventory waiting and forecasted for the wet bench and the availability of a single batch, the lot sequence can be optimized with multi-objective target function.

4 DISCUSSION

The above sections present a preliminary overview of SO applied to manufacturing in general, and more specifically, to semiconductor manufacturing. In addition it highlights some challenges, that SO could address, for the efficient operation of semiconductor manufacturing, with special focus on the front-end. Maximizing machine capacity (subsection 3.1) to meet customer deadlines is an important issue in semiconductor manufacturing so answering this question is important. An early example application of SO is Yang et al. (2004) where Tabu search (TS) optimization algorithm is used with discrete event simulation (DES). One of the best examples of solving capacity planning problem is Chung et al. (2008) but in their study and other later studies in this field like Chen et al. (2016) they assume deterministic features of production, while in practice they are stochastic. For cases like the photolithography area which is mostly considered for capacity planning in the literature some features like processing times and machine availabilities have high variability. Therefore, SO can be used as an effective means of addressing these problems because not only is it capable of dealing with stochastic features of the system but also it can provide a planning procedure. In other words, the simulation phase of SO can be used in the shop floor by considering a DES system to deal with uncertainties of the system and provide an evaluation method for production plans which are considered in the optimization stage. The optimization phase of SO can provide capacity plans (Uribe et al. 2003) and integration of simulation by these plans will provide an efficient DSS which is able to answer deterministic planning, stochastic features and dynamic situations of the semiconductor manufacturing capacity planning problems. A stochastic DES model can however be difficult to solve, both in how the optimizer is used to locate the optimal and also the computational aspects of the DES model, but cloud computing may overcome this last restriction (Kiss et al. 2015).

A cross-training policy can be regarded as a set of rules for determining the distribution of workers skills. These rules specify what decisions are made concerning aspects that are considered important in the development of a cross-training policy (Bokhorst 2005). Based on the literature review three steps are considered in cross-training are: 1) cross-training policy; 2) cross training configuration; 3) cross training performance evaluation. Rotondo et al. (2015) is an example of the use of SO in the allocation of operators in an assembly line that uses a multi-objective function that dynamically alters to conditions on the line.

Parallel scheduling problems are NP-Hard in terms of complexity (Arnaout et al. 2014). To answer a parallel scheduling problem we consider the research done by Yuan et al. (2017) which proposed a SO approach to solve the flow shop scheduling problem and considered a genetic algorithm integrated to a DES model. A possibility is to adapt their SO approach to the parallel scheduling problem in semiconductor manufacturing.

5 CONCLUSION

In the operational and tactical managerial levels of the semiconductor manufacturing, the concept of SO DSS approaches could be more widely applied to semiconductor manufacturing, to facilitate wider use of these tools. The classifications used so far in the literature of semiconductor manufacturing problems focused on particular streams of methods like optimization methods or just from operational aspects. To conclude, our review addressed different problems encountered in a Bosch semiconductor front-end fab and in addition provided a brief overview of future possibilities to extend SO applications in semiconductor fab problems.

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