Production Scheduling in Complex Job Shops from an Industrie 4.0 Perspective: A Review and Challenges in the Semiconductor Industry

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ABSTRACT

On the one hand, Industrie 4.0 has recently emerged as the keyword for increasing productivity in the 21st century. On the other hand, production scheduling in a Complex Job Shop (CJS) environment, such as wafer fabrication facilities, has drawn interest of researchers dating back to the 1950s [65, 18]. Although both research areas overlap, there seems to be very little interchange of ideas. This review presents and assesses production scheduling techniques in complex job shops from an Industrie 4.0 perspective. Based on the literature review, the authors' experience in the semiconductor industry and feedback and discussions with industry experts[1], this paper identifies challenges in production control. We identify four future directions: Decentralization and autonomous decisions, flexibility and adaptability, integration and networking and human aspects in an environment with rising complexity. While this review and certain challenges are motivated by semiconductor fabrication plants, the paper serves as a general overview of the state-of-the-art in job shop scheduling.

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CCS Concepts

•**Applied computing** → **Multi-criterion optimization and decision-making;** *Computer-aided manufacturing; Industry and manufacturing;* •**Computing methodologies** → *Machine learning;*

Keywords

Industrie 4.0; Job Shop; Scheduling; Semiconductor Manufacturing; Review; Industry Challenges

1. INTRODUCTION

In media, politics and science, Industrie 4.0, also called the fourth industrial revolution, has become the synonym for increasing productivity in the 21st century by applying digital technologies in manufacturing. While the term Industrie 4.0 is mainly used in Germany, similar ideas can be found in the concepts of the Industrial Internet, Smart Manufacturing or Made-In-China 2025. The main idea of Industrie 4.0 is that Cyber-Physical Systems (CPS), which interlink the digital and physical world, are connected in an infrastructure of the Internet of Things and Services (IoT&S) [19]. Industrie 4.0 is a "collective term embracing a number of contemporary automation, data exchange and manufacturing technologies" [23], including new Human-Machine-Interfaces (HMIs). Bischoff et al. [19] identified five functional areas which group research and application projects according to their main functions and usage:

- Assistance systems
- Networking and integration
- Decentralization and service-orientation
- Self-organization and autonomy

- Data collection and processing.

Modern production control systems in job shops, such as semiconductor fabrication plants, are a perfect example for Industrie 4.0, as they touch all five functional areas. Three aspects are already an integral part of the production scheduling: It serves as assistance system for shop floor operators. Data collection and processing play a crucial role in automated decision making in the control systems. Machine-2-Machine communication covers the networking aspect. Modern control systems exhibit a close integration into a supply chain network [51]. The remaining two aspects, decentralization and service-orientation and self-organization and autonomy, are being actively discussed in the field.

Over decades the semiconductor industry has been driven by Moore's law, which states that the number of structures per IC doubles every twelve months [79] (later revised to 24 months). After decades of exponential improvements, experts predict a slowdown of Moore's law with increasingly longer development cycles for new technology nodes [97]. Additional cost reductions have been achieved by increasing silicon wafer sizes and improving yield. However, a wafer diameter of 450mm in production has been repeatedly delayed [2] and yield is already in most production plants clearly above 90%. The potentials in these three areas are nearly exploited.

Therefore, operational excellence has been gaining importance in the semiconductor industry, as it promises further cost reductions and thereby a competitive advantage. Industrie 4.0 (or Smart Manufacturing) has become the heading for these activities [38, 42]. The semiconductor industry offers a good foundation for Industrie 4.0: Already in the 1970s, the industry started using it's own products in it's production facilities. Starting in the 1990s, semiconductor manufacturing has been used as an application scenario for job shop scheduling solutions [32]. In the early 2000s, semiconductor wafer facilities had a very high level of digitization and automation [51]. This high level of implementation of Computer Integrated Manufacturing (CIM), associated with the third industrial revolution, is the foundation for Industrie 4.0.

This review assesses job shop scheduling techniques in complex job shops, such as wafer fabrication plants, under the aspects of Industrie 4.0. The problem description is given in Section 2. Since many different solutions have shown good results for the scheduling problem, the frontiers and areas of research are vast. This paper focuses on general solutions which are used in or targeted towards semiconductor manufacturing. The main methodologies and techniques in practice and science are presented based on relevant examples: Section 3 starts with dispatching heuristics, in Section 4 hyper-heuristics and scheduling with machine learning are presented, Section 5 focuses on mathematical programming and Section 6 is dedicated towards promising approaches. To the best of our knowledge, this is the first time these approaches are discussed with respect to Industrie 4.0.

From the authors' experience at Infineon Technologies AG, an exchange and feedback from Elmos Semiconductor AG and the literature review challenges in shop job scheduling and industry-specific challenges for production control in wafer facilities are derived in Section 7. Motivated by new concepts in Industrie 4.0, this paper proposes directions for future research.

For a complete review of scheduling in semiconductor manufacturing we refer to more extended reviews [32, 88, 73, 74, 11] and for scheduling in general to the following books [90, 16].

2. COMPLEX JOB SHOPS AND OBJECTIVES

A job shop is characterized by a layout which groups similar production devices or work systems in closed units [106]. Different products can take different routes through the fab [106]. A job shop is called flexible, if processes can be handled by several tools (identical tools work in parallel). Under the following conditions, a flexible job shop is considered a complex job shop [67, 46, 74]:

- Re-entrant flow of the jobs (e.g. one job needs to be processed on one equipment several times)
- Sequence-dependent setup times
- Time coupling between processes
- Frequent machine breakdowns and other types of disturbances
- Unequal process times of the jobs at one equipment
- Prescribed due dates of the jobs
- Different types of processes, e.g. single job vs. batch processing
- Different lot sizes

The properties are explained in figure 2.

The semiconductor manufacturing process consists of four main steps: wafer fabrication, probing, assembly or packaging and final test. In this review the focus lies on wafer fabrication as this step is considered the most complex. Wafer fabrication plants satisfy the conditions of a complex job shop environment. A semiconductor fabrication produces lots of 25 wafers, which can contain over 10,000 Integrated Circuits (ICs). The main processes are deposition (physical/chemical vapor deposition, electrochemical deposition, molecular beam epitaxy), patterning (lithography), removal (wet/dry etching, chemical-mechanical polishing, plasma ashing) and modification of electric properties (ion implantation, furnace annealing).

The factory scheduling problem is often decomposed into tool scheduling problems (single machine), work center scheduling (parallel machines), work area scheduling (flexible job shop) and full wafer fab scheduling (complex job shop) [73]. This paper will focus on the full wafer fab scheduling, which needs to integrate the other layers. All timing constraints which have to be respected are modeled with a disjunctive graph (nodes represent tasks, edges represent time constraints), which is the starting point for more complex models [12].

Scheduling is the planning process that "deals with the allocation of resources to tasks over given time periods and its goal is to optimize one or more objectives" [90]. In the context of job shop scheduling, jobs will be assigned to machines for a specific period in the future [7], "with the basic aim to ensure an effective and efficient use of the available resources" [11]. In contrast to the planning process "scheduling", dispatching is a JIT activity: When a machine becomes

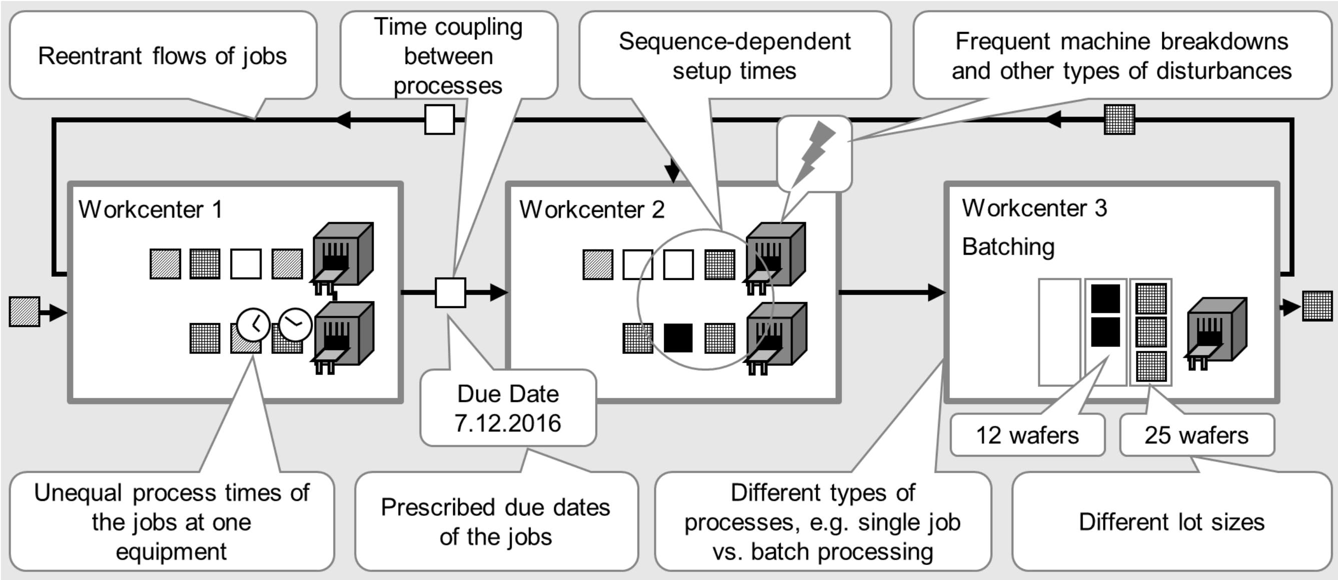

Figure 1: Definition of a complex job shop [67, 46, 74].

available, the dispatching algorithm assigns the job with the highest priority from a set of waiting jobs to the machine. The priorities may be determined by schedules or by dispatching rules.

Deterministic scheduling assumes fixed input values, while stochastic scheduling replace the deterministic values with probability distributions [90]. For static problems, all jobs are already available, while in dynamic problem settings the system has to deal with different ready-times of jobs. The mathematical scheduling literature focuses on deterministic scheduling in both static and dynamic cases.

Logistic objectives can be divided in logistic performance and logistic costs, both with an external and internal view (following [110, 64]). Logistical performance from an external view for a Build To Order (BTO) production can be evaluated by the lead time, deviation from the delivery date and the delivery reliability, which is the percentage of on time deliveries within a certain delivery tolerance. For a Build To Stock (BTS) production, the only external performance indicator is the service level. For both BTO and BTS the objective for logic costs is the price. Internal objectives for the logistic performance are cycle time, cycle time deviations and due date reliability. Internal logistic costs are the inventory, the utilization of resources and opportunity cost and default. For optimization problems either one key objective has to be chosen, or the objectives have to be weighted. In the job shop scheduling literature for semiconductor manufacturing the most used objectives are Total Weighted Tardiness (TWT), cycle time and throughput [73]. The tardiness for job j is defined as $T_j = \max(C_j - d_j, 0)$, where C_j is the completion time and d_j presents the due date. The TWT can then be written as $\sum_{j \in \{\text{all jobs}\}} w_j \cdot T_j$ with weights w_j.

For an assessment of the performance of a complex job shop production or general decisions on a management level tools from Factory Physics [41] are often used, which are based on mathematical queuing theory (Little's law [63], Kingman's formula [53]). These stochastic measures can give guidance on controlling the general Work-In-Progress (WIP) level, on the stability of the production or on capacity planning, but have hardly any implications on specific scheduling decisions.

Deterministic job shop scheduling problems can be solved optimally by mathematical programming. Still, real world systems often exhibit a high level of complexity which makes these methods unsuitable for practical problems, mainly due to a high implementation effort and long computational runtimes [11]. Especially in a stochastic and dynamic environment, the computational time to get a solution becomes crucial. Job shop scheduling and most variants are NP-hard (non-deterministic polynomial-time hard) [29], which is the most difficult complexity class in computational complexity theory. In a semiconductor wafer fabrication facility these events might be machine breakdowns, new job arrivals, stochastic processing times or changes of due dates. Therefore the use of heuristics is common [11].

This is also a position which Industrie 4.0 takes: Rising complexity and volatility of markets prevents planning over long time periods [101]. Instead of investing in more advanced planning capabilities, the approach of Industrie 4.0 is to increase the flexibility and adaptability of production to enable Just In Time (JIT) decision making[101]. For example, SEW-EURODRIVE has reduced their planning horizon in their Sm@art Factory, an Industrie 4.0 showcase factory, from weeks to a maximum of three hours [48].

3. DISPATCHING HEURISTICS

Dispatching rules are still the dominant shop floor control method for wafer manufacturing. Advantages are the real-time capabilities and the fact, that results are easily comprehensible for operators. Normally a hierarchy of several dispatching rules is used [25]. E.g. if two processes have a time coupling for proper execution, the time coupling overrules other dispatching approaches targeting the due date.

Approaches to use a single set of dispatching rules for all tools have not proven successful [25]. Popular dispatching rules are [32]:

- First In First Out (FIFO): The rule describes simple queuing. The lot with the longest waiting time is processed first.
- Shortest Processing Time (SPT) [99]: The lot with the shortest processing time has the highest priority. This policy reduces the WIP in front of the machine.
- Shortest Setup Time (SST)/ Least Setup Cost (LSC): The rule minimizes setup times. This is especially relevant for tools with sequence-dependent setup times, e.g. ion implanters in semiconductor manufacturing. In practice SST leads to batch processing.
- Shortest Remaining Process Time (SRPT): This policy reduces the total WIP in the production.
- Earliest Due Date (EDD) [45]: The job with the earliest delivery date has the highest priority.
- Operation Due Date (ODD): The expected total cycle time is divided proportional to the single process times of individual process steps. In practice, the single process time is multiplied by a Flow-Factor (FF), also called X-factor, to determine the expected total completion time of each process step. Based on the delivery due date a planed starting date for each process step is calculated. The priority of a lot rises if the actual date deviates from the planned date.
- Least Slack (LS): For a due date d_j and a remaining total processing time p_j (including minimum inter-operations times) the slack is defined as $s_j = d_j - p_j$. The lot with the least slack has the highest priority.
- Apparent Tardiness Cost (ATC) [105]: Weighted combination of SPT and Least Slack (LS). By setting weights and a scaling parameter κ the rule can be adjusted to different settings.
- Critical Ratio (CR): The ratio between EDD and SRPT. The performance of the dispatching rule is mainly influenced by a realistic due date setting [91].

A special case of dispatching heuristics are look-ahead rules "that take information related to future job arrivals into account" [74]. Their advantages are particularly revealed in batching or sequence-dependent setup times scenarios. An early example for batching is the Dynamic Batching Heuristic (DBH) [30]. Already the consideration of the next arrival unlocks half of the potential of DBH [30]. Motivated by this insight are the Next Arrival Control Heuristic (NACH) for several different products [26] and NACH+, which controls "incoming inventory into the batch operation" [35].

Except as examples for look-ahead rules, dedicated batching heuristics are not discussed here. For a more complete overview of common dispatching rules we refer to Sarin et al. [95].

In science, dispatching rules are normally evaluated in simulations and computational studies (e.g. [104]). The rules are assessed under the objectives of mean cycle time, average tardiness, number of tardy jobs and maximum lateness. Uzsoy et al. [104] conclude that no rule performs well under all objectives. In an extensive and rigorous simulation study, Holthaus and Rajendran [40] also conclude that no rule optimizes all measures. An additive combination of different rules perform well in certain scenarios. Wiendahl and Nyhuis investigate the influence of the WIP level on the performance of different dispatching rules and conclude, that the performance of different rules with regard to cycle time depends on the WIP level [82, 110].

In industry, dispatching rules are either modeled using expert knowledge of operators or sometimes in simulation studies. The industry standard for semiconductor manufacturing is the Real-Time Dispatcher (RTD) by Applied Materials, Inc. [34, 3]. The RTD has " greatly improved productivity for the last two decades" [34]. Even if more advanced techniques like mathematical programming are used, they normally determine priority lists which are executed by the RTD. Applied Materials offers an optimization based scheduling system SmartSched [4] and a simulation environment AutoSched AP [5], which are both integrated into the RTD.

Dispatching heuristics are a part of Computer Integrated Manufacturing, today often called Industrie 3.0. The systems are not adaptive, learning or flexible, but they can serve as the foundation for more advanced solutions in Industrie 4.0.

4. HYPER-HEURISTICS AND MACHINE LEARNING

Modeling dispatching rules for certain tools or processes can be tedious and time consuming. Hyper-heuristics have emerged as a way to automate the design of heuristics. Hyper-heuristics are defined as "an automated methodology for selecting or generating heuristics to solve hard computational search problems" [13]. The process of automated generation of heuristics is frequently performed with current machine learning techniques. Here, hyper-heuristics and pure machine learning for semiconductor scheduling are merging into each other. Theoretically hyper-heuristics are starting from a set of given heuristics which are recombined, while machine learning is about the discovery of new rules without existing knowledge. Still, in practice these notions are often not separable.

For simple hyper-heuristics, the weighted sum is often used to calculate a priority I_{lot} as a superposition of several dispatching rules:

$$I_{lot} = \sum_{i=1}^{F} w_i \cdot f_{i,lot}$$

where $f_{i,lot}$ is one of the F features of the job and w_i is the corresponding weight. Hyper-heuristics can be divided into systems that select one specific rule ($w_i \in \{0, 1\}$) or generate a new heuristic [13]. Still, a weighted sum is often too restrictive and more advanced combinations are used. These include arithmetic, logic and standard mathematical operators (max, min, avg,...) to combine existing heuristics [10].

Hyper-heuristics which have been trained on static, deterministic instances can be applied to a stochastic environment. Although it has been shown, that hyper-heuristics trained on dynamic, stochastic problems perform better in an stochastic environment [37, 80]. Still, the definition of stochastic benchmarking problems is harder than for static problem sets.

In general, learning of hyper-heuristics can be supervised or unsupervised. Supervised learning strategies suffer from the limitation that an optimal solution has to be obtained first, which is not always possible. Still, supervised machine learning techniques such as neural networks [22, 21, 109, 10] or logistic regression [43] have been used successfully as learning algorithms. Olafsson and Li have used decision trees with an genetic algorithm by Wu [111] to derive new single machine dispatching rules from optimal scheduling data [84].

Mönch et al. [78] use a neural network to adjust the κ-value in the ATC dispatching rule for parallel batch machines. The ATC dispatching supported by the neural network performs only 1-2% under "schedules that are calculated by using a near-to-optimal look-ahead parameter k" [78] but, "the computational effort is much smaller by following the machine learning approach" [78].

Like all learning algorithms, feature selection is a hot topic for hyper heuristics [11]. From an extensive literature study, Branke et al. conclude that "it appears that it is best to provide hyper-heuristics with attributes in their most basic form and let the hyper-heuristics search for good combinations" [11]. Only the eligible jobs are taken into consideration - normally only the waiting jobs before a machine (e.g. [89, 102]), but sometimes future job arrivals are also included (e.g. [58, 6]).

The concepts of decentralization, autonomy and self-organization, which are closely associated with Industrie 4.0, are also part of the hyper-heuristics research. Machine learning techniques make hard-coded heuristics flexible and adaptive to changes in the production and enable faster learning and improvement cycles. The automated generation and discovery of heuristics, previously a task of a skilled engineer, is an example for "automation of knowledge work" [69], which in Industrie 4.0 is the next step of automation beyond robotics.

Big data solutions are quickly gaining importance in semiconductor manufacturing. The applications are usually connected to data lakes, which collect data from various sources. This is especially relevant for machine learning applications. With an increased availability of training data, the performance of machine learning methods is expected to increase in industry applications.

5. MATHEMATICAL PROGRAMMING

Research on mathematical programming dates back to the 1950s, but only in the last 10 years increases in computational power made the algorithms interesting for industry applications. Problems are formulated using Linear Programming (LP), Mixed Integer Programming (MIP), Constrained Programming (CP) or Dynamic Programming (DP). Normally commercial optimization software such as Gurobi Optimizer [33], IBM ILOG CPLEX [44] and FICO Xpress [24], which have all demonstrated an impressive increase in performance in recent years [70, 57], are then used to determine the optimal solution.

Still, the NP-hardness of the problem [29], which leads to exponential scaling of computational runtimes with problem size, limits the approaches to smaller problem sizes. In literature and in industry (to the best of the authors' knowledge) there doesn't exist a semiconductor wafer production which is only controlled by mathematical optimization. A common approach in industry is to use mathematical programming only for bottlenecks (single machines or work centers) and heuristic dispatching for all other operations [36, 31, 34]. The optimal schedule is then integrated by determining priorities based on the schedule and executes the schedule according to the priorities at the bottleneck work center. Another approach is to couple deterministic methods, here MIP, with Discrete Event Simulation (DES) with a rolling horizon [54]. The DES employs heuristics and simulation based optimization to speed up the MIP with boundaries for optimization parameters and a good initial solution.

Another approach are decomposition methods, where a problem is decomposed into a number of smaller sub-problems. These solutions are then assembled to represent a solution to the initial problem [54, 85]. For example, lots are distributed into groups and the optimal sequence is determined for each group separately. Decomposition is normally motivated by physical attributes of the jobs [54, 85]:

- Temporal decomposition
- Work center-based decomposition
- Job-based decomposition
- Operation-based decomposition

Problem formulations tend to be quite complex and time consuming. Results may be counter-intuitive for operators, which requires a certain level of trust [11].

Optimization to increase productivity is a hot topic in Industrie 4.0, but it hardly refers to mathematical optimization. A possible explanation would be, that most industries are only starting to digitize their production and mathematical optimization will be the next step. Still, most processes can not to be described in a mathematical way. "Soft" approaches like Continuous Improvement Processes (CIP) are more common in production than rigorous mathematical optimization. As formulations and implementations of mathematical optimization are complicated, they require very stable processes which do not change over years. Mathematical optimization has proven to deliver some remarkable improvements in the semiconductor industry [55, 54], but only plays a minor role in Industrie 4.0.

6. FURTHER PROMISING APPROACHES

The job shop scheduling problems has attracted many researchers from different fields. In this section three specific approaches are presented: Shifting Bottleneck Heuristics (SBH), Genetic Algorithms (GA) and Multi-Agent Systems (MAS).

6.1 Shifting Bottleneck Heuristic

The Shifting Bottleneck Heuristic is an iterative heuristic that tries to minimize the influence of bottlenecks on the production. Shifting bottleneck heuristics with disjunctive graphs can be used to relieve critical scheduling problems (e.g. single tools groups) within the factory wide scheduling problem [67]. The identified sub-problems can be optimized with different approaches. A shifting bottleneck heuristic combined with a genetic algorithm has been assessed with a rolling horizon setting in a DES, which outperforms common dispatching rules [75]. Sub-problems can be rescheduled with an event-driven approach to handle dynamic events [86].

Mason et al. present a Modified Shifting Bottleneck Heuristic (MSBH), "that accommodates the various types of machine-tool group sub-problems that arise within a wafer fab (CJS)" [67]. Mönch and Driessel [72] implemented a two-layer hierarchical approach, the Distributed Shifting Bottleneck Heuristics (DSBH) based on MSBH. On an aggregated model due dates are determined and then used to optimize the base layer with a shifting bottleneck heuristic. DSBH shows a "similar solution quality" [72] as MSBH.

Shifting bottleneck heuristics can outperform MIP solvers with limited time (best solution found after a certain time span, sometimes called MIP heuristic) for larger problem instances [66]. Shifting bottleneck heuristics are an interesting approach for decomposition and iterative improvements of large-scale complex job shop problems.

6.2 Genetic Algorithms

Genetic algorithms are a class of meta-heuristic optimization algorithms which are inspired by biological evolution [80, 32]. The iterative process starts with one (or several candidate) solution(s), whose properties are encoded into chromosomes. New candidate solutions are created out the initial candidate(s) by recombination and/or mutations of the chromosomes. A fitness function then evaluates the performance of the new candidates and selects the fittest.

Wang and Uzsoy [108] combine dynamic programming with a genetic algorithm for batch processing machines with "excellent average performance with reasonable computational burden" [108]. Cavalieri et al. [15] presented a genetic algorithm which solves job shop scheduling problems in a semiconductor production of STMicroelectronics N.V., which outperforms the FIFO approach used in the plant.

Genetic algorithms may also be combined with hyper-heuristics [89] (see Section 4). They show very good results at single machines and cluster tools (e.g. in [20]). Since genetic algorithms have low computational time, they are an interesting field for factory-wide scheduling solutions.

6.3 Intelligent Multi-Agent Systems

A multi-agent system is a software system which consists of multiple interacting autonomous entities (agents), which are able to perceive their surrounding and perform certain actions [93, 98].

Krishnaswamy and Nettles [56] suggest that multi-agent systems may be a promising approach for full wafer fab scheduling [73]. The feasibility has been demonstrated with a hierarchical prototype called FABMAS with ten different types of agents [76, 77]. An implementation by Yoon and Shen [112] controls the Intel Mini Fab model [52], but the logic is encapsulated in scheduling agents.

Closely related to the Multi-Agent System Approach is Ant Colony Optimization (ACO), metaheuristic optimization based on swarm intelligence. Several successful implementations exist for unrelated parallel machines [62], parallel batch processing machines [61, 47] and decomposition-based wafer fabrication systems [61].

Mutli-agent systems are decentralized and involve autonomous decisions. They are a perfect showcase of Industrie 4.0 as reconfiguration on the fly and self-organization are fundamentally build into the systems [50]. Industrial companies tend to be careful concerning the systems, as they require a radical change of paradigms.

7. CHALLENGES AND FUTURE DIRECTIONS

This section will discuss challenges identified in the literature review and derived from industry experience at Infineon Technologies AG and Elmos Semiconductor AG. The challenges are grouped under four headings: Decentralization and autonomous decisions, flexibility and adaptability, integration and networking and human aspects in an environment with rising complexity. The four topics are inspired by the vision of Industrie 4.0 and serve as directions for further research.

The research project "IWePro - Intelligente selbstorganisierende Werkstattproduktion" (engl.: Intelligent self-organizing job shop production) by Fraunhofer IPK (Institute for Production Systems and Design Technology) and an industry consortium designs a self-organizing, decentralized job shop production for automotive transmission [59, 39]. Although the project focuses on job shops for the automotive sector with different characteristics than in the semiconductor industry, the research directions of this Industrie 4.0 project align well with the first three research directions identified in this paper.

7.1 Decentralization and Autonomous Decisions

In order to deal with the rising complexity in semiconductor production and supply chains [1], decisions should - if possible - be taken on a local level. Still, many local decisions might not lead to a global optimum. Modern semiconductor production facilities produce an amount of data which can not be centrally analyzed in real time. Therefore, suitable data black boxes need to be defined, which are able to take some decisions on there own and only provide a limited number of information to the outside. As computational complexity is an issue (especially for mathematical programming, see Section 5), this approach ensures real time capabilities of IT systems. Future research needs to show that decisions in data black boxes lead to a global optimum. This topic can be addressed by two specific aspects:

- Feature selection/ Attribute selection/ Eligible jobs: The performance, but also the computational time, of dispatching and scheduling approaches depend on the selection of information available to them. Especially the next incoming jobs and the equipments in the next processing steps can influence the decision in one queue. Machine learning systems may be able to choose relevant parameters themselves. This is also a relevant topic if more data sources become available (see Section 7.3).

- Decomposition of scheduling problems: As already discussed in Section 5, the success of fab-wide mathematical optimization will depend on the ability to decompose a large problem into sub-problems and still achieve a global optimal solution.

Industrie 4.0 promotes a dehierarchization to enable "complexity management in times of Industrie 4.0" [96]. Still, the semiconductor industry rather tends towards hierarchical structures [71].

7.2 Flexibility and Adaptability

Increasing uncertainty and volatility in markets, like the dot-com bubble or the financial crisis of 2007-08, force companies to react faster to changing demand. Flexibility is the property of having the potential to change in an appropriate way. An adaptive system is able to readjust to changes autonomously, meaning it has a certain level of self-organization. Modern manufacturing systems need to show these properties. There are several steps which lead in this direction:

- Rescheduling strategies [68, 73]: Schedules in semiconductor fabrication plants are normally rescheduled after a defined time period. Rescheduling strategies evaluate which events require a rescheduling and which events do not influence the current schedule. Govind et al [31] determine that the majority of events which require rescheduling in a lithography work center is under five minutes. A rescheduling strategy could increase flexibility in presence of stochastic disturbances.

- Process Qualification Management (PQM). A dedication matrix contains the information which tools are qualified to run certain processes. The dedication matrix limits the number of possible schedules. Active PQM allows for the needed flexibility in case of machine breakdowns. On the other hand, it ensures high Overall Equipment Effectiveness (OEE, SEMI E10 Standard): First results look promising [27, 92].

- Influence of hot/rocket lots: Hot/rocket lots are produced considerably faster by reducing all waiting times. Companies use hot/rocket lots for faster development cycles and urgent customer orders. In our experience, already a small number of hot/rocket lots can significantly influence production performance. Modern control systems for complex job shop scheduling need to integrate different speed corridors without compromising capacity.

- Adaptability to different product portfolios: Most dispatching systems in industry can not adapt automatically to changing production portfolios. Creation of dispatching rules is often made by experts, but without a proper review of "before" and "after" metrics [25]. It is time-consuming and complex to capturing tool and process characteristics and customize dispatching or scheduling to specific case. Self-organizing systems do no manual interference to react to changes in the product portfolio or new machines.

- Robustness towards missing data: Automated decision systems rely on a high availability of data. In practice, data might sometimes be available with delay, corrupted or even missing completely. Modern control systems have to detect corrupted data and be able to deal with missing data, for example by statistical interpolation. Fuzzy logic may also be a suitable approach [8, 87].

7.3 Integration and Networking

Horizontal and vertical Integration of IT systems are key elements of Industrie 4.0 [94, 9]. The quality of dispatching and scheduling decisions will profit from additional data sources, but realtime abilities may be affected by the additional computational complexity. We see a high potential for the following data sources:

- Integration of supply chain data into scheduling and dispatching decisions: Changes in demand or production promises concerning due dates have to be considered in the production automatically. A first approach for a simulation of multiple coupled wafer productions can be found in Gan et al. [28]. For an extended review of challenges and future research see Chien et al. [17].

- Integration of automated material handling system (AMHS) data into dispatching systems [107]. AMHS are quickly gaining significance due to increased head-count cost, higher reliability of automated systems compared to human operators and a growing lot weight due to an increase in wafer size [107]. Dispatching and scheduling systems need to take the rising importance of AMHS into account and integrate its properties. The behavior of AMHS can be better predicted and surveyed than the behavior of human operators which leads to less uncertainty and fluctuations.

- Integration of Cluster Tools into fab-wide scheduling: Cluster tools in semiconductor manufacturing often have very sophisticated scheduling algorithms (e.g. [103]), but operate like black boxes. First approaches can be found in Niedermayer et al. [81] and for performance metrics in Oechsner et al. [83].

- Integration of Statistical/Advanced Process Control (SPC/APC): New objectives like expected yield could add a new layer to the scheduling systems. A first integration of APC Data into single-machine scheduling is presented by Cai et al. [14]. A literature review and an outlook on APC and scheduling is presented by Yugma et al. [113].

7.4 Human Aspects in an Environment of Rising Complexity

Human operators take an important role in Industrie 4.0, although their tasks change from repetitive actions to creative elements which require a good knowledge of production [101]. Assistance systems are necessary to help operators and white-collar workers to deal with higher complexity and uncertainty. This requires a high level of trust into the systems. New forms of Human-Computer Interactions (HCI) - like spoken dialogues - might enable workers and experts to better understand automated decisions. Next to human-computer interactions, human-2-human communication is also challenging in complex environments:

- Trust and interpretability [11]: In wafer fabrication plants with a high manual effort for operators dispatching compliance is a major issue. Experts in local areas might perceive decisions of the global systems as sub-optimal and reject the solutions of the automated decision making system. Kuyumcu presents an algorithm to calculate and analyze dispatch compliance [60]. The influence of comprehensiveness on dispatching compliance of operators and line experts is still an open topic.

- Transfer from science to industry [73]: Wafer fabrication facilities require a stable and reliable operation. The willingness to try out new measures is often low. The simulated systems in science often do not capture the complexity of semiconductor fabrication facilities. A closer cooperation and knowledge transfer might solve this issue.

8. CONCLUSIONS

This paper reviewed existing production control methods for complex job shops from an Industrie 4.0 perspective. While there already exist successful solutions for dispatching heuristics and mathematical programming, new possibilities, e.g. machine learning, and concepts from Industrie 4.0 offer new opportunities and potentials for an increase in operations efficiency. The paper highlights four directions for future research: Decentralization and autonomous decisions, flexibility and adaptability, integration and networking and human aspects in an environment with rising complexity. From a methodological view machine learning and multi-agent systems are promising approaches.

Although there has been little interchange of ideas between job shop scheduling and Industrie 4.0, the main ideas and directions in both fields are the same. Interestingly, we found a discrepancy in the area of mathematical programming: While semiconductor manufacturers have increased productivity by employing mathematical programming in manufacturing control systems, it plays a minor role in Industrie 4.0. Reasons may be the availability of production data and the flexibility considerations.

In practice, hybrid approaches, which combine several of the methods and techniques presented in this paper in one complex job shop, show the best results. Therefore, a standardized, robust and flexible Manufacturing Execution System (MES) for provisioning of data and for execution is needed. Different dispatching and scheduling algorithms can then easily be implemented on this platform. Furthermore, a standardized simulation environment which can load the MES data is needed to benchmark different approaches before implementation in production.

The paper shall foster the exchange with other industries which manufacture in high-volume job shops such as the chemical, pharmaceutical, textile, printing and metal processing industries [49, 100]. Researchers are provided with an abstract definition of a complex job shop, a model that covers all major features of a semiconductor wafer fabrication in terms of production control. Furthermore, industry challenges and further directions are highlighted, which may guide future research. Practitioners find a review of the state of the art of methods in production control for complex job shops.

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