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BACKWARD SIMULATION FOR PRODUCTION PLANNING - RECENT ADVANCES IN A REAL-WORLD USE-CASE

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ABSTRACT

The focus on customer orientation as well as on-time production and delivery portray the competitive environment for manufacturing companies in the semiconductor industry. Customer-specific products must be manufactured due to specified lead times and according to promised delivery dates. In this context, questions as to whether the production target is feasible and if all previously promised delivery dates will be met are often answered with backward-oriented planning approaches without taking into consideration any uncertainty or alternatives, that arise during operations. Regarding complex manufacturing systems (here semiconductor with re-entry cycles), these questions can be answered in a more detailed and robust by a discrete event-based simulation (DES) approach used in a backward-oriented manner. Research results show that the taken approach can be applied successfully for the scheduling of customer-specific orders in a real-world setting.

1 INTRODUCTION

The intensification of global business and an advancing digital transformation, together with more customer-oriented and on-time production and delivery, are defining competitive factors for manufacturing companies. The constant development of the vision of Industry 4.0 - in the future also Industry 5.0 (Breque et al. 2021) - and the concept of a "smart factory" for customisable products in small batch sizes continuously pose new challenges for work preparation as well as operative production planning in connection with high cost, time and quality pressure. However, modern, complex and highly automated production systems must be operated in an "optimal operating state" as far as possible in order to be economically successful. Promised delivery dates and throughput times defined in framework agreements must be ensured and require a permanent (effective) adjustment of production planning and control in daily execution. All other general conditions of economic production remain unchanged and continue to apply.

Compared to other industries, the production systems and processes of semiconductor manufacturing addressed in this article have an exceptionally high level of complexity. The production technologies used in the micro- and nanometre range are very sensitive with regard to process stability, resulting in complex control logics. Depending on various characteristics defined in advance, individual production batches also require a very large number of production steps (sometimes more than a thousand). In some cases, individual production batches within the ordered product mix must be processed several times with a high level of automation and under cleanroom conditions using special and sometimes the same machines and transport routes (re-entry cycles). The complexity often results in rejects of manufactured products of a relevant magnitude, which must be compensated for at short notice by additional infeeds. In most cases, questions in the context of detailed production planning can only be answered inadequately or not at all by

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means of existing tools for generating flow charts and, consequently, conventional planning procedures. Incalculable repercussions of such inadequate sequence planning have a considerable influence on the overall performance and, in view of the increasing competitive situation and the company's own position on the market, hold immense optimisation potential for manufacturing companies in the field of semiconductor production as well as in general.

Within the EU-ECSEL research project iDEV40 (presentation of the overall project at www.idev40.eu), application scenarios of backward-oriented material flow simulation in semiconductor manufacturing are being developed. Although the basic feasibility of this method at the factory level was proven in relevant preliminary work (Arakawa et al. 2002; Graupner et al. 2004), it had to be adapted to the specifics of the semiconductor industry and re-tested in the project. As a significant extension to the authors' own previous work (e.g. Scholl et al. 2014) and a first publication from the research project with a test model (Laroque et al. 2020), this article describes more recent results based on a "real-world use-case" and thus shows the potential and limitations of the method more specifically than before.

After a brief presentation of the scientific state of the art and an explanation of the principle solution approach, project results will be described and presented in detail. Finally, a summary describes the next steps in the project.

2 BACKWARD SIMULATION

In line with ensuring competitiveness, production planning and control (PPC) today focuses on a number of key measures. These include, in addition to shortening lead times, meeting quality requirements while keeping inventories as low as possible and meeting promised delivery dates, equally increasing throughput as well as the current availability and added value of individual production facilities (Overall Equipment Effectiveness). The target variables described here and the resulting planning tasks are decisively influenced by production planning and scheduling mechanisms, making overarching optimization approaches necessary to bring about a noticeable improvement (Jain and Chan 1997).

Besides conventional methods of mixed-integer optimization, different heuristics or simple forward or backward scheduling (with or without capacity constraints), this paper deals with a discrete event-driven simulation (DES) approach in terms of backward simulation. Models for DES can represent an exact replica of a real system according to its operation over time, are easy to parameterise and take into account the variability of reality by allowing random effects to be incorporated into the models via stochastic components (Banks 1998; Law and Kelton 2000). In addition, DES can represent equally nested resource relationships, maintenance procedures and specific flow, priority, batch or set-up rules. Based on this and the input of a concrete production target into such a simulation model, DES can be used to answer questions regarding the feasibility of the production target and compliance with previously agreed delivery dates (in the best possible way). Such an application is particularly suitable for planning in the field of semiconductor production.

The approach for the analysis of temporally backward planning problems (in the following: backward simulation) concretises a reversal of the flow logic of a simulation and the resulting backward execution of the same. According to this, the advantages of simulation also come to bear in the application of backward-oriented planning (Huang and Wang 2009; Schumacher and Wenzel 2000). According to Jain and Chan (1997), backward simulation can be regarded as an efficient tool for implementing backward scheduling. Following this, sequencing and scheduling based on backward simulation combines the solution quality of conventional scheduling approaches and the execution speed of simulation-based scheduling approaches. Initial application studies in which jobs are scheduled backwards using backward simulation have been available for more than fifteen years. Watson et al. (1993 and 1997), Ying and Clark (1994) and Jain and Chan (1997) use such methods to calculate the release times of orders or lots even under stochastic characteristics of the models.

Modelling a backward execution of a flow simulation requires some careful considerations beforehand in order to be able to make a correct reversal in the context of the material flow to be modelled and to break away from the mindset of a forward modelling. These considerations relate in particular to a reversal of individual production processes - for example, an assembly into a disassembly - and intended control rules (Jain and Chan 1997). However, the latter control rules cannot always be transferred one-to-one to the corresponding backward counterpart. Analogous to backward scheduling in PPS systems, backward simulation is also carried out in combination with forward simulation runs in order to once again validate the resulting plans. According to Graupner et al. (2004), such a combined execution can unite the advantages of both simulations and compensate for possible modelling discrepancies of the backward simulation.

Basically, modelling a backward-oriented execution of a flow simulation always entails a reversal of the source-sink relationship. In concrete terms, this means that orders or batches are fed into the system at the points where they leave it in the forward-oriented execution. Conversely, they leave the backward counterpart at the insertion points of the forward-oriented process simulation ("from product to raw material"). Nevertheless, the backward simulation is not to be understood as a pure "inverse function" of the forward simulation. Forward and backward simulation do not have to have the same state at the same calculated simulation time (Ying and Clark 1994).

In the domain of semiconductor manufacturing, the authors have successfully realised and published initial examples in recent years (Scholl et al. 2014; Laroque et al. 2020). Following on from this, the model considered in this paper will now also take into account special properties of semiconductor manufacturing (see above).

3 RESULTS

The modelling of a pre-assembly process from the area of semiconductor manufacturing (Fig. 1) represents the starting point for the investigations described below in the course of backward modelling and simulation. The model is provided by an industry partner for testing the methodological approach to backward simulation and can be considered "valid" (face validity) according to Sargent (2010).

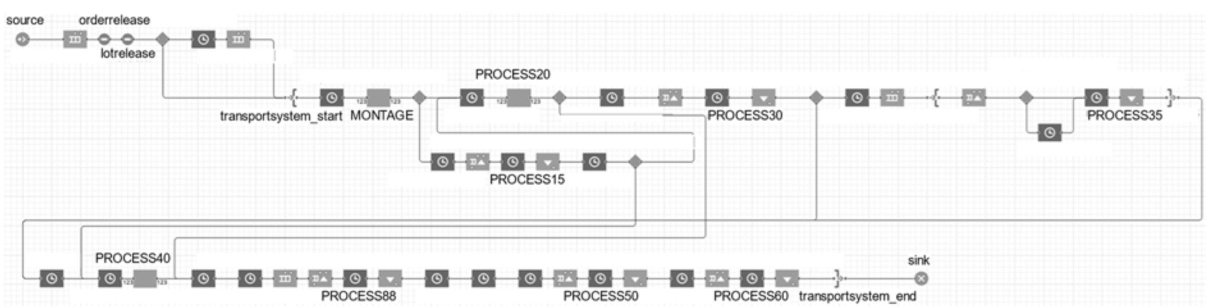

Figure 1: Overview of the model structure of the real model example

In the selected process section, various machine systems of different complexity are used, which were essentially mapped within the main model MAIN. Complex sub-processes in the form of the machine systems MONTAGE, PROCESS20 and PROCESS40 were mapped in sub-models of the same name and embedded in the main model accordingly. The embedded sub-models follow a developed set of rules that is supposed to emulate a so-called same-setup rule and in this way coordinate and process the incoming batches within the simulation. Following this, the sub-model MONTAGE, for example, comprises a total of four parallel process chains that map the available sub-machines for this process step. Depending on a certain batch-related parameter, the incoming batches are then transmitted to a suitable (free) machine. If all the machines that are suitable for a specific batch are occupied, a free sub-machine is forced to retool and the batch is transmitted accordingly to the model component concerned. The coordination and processing of incoming batches is also (additionally) carried out in most parts of the model according to the heuristic priority rule procedure First In First Out (FIFO).

The starting point of the forward-looking simulation model (starting point of the analysis) are job data, which are fed into the model in tabular form over a period from December 2019 to April 2020. The jobs are defined by a series of parameters (e.g. *processgroup*, *basictype* or *producttype*) in order to ensure that the incoming batches can be assigned throughout the entire simulation run. Accordingly, special routes result depending on the product type (parameter *producttype*) of an job. In the course of this, various condition-based divisions of the selected process section into *Product A*, *Product B* and *Product C* as well as *Product D* are possible, for example.

As a result of modelling a discrete-event backward simulation (Fig. 2), the main model MAIN served as the starting point. The embedded sub-models MONTAGE, PROCESS20 and PROCESS40 as well as less complex machine systems (for example PROCESS50 and PROCESS60) are considered and modelled in reverse order. The used same-setup rule could easily be adopted and integrated into the backward modelling. In contrast, the heuristic priority rule procedure First In – First Out (FIFO) is reversed to Last In – First Out (LIFO) following a forward-looking view, but in the course of a way of thinking regarding the backward flow within a backward-looking execution of the simulation model, it is equally adopted as First In – First Out (FIFO). In addition, the resulting discrete-event backward simulation has taken job-specific information from the forward modelling and served as the basis for various extensive simulation experiments in order to be able to best emulate the model behaviour and to exclude temporal discrepancies in the simulation as far as possible. Some of the resulting results will be presented in the following.

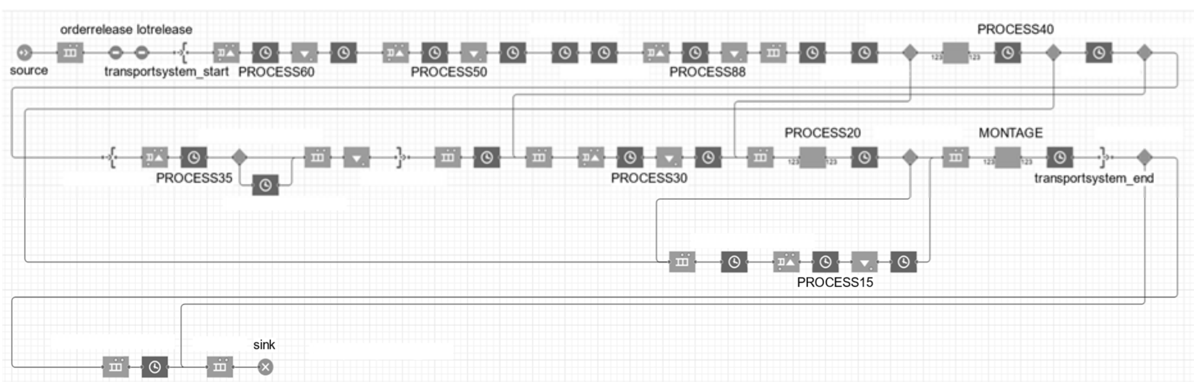

Figure 2: Model structure of the discrete-event backward simulation

The starting point for the experimental trials are delivery dates (due dates) generated by a forward simulation run (based on the originally stored job data). As a result of an adjustment, the resulting delivery dates form the input data for the actual backward simulation. The necessity of adjusting the resulting delivery dates is due to the fact that existing simulation tools look at the underlying planning period of a simulation from a forward perspective. A "simple" input of the resulting delivery dates in time-descending order into the backward counterpart of the simulation model therefore remains without a positive result, so that the delivery dates generated from the forward simulation first had to be adapted with regard to a backward execution of the sequence simulation. The adjustment of the resulting delivery dates, which are assumed to be "real" delivery dates in the following, resulted in a delay in the start of the simulation time (December 2019 to April 2020) compared to the scheduling *VWS0*, starting from the last completed job (job no. 2119). For the further adjustment, the delivery date of the last completed job was then added to the difference between its *dueDateVWS0* and a *dueDateVWS0* of an earlier delivery date. The resulting scheduling *RWS1* (Fig. 3) was then entered into the simulation model for a backward-calculated execution. In the context of a renewed adjustment and a scheduling *VWS1* (Fig. 4), an answer can then be given to the question of when concrete production jobs are to be scheduled in order to ensure that promised delivery dates are feasible and fulfilled in terms of time. According to Sargent (2010), this necessary confirmation through the forward simulation *VWS1* simultaneously validates the simulation results (scheduling) from the backward simulation *RWS1* (event validity).

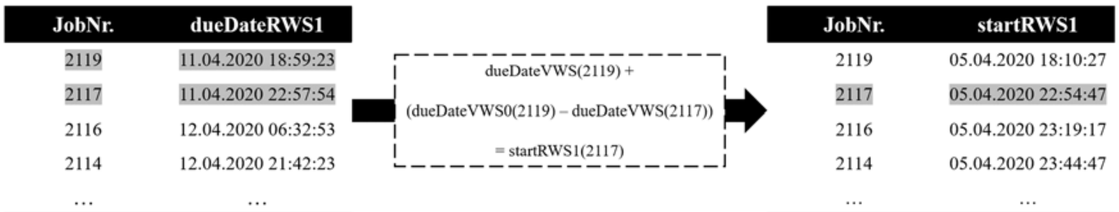

Figure 3: Adjustment in accordance with a scheduling RWS1

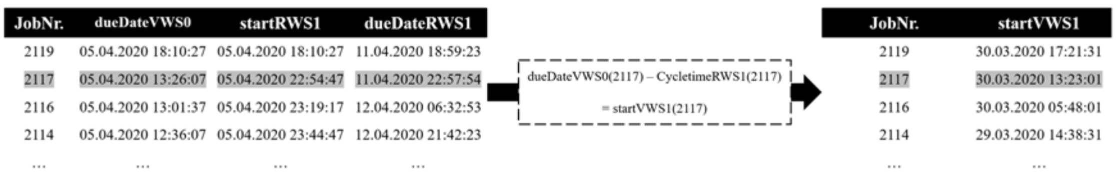

Figure 4: Adjustment in accordance with a scheduling VWS1

For a categorisation and evaluation of delivery dates resulting from the backward simulation and a subsequent forward simulation, the time intervals *much earlier*, *earlier*, *on time*, *later* and *much later* were defined. These time intervals are each dependent on the original due dates. The time interval *much earlier* is used to categorise all jobs that have a delay t > 6h due to the scheduling of the backward simulation. In contrast, the time interval *much later* categorises jobs that show a delay t > 6h. The time intervals *earlier* and *later* indicate, analogously, an early arrival or delay of t ≤ 6h as well as t > 3h, while the time interval *on time* includes all jobs within t ≤ 3h around the "real" delivery date.

In a first step, and with the aim of comparing the solution quality of the scheduling *VWS1* determined from the backward simulation with competing scheduling methods of capacity-constrained backward scheduling, the scheduling from the backward simulation, a backward scheduling *RT1* according to the difference of *dueDatesVWS0* and *avCycletimeVWS0* as well as a backward scheduling *RT2* according to the difference of *dueDatesVWS0* and *avCycletimeVWS0* are compared according to *product type* (Tab.1).

Table 1: Comparison of backward simulation with planning procedures of deterministic backward scheduling

	much earlier	[%]	earlier	[%]	on time	[%]	later	[%]	much later	[%]
VWS1	668	31.49	489	23.06	874	41.21	43	2.03	47	2.22
RT1	1848	87.13	0	0.00	0	0.00	0	0.00	273	12.87
RT2	1987	93.68	38	1.79	42	1.98	7	0.33	47	2.22

The results of the contrasted methodological approaches for generating a scheduling by backward simulation and competing planning procedures of deterministic backward scheduling indicate that the method of backward simulation can make the scheduling in connection with the resulting delivery dates much more reliable. Consequently, 41.21 percent of all jobs are completed *on time* in a time interval t ± 3h according to a scheduling *VWS1*, while the competing scheduling methods of deterministic backward scheduling only achieve a value of 0.00 percent according to a scheduling *RT1* and a value of 1.98 percent according to a scheduling *RT2*. In addition, the results show, more or less, clear advantages on the side of an scheduling by backward simulation with regard to a time interval t > 6h (before and after the assumed "real" delivery date), i.e. that the resulting delivery dates scatter much more precisely around the fixed (or assumed) delivery dates.

In the following, the solution quality of the scheduling *VWS1* determined from the backward simulation is compared to a scheduling with stochastic backward simulation *mSTO* (Tab. 2) after several test runs *STO1* to *STO10* (*mSTO* is the mean value of the determined scheduling dates). The resulting values tend to show more delays for the test runs with the mean *mSTO* compared to the deterministic backward simulation.

Table 2: Results of stochastic backward simulation on average

	much earlier	[%]	earlier	[%]	on time	[%]	later	[%]	much later	[%]
VWS1	668	31.49	489	23.06	874	41.21	43	2.03	47	2.22
mSTO	759	27.31	467	22.01	842	39.70	127	5.98	106	5.00

In general, it must be noted that the categorisation of the resulting delivery dates and the associated definition of the time intervals described here is not (always) optimal compared to the assumed original delivery date. Accordingly, the resulting delivery dates of the jobs, both in relation to a backward simulation and according to competing planning procedures of capacity-constrained backward scheduling, sometimes arrange themselves only slightly later or earlier in the nearest time interval.

A subsequent investigation determines, on the basis of the scheduling of stochastic backward simulation after several test runs, an additional scheduling according to a certain relative size of an order (Tab. 3). Within the framework of the resulting scheduling and the simulation runs *KK3* to *KK9*, the third earliest (*KK3*) to second latest (*KK9*) scheduling dates from the stochastic backward simulation *STO1* to *STO10* are taken over.

Table 3: Results of stochastic backward simulation after several test runs according to a certain relative size of a job

	much earlier	[%]	earlier	[%]	on time	[%]	later	[%]	much later	[%]
VWS1	668	31.49	489	23.06	874	41.21	43	2.03	47	2.22
KK3	1545	72.84	233	10.99	192	9.05	46	2.17	105	4.95
KK4	1508	71.10	284	13.39	205	9.67	41	1.93	83	3.91
KK5	1448	68.27	310	14.62	246	11.60	46	2.17	71	3.35
KK6	1406	66.29	300	14.14	283	13.34	40	1.89	92	4.34
KK7	1260	59.41	389	18.34	359	16.93	33	1.56	80	3.77
KK8	1250	58.93	398	18.76	381	17.96	25	1.18	67	3.16
KK9	1194	56.29	365	17.21	427	20.13	50	2.36	85	4.01

The results of a stochastic backward simulation according to a certain relative size of a job and, following this, the simulation runs *KK3* to *KK9* show that the number of *on time* completed jobs amounts to a share between about 9.1 percent and 20.1 percent. With regard to a time window of t ± 6h compared to the assumed "real" delivery date, on the other hand, between 22.3 percent and 39.7 percent of the jobs are completed. The 39.7 percent refer to the simulation run with the second latest delivery date of each job, while the 22.3 percent refer to the simulation run with the third earliest delivery date. This fundamentally illustrates once again the previously highlighted advantages of the methodical approach of backward simulation, in that the determined delivery dates still scatter precisely around the assumed "real" delivery dates than with the two planning procedures of deterministic backward scheduling used. Furthermore, on the basis of simulation runs *KK3* to *KK9*, it can be stated that later scheduling (for each job individually) results in more reliable delivery dates overall compared to the assumed "real" delivery dates. In the following, this paper will now concentrate on a comparison of the onboarding scheduling *VWS1* determined from the backward simulation and the onboarding scheduling *RT2* resulting from the backward scheduling.

In a direct comparison, 98.4 percent of the jobs are inserted earlier into the test model following an scheduling *RT2* compared to an scheduling *VWS1* determined from the backward simulation. Such an earlier scheduling, which is shown in Figure 5 as an example over a period of two weeks, takes place in an average time window of 28.7 hours. The remaining 1.6 percent, on the other hand, can be assigned to a later insertion date and a subsequent later scheduling within a time window of 10.3 hours on average.

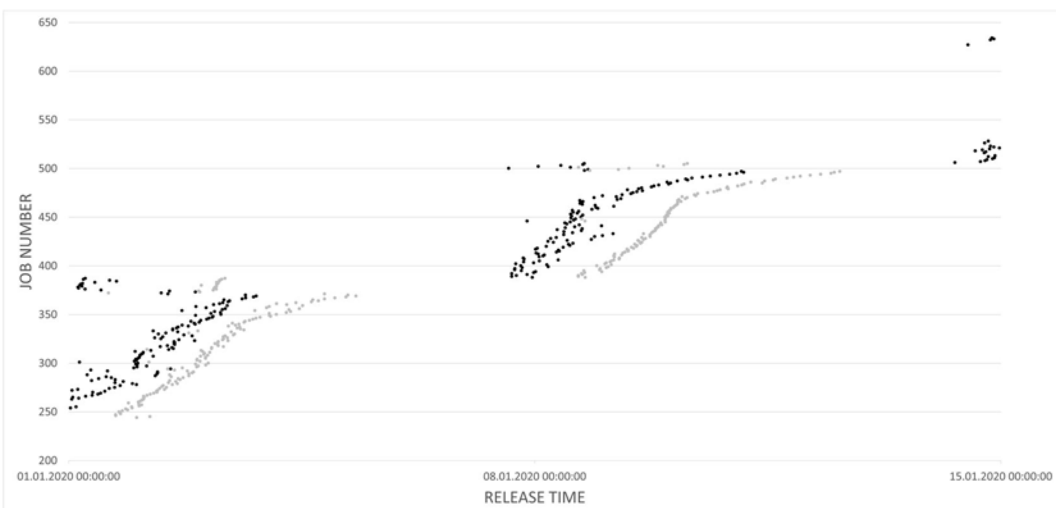

Figure 5: Comparison of a scheduling VWS1 (grey) and a scheduling RT_2 (black)

As a result, these results once again show clear advantages with regard to a scheduling *VWS1* following the backward simulation. Accordingly, jobs can be scheduled significantly *later* on average within a scheduling *VWS1* and yet 97.8 percent of all jobs on which this study was based meet the assumed "real" delivery date. Within a scheduling *RT2* and a time interval *much earlier* up to and including *later*, the number of jobs that meet the assumed "real" delivery date is also 97.8 percent, but most of them have to be scheduled twice as early on average as within a scheduling *VWS1* - in direct comparison to a scheduling *VWS0*. Whereas according to *VWS1*, an earlier scheduling compared to an scheduling VWS0 takes place in a time window of 8 hours on average and a *later* scheduling in a time window of 32.5 hours on average, according to *RT2*, an earlier scheduling in this respect takes place in a time window of 16 hours on average and a later scheduling even in a time window of 21.5 hours on average. In addition, 93.7 percent of the jobs can be assigned to a time interval *much earlier*, i.e. the jobs are completed according to an early start t > 6 hours and lead in this context to an increase in stock. The methodical approach to generate a scheduling by backward simulation can contribute noticeably to a reduction of the warehouse stock or to a maintenance of low stocks.

A subsequent comparison of the onboarding scheduling VWS1 determined from the backward simulation with onboarding scheduling according to stochastic backward simulation mSTO in the sense of several test runs (STO1 to STO10), which is shown once again in Figure 6 as an example over a period of two weeks, illustrates that the methodical approach for generating onboarding scheduling by backward simulation can also deliver promising results when stochastic influences are taken into account. Accordingly, as a result of an scheduling according to stochastic backward simulation mSTO compared to an scheduling VWS1, 87.1 percent of the jobs are still inserted into the test model earlier, but such an earlier scheduling takes place in an average time window of 4.7 hours. The remaining 12.9 percent can then be assigned to a later scheduling date and subsequently to a later scheduling in a time window of 2.8 hours on average. Compared to RT_2, this still indicates a clear lead.

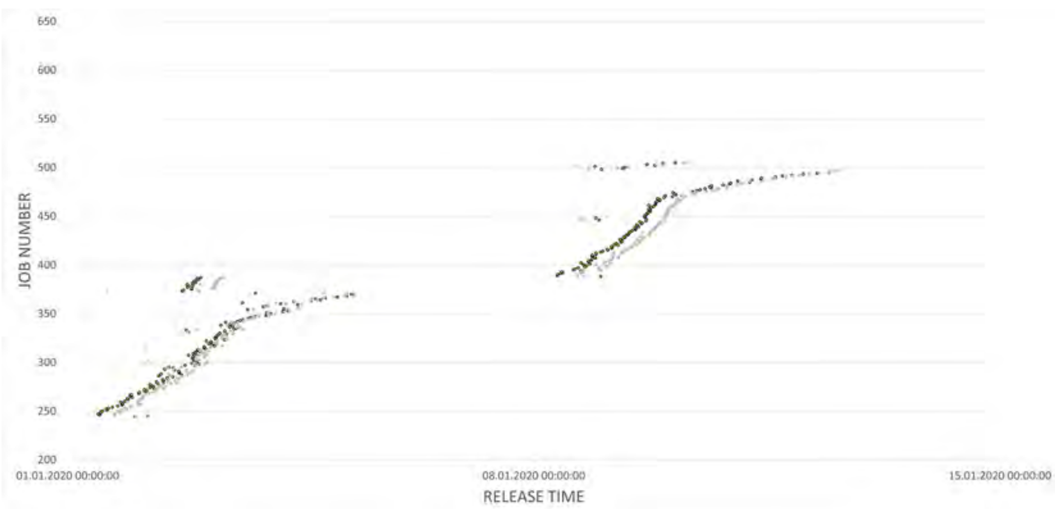

Figure 6: Comparison of a scheduling VWS1 (grey) and a scheduling mSTO (black)

The results within this paper underline the statements formulated in the state of the art in that the advantages of simulation also come to bear in the application of backward-oriented planning. Furthermore, the determined scheduling indicates the potential of such a methodical approach for answering questions in the context of detailed production planning to the specifics of semiconductor manufacturing (as well as taking into account stochastic influences).

4 CONCLUSIONS AND FUTURE WORK

The results generated on the basis of a "real-world use-case" show that the methodical approach for generating a scheduling by backward simulation works under the specifics of semiconductor manufacturing and under consideration of stochastic influences and can deliver promising results. Using several models, it has now been demonstrated that backward simulation can serve as a powerful tool for onboarding scheduling that takes stochastic influences into account. A next step in the project is to integrate and test the methodical approach into the operational simulation tool at the industrial partner (AutoSched AP).

In the future, it would be possible to further develop the procedure used here with various heuristics into a simulation-based optimisation (backward-looking). Following on from this, the applicability of the procedure itself as well as such simulation-based optimisation combinations should be tested in other domains.

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REFERENCES

Arakawa, M., M. Fuyuki, and I. Inoue. 2002. *A Simulation-based Production Scheduling Method for Minimizing the Due-date-deviation*. International Transactions in Operational Research 9 (2): 153-167.

Banks, J. 1998. *Handbook of simulation: Principles, methodology, advances, applications, and practice*. New York: Wiley.

Breque, M., L. De Nul, and A. Petridis. 2021. *Industry 5.0 – Towards a sustainable, human-centric and resilient European Industry*. Luxembourg: Publications Office of the European Union.

Graupner, T. D., M. Bornhäuser, and W. Sihn. 2004. *Backward simulation in food industry for facility planning and daily scheduling*. In: *Proceedings of the 16th European Simulation Symposium (ESS)*, 17th-20th October, Budapest (Hungary).

Huang, C., and H. Wang. 2009. *Backward Simulation with Multiple Objectives Control*. In: *Proceedings of the International MultiConference of Engineers and Computer Scientists (IMECS) Vol. II*, 18th -20th March.

Jain, S., and S. Chan. 1997. *Experiences with Backward Simulation Based Approach for Lot Release Planning*. In: *Proceedings of the 29th Winter Simulation Conference (WSC)*, 7th – 10th December, Atlanta (USA), 773-780.

Laroque, C., C. Löffler, W. Scholl, and G. Schneider. 2020. *Einsatzmöglichkeiten der Rückwärtssimulation zur Produktionsplanung in der Halbleiterfertigung*. In: *Proceedings ASIM SST*. Wien: RGESIM Report AR 59: 397-401.

Law, A., and D. Kelton. 2000. *Simulation Modeling and Analysis*. 2nd Edition. New York: McGraw Hill.

Sargent, R. 2010. *Verification and Validation of simulation models*. In: *Proceedings of the 2010 Winter Simulation Conference (WSC)*, 5th -8th December 2010, Baltimore (USA), 166-183.

Scholl, W., C. Laroque, and G. Weigert. 2014. *Evaluations on Scheduling in Semiconductor Manufacturing by Backward Simulation*. In: *Proceedings of the 2014 Winter Simulation Conference (WSC)*, 7th -10th December, Savannah (USA), 2552-2560.

Schumacher, R., and S. Wenzel. 2000. *Der Modellbildungsprozess in der Simulation*. In: *Referenzmodelle für die Simulation in Produktion und Logistik*. Gent: SCS-Europe BVBA:. 5-11.

Watson, E. F., D. J. Medeiros, and R. P. Sadowski. 1993. *Generating Component Release Plans with Backward Simulation.* In: *Proceedings of the 25th Winter Simulation Conference (WSC)*, 12th-15th December, Los Angeles (USA), 930-938.

Watson, E. F., D. J. Medeiros., and R. P. Sadowski. 1997. *A simulation-based backward planning approach for order-release*. In: *Proceedings of the 29th Winter Simulation Conference (WSC)*, 7th-10th December, Atlanta (USA), 765-772.

Ying, C. C., and G. M. Clark. 1994. *Order release planning in a job shop using a bidirectional simulation algorithm*. In: *Proceedings of the 26th Winter Simulation Conference (WSC)*, 11th-14th December, Orlando (USA), 1008-1012.

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