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REVERSE ENGINEERING THE FUTURE – AN AUTOMATED BACKWARD SIMULATION APPROACH TO ON-TIME PRODUCTION IN THE SEMICONDUCTOR INDUSTRY

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ABSTRACT

Researchers are investigating innovative techniques and tools to improve operational production planning, as manufacturing processes are increasingly influenced by new product demands, innovation, and cost-effectiveness. Backward-oriented discrete event simulation (SimBack) is one such tool that has shown great promise in this area. However, conducting multiple simulation runs for backward simulation can be time and resource-intensive, hampering its efficiency. To address this issue, this paper proposes an automated approach for executing and evaluating simulation experiments within the framework of backward-oriented discrete event simulation for scheduling and capacity planning. The authors illustrate their approach by applying it to a simulation model of the Semiconductor Manufacturing Testbed 2020 (SMT2020).

1 INTRODUCTION

Manufacturers are facing competitive pressures due to global business, the accelerating digital transformation, and the need for timely production and delivery. To achieve an efficient flow of manufacturing processes, production planning and control (PPC) is critical. Manufacturers must continuously monitor and adopt new practices for PPC to maintain an optimal operating state and organize all manufacturing processes efficiently. Uncertainty in PPC and the resulting adjustments can have unforeseen consequences on production system performance, leading to wasted time and resources. To ensure ongoing effective PPC, manufacturing companies must be flexible in their structure to adapt to constantly changing market situations and customer requirements.

The semiconductor industry is characterized by highly complex production systems and processes, surpassing the complexity level of other industries, and is expected to become even more complex in the future (Bureau et al. 2006; Mönch et al. 2011; Mönch et al. 2013). Recent developments have shown an increase in product diversity, smaller batch sizes, and a more rapidly changing product range. Moreover, the growing automation in the industry has resulted in increased interconnections between equipment groups, making PPC more challenging. Several factors such as limited equipment capacities, stochastic processing, setup, waiting and transport times, preventive maintenance, setup changes, dynamic time and/or capacity constraints in queues, or multiple production stages may lead to potential dependencies that need to be considered in the planning process (Lendermann et al. 2020).

During the years, while application studies on backward simulation methods appeared continuously (including Jain et al. 1990; Watson et al. 1993 and 1995; Jain and Chan 1997; Mejtsky 2007; Okubo and Mitsuyuki 2021), promising results are described in Laroque et al. (2021, 2022) according to a methodological approach to backward simulation under the specifics of the semiconductor industry and considering stochastic influences. The application of several simulation models and a series of experiments show that backward simulation in terms of combined execution can be a powerful tool for operational production planning. However, depending on the complexity and dimension of the decision and planning problem under consideration, the combined execution of the simulation model can be very time-consuming and resource-intensive, resulting in a need for research in the context of developing and implementing operational decision support. Furthermore, the underlying data in previous work remains largely unchanged (in the sense of optimization). Accordingly, the potentials of simulation models for targeted data generation and evaluation as well as application of resulting insights have hardly been used so far.

According to Sanchez (2021), such targeted data generation and evaluation can be understood as data farming and is intended to increase the amount of data related to the decision and planning problem under consideration and to improve the derivation of recommendations for action (Feldkamp 2020). Assuming valid modeling, both forward and backward execution of a simulation model require generating and processing huge amounts of data (in an automated way) to make high-quality statements about the mimicked system through a sufficiently careful Design of Experiments (DoE). The extension of a backward simulation in the sense of a combined design by the approach of data farming should significantly increase the informative value of the simulation study to be performed and at the same time address the difficulty of representing the dynamics and stochasticity of production systems and processes (in the semiconductor industry) sufficiently accurately (Lendermann et al. 2020).

In this paper, the Semiconductor Manufacturing Testbed 2020, shortly SMT2020, in form of the low-volume/high-mix simulation model (Kopp et al. 2020a) will be used to present an approach for automated execution and evaluation of extensive simulation experiments in the context of backward simulation. Accordingly, the AutoSched AP model developed and validated by Kopp et al. (2020a) is to be automatically reversed and executed (in both directions) using the open-source development platform KNIME. With this approach, the authors aim to achieve a considerable time saving with respect to the need to run the simulation model twice for each configuration and to reduce the error-proneness compared to a manual transformation. After a brief presentation of the scientific state of the art as well as a detailed explanation of the principal solution approach using the simulation tool AutoSched AP and the open-source development platform KNIME, experimental results of a sensitivity analysis are described in this paper. The summary of the paper describes the authors' future approach to the development and implementation of a machine learning-based decision support for operational production planning in the semiconductor industry.

2 BACKWARD SIMULATION

In addition to existing methods of mixed integer optimization, simulation-based heuristics, and simple forward or backward scheduling, simulation-based optimization is becoming more and more important for manufacturing companies in many industries, see Block et al. (2017) and Lendermann et al. (2020). Gutenschwager et al. (2017) point that, it is regularly shown that the use of simulation in the planning of complex dynamic production and logistics systems leads to secured and more comprehensible planning results. Accordingly, existing methods of mixed integer optimization often use only rather simple models to keep computation time within reasonable limits; however, discrete event simulation (DES) can handle much more complex models.

Models for discrete event simulation describe systems already in existence or in the planning stages, regarding their operation over time. These models can be parameterized well and consider variability of reality by including random events into the models. Discrete event simulation can also be used to consider nested interactions between resources to be modelled, maintenance actions, and characterization rules according to sequences of steps, batch processing, and setup. Discrete event simulation is suitable in general and in connection with an input of a concrete production program to consider feasibility of concrete production program as well as adherence by firms to completion and/or delivery dates promised in advance, see Laroque et al. (2022).

Discrete event simulation models are used individually or in combination with heuristics in the context of simulation-based optimization to study for-ward-time decision and planning problems. One approach of discrete event simulation with respect to time-backward decision and planning problems has been described in the literature as backward simulation, which involves reversing the flow logic of the simulation along with the implemented control and priority rule procedures and running them backward.

According to Jain and Chan (1997) and Laroque (2007), a backward simulation can be used to make well-founded statements about the target values to be achieved in the context of promised delivery dates. Furthermore, backward simulation is an efficient tool for implementing the procedures of (simple) backward scheduling, whereby both the solution quality of a conventional production planning and scheduling mechanism and the execution speed of simulation-based scheduling approaches become effective, see Jain and Chan (1997). For a validation of the resulting solution set in terms of start dates, a forward simulation is to be connected following an inversion of the solution set on the time axis for the generation of a valid injection planning. Such a combination of a forward and backward simulation shall be understood as a combined execution in the sense of the backward simulation (SimBack), see Figure 1. As Leißau and Laroque (2023) show, multiple other applications of backward-oriented approaches have been carried out in the past.

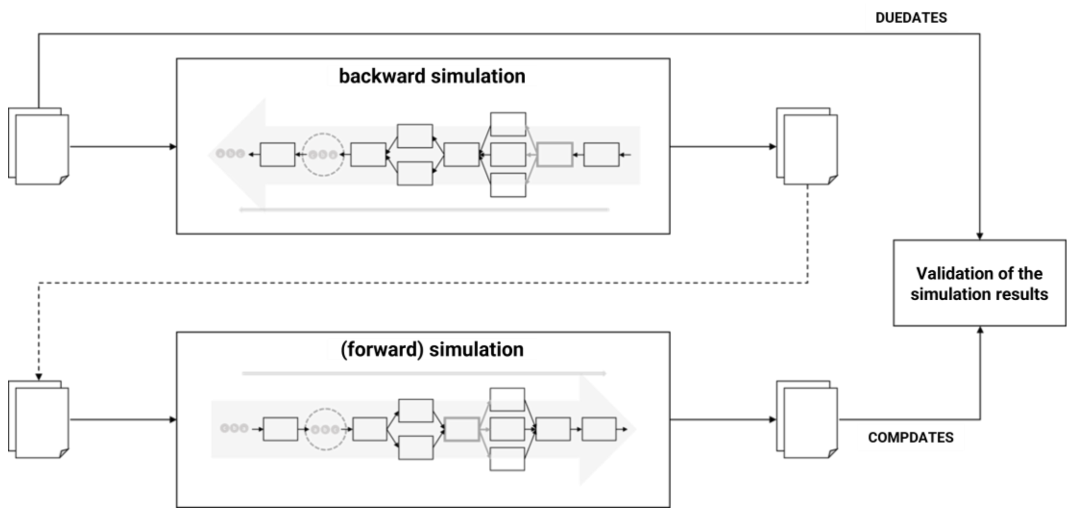

Figure 1: Combined execution (SimBack).

3 IMPLEMENTATION OF THE SOLUTION APPROACH

As mentioned above, backward simulation in the sense of a combined execution of a simulation model can be very time-consuming and resource-intensive, depending on the complexity and dimension of the decision and planning problem to be considered and the related issues. So far, the (forward) time updates in existing simulation tools and the resulting transformation steps concerning the input and result data require a manual adaptation as well as the execution of individual configurations and corresponding forward and backward simulation runs.

In this paper, the authors propose an approach for automated execution and evaluation of extensive simulation experiments using the simulation tool AutoSched AP and the open-source development platform KNIME. Here, KNIME as a development environment offers the possibility to work completely with the drag-and-drop interface and/or a preferred programming language. For the implementation of the solution proposed in this paper, the authors make use of the extensive spectrum of available building blocks (nodes) and supplement the functionalities selectively with Python scripts.

3.1 Model Inversion

The Semiconductor Manufacturing Testbed 2020, shortly SMT2020, according to Kopp et al. (2020a) includes four simulation models, which are supposed to represent the complexity of modern fabs in the semiconductor industry sufficiently detailed and can be regarded as an update or extension of the MIMAC simulation models. A detailed description of the models is given, for example, by Kopp et al. (2020a) and Kopp et al. (2020b). In addition, the models (AutoSched AP models and raw data) can be downloaded from https://p2schedgen.fernuni-hagen.de/.

For the implementation of the approach proposed in this paper, the authors choose the AutoSched AP model developed and validated by Koop et al. (2020a) of a low-volume/high-mix scenario (Dataset 2) with more than 900 machines (*STN*) according to 105 machine types (*STNFAM*) distributed over 11 functional areas (*STNGRP*) and 10 product types (*PART*) with routings (*ROUTE*) and associated operations (STEP) ranging from 242 operations for product type 5 to 585 operations for product type 3 (Kopp et al. 2020a). With respect to a model inversion, the considerations in the following focus on the machine list (tool.txt), the routings (route_{1-10}.txt) and the order list to be considered (order_{...}.txt).

In the machine list, the focus is on questions concerning scheduling for distribution to the machines of a machine type (*FWLRANK*) and then scheduling on the corresponding machines themselves (*RULE*). Scheduling according to a pure prioritization, for example according to higher priority (*rank_HP*), of orders or batches is to be retained. As a result, the prioritized orders tend to be dispatched later because of the backward simulation, but they can still fulfill the underlying planning data (due dates) within an acceptable time frame for planning, following the prioritization in the required operations. In contrast, scheduling according to the critical ratio (*rank_CR*), i.e., the ratio of the remaining time against the planning data and the remaining process time, must be discarded in the context of backward simulation due to the missing reference value.

While the transformation of the input data in the routings is primarily focused on the inversion of the required operations, for example from operation number 242 to operation number 1 for product type 5, equally definitions of an assignment in terms of rework or critical queue time and an assignment of a unique machine dependency in terms of an order for operations on the same machine type are to be reversed. The definition of a machine dependency for an order in operation 247 for operation 270 is to be set subsequently and during the transformation of the input data in the routings inversely in operation 270 for operation 247.

Concerning the definition of critical queue times, the authors point out that, when running the simulation model backwards and validating it, a way to deal with possible scrap has to be found. In this paper, and following Kopp et al. (2020a), the definitions of an assignment in terms of critical queue times are initially provided in the modelling but are not yet functionally implemented. Kopp et al. (2020b) provide general results regarding the implementation of critical queue times in the low-volume/high-mix simulation model of the SMT2020.

Based on the planning data, a backward scheduling of the orders can be done based on the order list to be considered. The scheduling of the orders is done according to the goal of zero delay and the time feasibility of the promised planning data starting from the latest possible completion date.

The automation of the transformation steps described here for backward simulation (see Figure 2) implemented by the authors offers numerous advantages, especially for planners and decision-makers who do not have sufficient knowledge regarding simulation and especially backward simulation. The intuitive user interface, see Figure 3, allows the user to select the order list to be considered and to define the planning horizon accordingly, while the underlying transformation process can be executed as often as required. A table view also offers the possibility to trace the transformation of the order list under consideration.

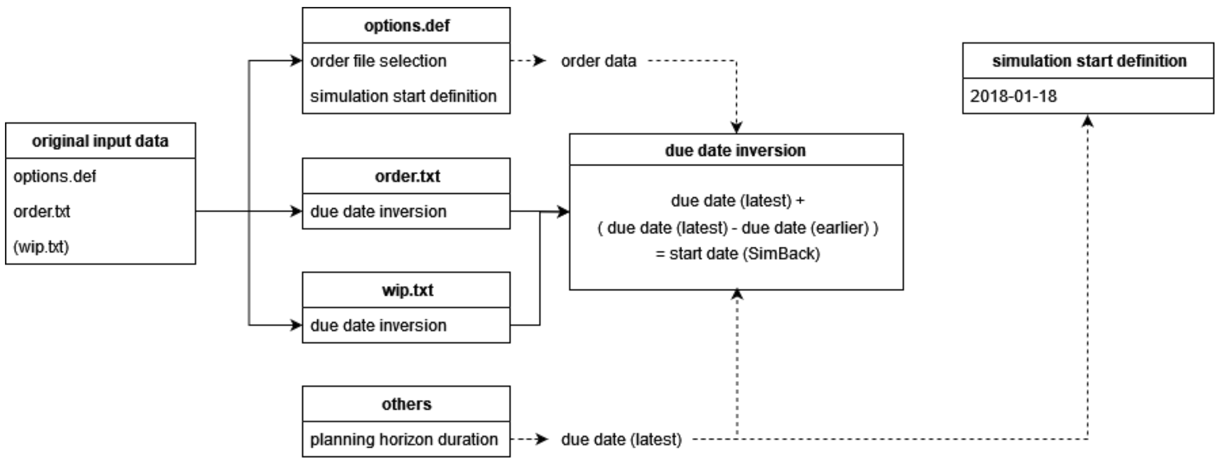

Figure 2: Order specific transformation steps for backward simulation.

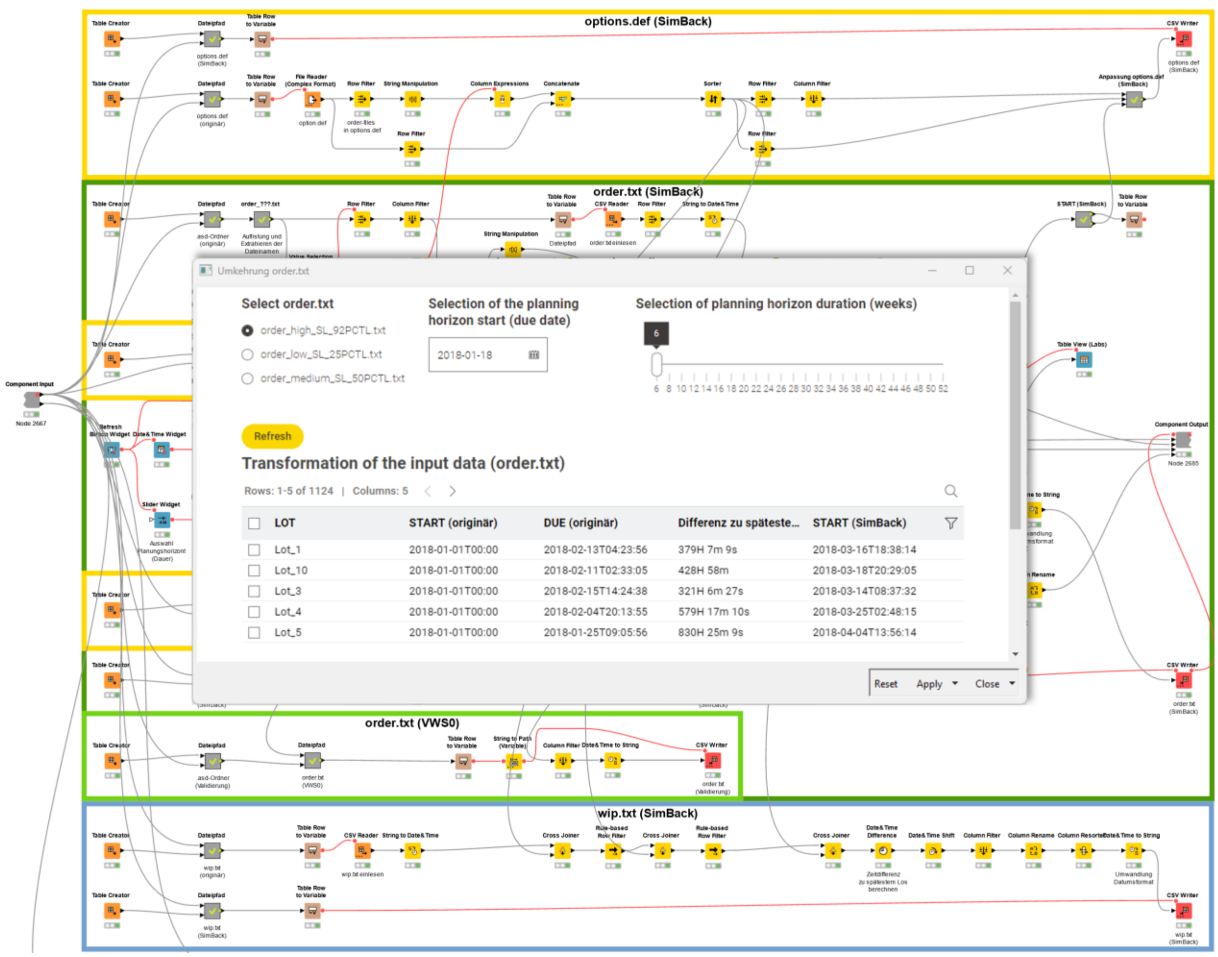

Figure 3: User interface and underlying process flow for selecting the order list to be considered and the planning horizon.

3.2 Design and Execution of Experiments

Existing simulation tools have insufficient capabilities in terms of experiment design for backward simulation; the transformation of result data from a backward simulation run and the subsequent validation against a forward simulation is a crucial sub-step to be automated to ensure an integrated validation of the backward simulation results.

To perform the sensitivity analysis envisioned in this paper, the authors again implement a prototype user interface for selecting and defining factor configurations. Radio buttons can first be used to select whether the selection should apply to the entire production process or only to specific functional areas that can be selected via a dual list. In addition, users can also specify the step mode and subsequently the selection of an exact percentage or step-by-step integer setting of the number of machines for the corresponding machine types of the selected functional areas, see Figure 4.

Figure 4: User interface and underlying process flow for the selection of factors for the design of experiment.

In the experimental execution, defined factor configurations are simulated several times to be able to make high-quality statements about the mimicked system. The authors simulate the individual factor configurations following the original forward loading and follow the backward simulation in the sense of a combined execution. For this purpose, the factor configurations are executed in sequence via a chunk loop using appropriate Python scripts from KNIME directly in AutoSched AP. The result data (.rep files) for each simulation run are automatically stored under a specific file path for the executed experiment together with a listing of the executed configurations and information regarding the planning horizon.

3.3 Data Preparation and Analysis

The availability of all result data after completion of all configurations of one or more experiments enables immediate data preparation and analysis. In this context, the one-time creation of a workflow in KNIME again offers the advantage that each new configuration series in the form of an experiment can be analyzed at the push of a button. The resulting evaluations can be viewed via an interactive dashboard. The authors have implemented four different views for the dashboard, see Figure 5. The first three views refer to a single configuration of an experiment. In the fourth view, the evaluations focus on a whole set of configurations. Selections can be made using radio buttons, and experiments (and configurations) can also be selected using drop-down lists. The dashboard view is automatically updated with each new selection.

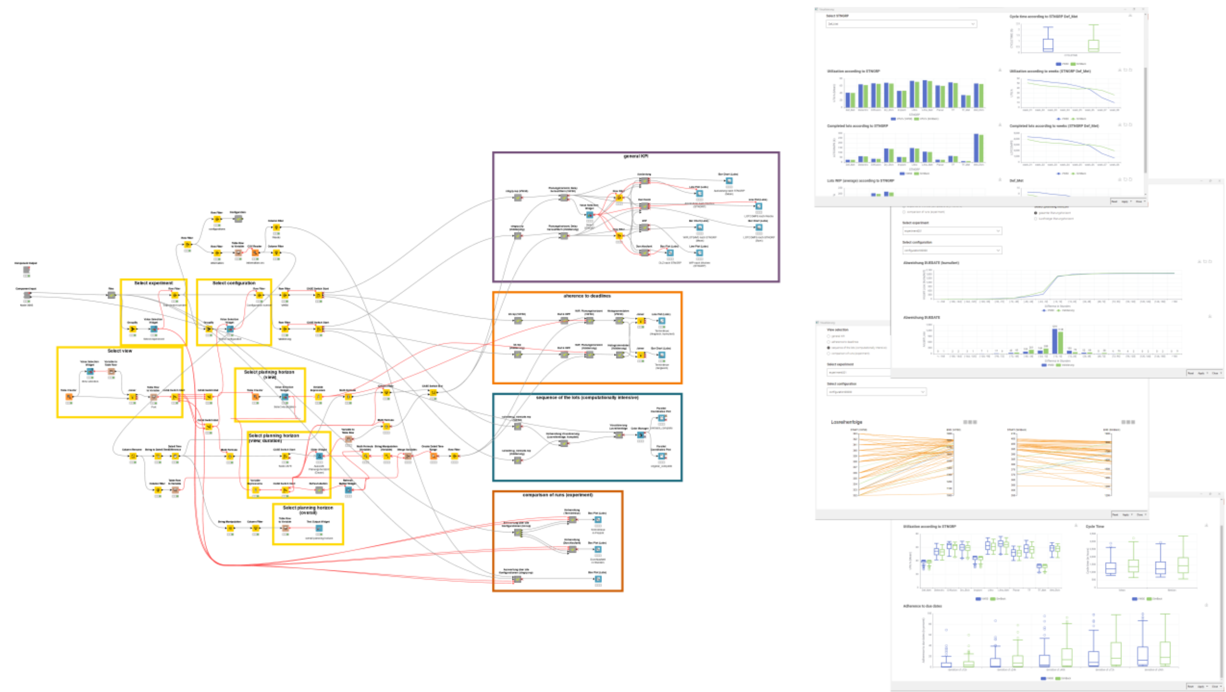

Figure 5: Different views and underlying process flow of the interactive dashboard for evaluating the simulation results.

4 RESULTS OF A SENSITIVITY ANALYSIS

With the proposed solution approach for automated execution and evaluation of extensive simulation experiments in the context of backward simulation, the authors try to achieve several goals. Respectively, the authors initially address the difficulty of performing experiments in the context of a sufficiently careful design of experiments and the need to automate backward simulation. In this regard, the implementation of a comprehensive solution approach to automate model inversion, design and execution of experiments, and data preparation and analysis not only lead to time savings for simulation experts, but also enable, at least in principle, the execution of experiments by trained users. The series of experiments itself achieves a significant increase in efficiency and lower susceptibility to errors due to the absence of manual intervention.

By means of the described approach, the backward simulation approach is to be transferred to a more complex model and the applicability of the proposed solution approach for the automated execution and evaluation of extensive simulation experiments in the context of backward simulation is to be presented in principle. Within the framework of a sensitivity analysis, the authors have investigated the impact space in terms of the number of machines for the machine types of selected functional areas (*Dielectric*, *Diffusion*, *Dry_Etch*, *Litho*, *Litho_Met*) and a reduction of these by half. The resulting 57 experimental runs (including initial configuration) were started using the developed solution approach on an octa-core Intel Xeon Silver 4215 processor and 256 GB physical memory. According to a comparability of the result data, the solution approach starts with the processing of the original (forward) simulation run, called VWS0, and follows the backward simulation in terms of the combined execution of the simulation model. The underlying planning horizon was set in one case at 8 weeks (experiment001) and in another case at 12 weeks (experiment002).

As already mentioned in section 2, discrete event simulation is suitable in general and in connection with an input of a concrete production program to consider feasibility of concrete production program as well as adherence by firms to completion and/or delivery dates promised in advance. The analysis carried out in this paper is then initially based on the results of the original (forward) simulation run and compares these with the results of the subsequent backward simulation. In the context of the sensitivity analysis performed, the following statements always refer to a comparison of the results obtained by scheduling the original (forward) simulation with the results of a backward simulation in terms of the combined execution of the simulation model. According to the time feasibility of promised planning data, comparable results can already be achieved for the initial configuration, in other words, without adjusting the number of machines. Figures 6 and 7 show the result data according to a deviation in hours and corresponding time intervals.

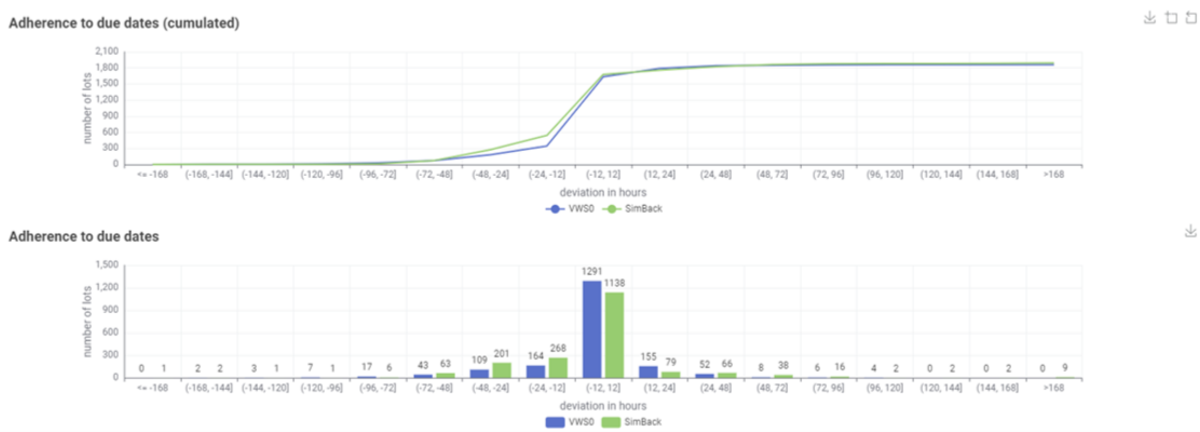

Figure 6: Adherence to due dates according to a deviation in hours and time intervals for a planning horizon of 8 weeks.

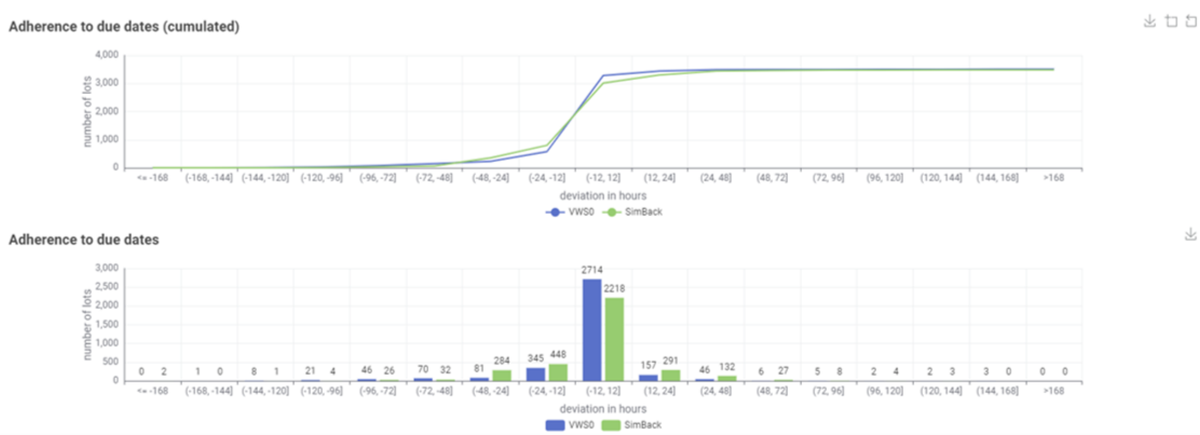

Figure 7: Adherence to due dates according to a deviation in hours and time intervals for a planning horizon of 12 weeks.

Subsequently, the results of the test experiments across all configurations show that the backward simulation can achieve promising results in terms of the time feasibility of the promised planning data, starting from the latest possible completion date, compared to the scheduling of the original (forward) simulation. The simulations show a higher average and median cycle time of the lots in relation to the mimicked system, but at the same time they show a higher time feasibility according to a deviation of ±12 hours up to ±96 hours compared to the underlying planning data. The utilization of the individual functional areas, on the other hand, is almost unchanged compared to the scheduling of the original (forward) simulation, see Figures 8 and 9.

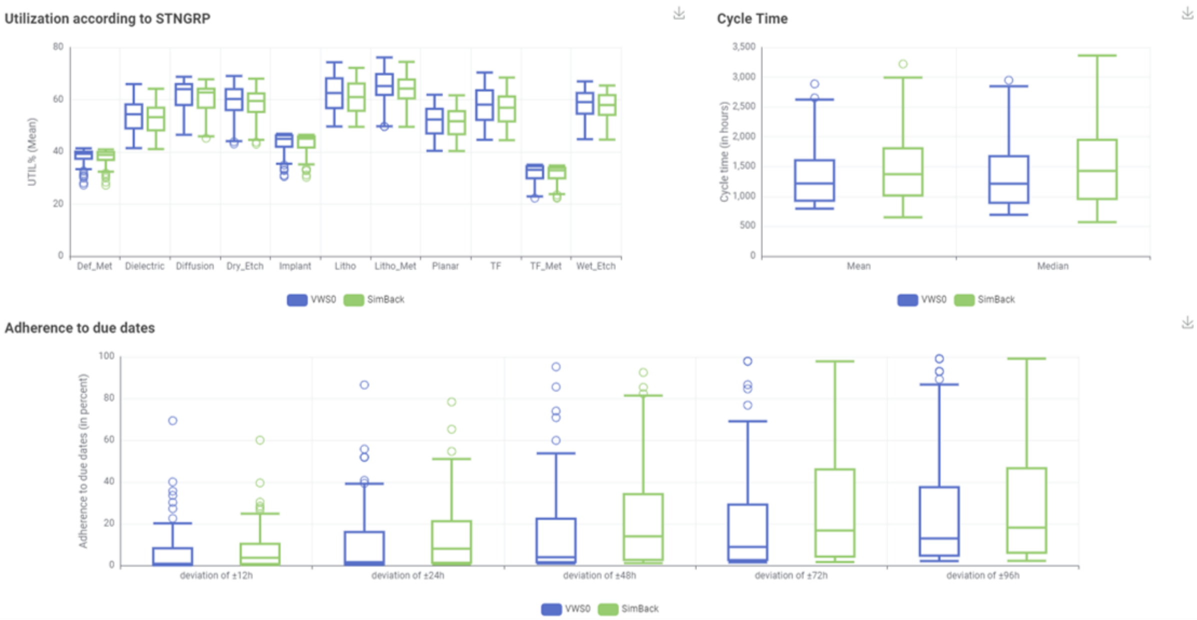

Figure 8: Results of the test experiments across all configurations for a planning horizon of 8 weeks.

For a planning horizon of 8 weeks, half of the simulation runs for VWS0 are between 0.69 and 16.06 percent adherence to due dates according to a deviation of ±24 hours, while SimBack lies in a value range of 1.29 and 21.19 percent. According to a deviation of ±72 hours, the values are 2.57 and 29.19 percent (VWS0) and 4.28 and 46.02 percent (SimBack). In contrast, half of the simulation runs for VWS0 have a mean cycle time between 38.76 and 67.00 days and a mean of 56,51 days, while SimBack measures values between 42.41 and 75.33 days and a mean of 62,12 days.

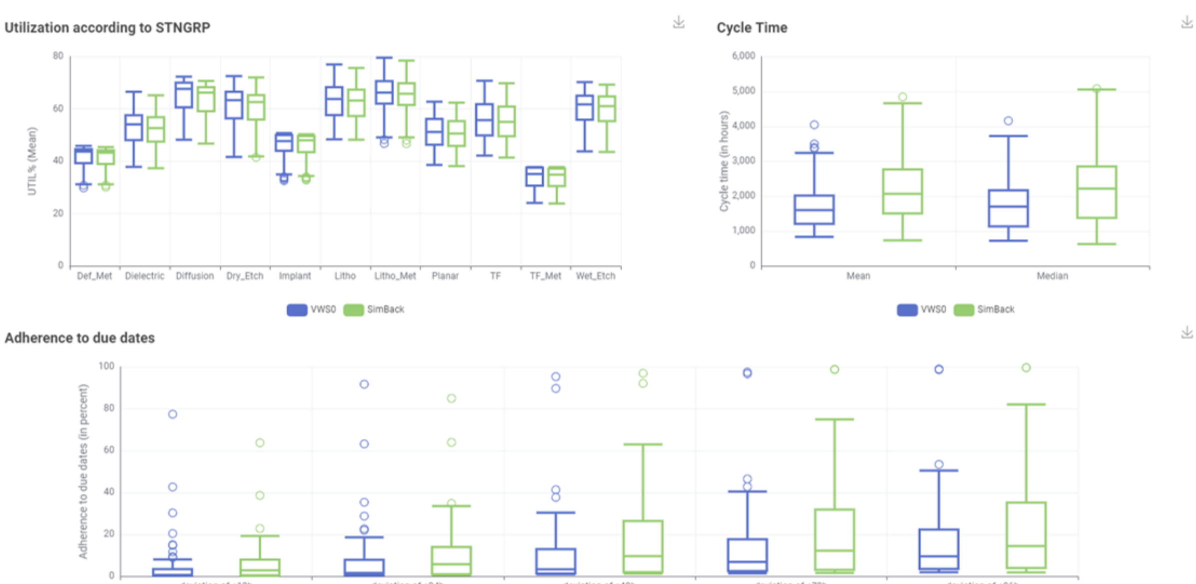

Figure 9: Results of the test experiments across all configurations for a planning horizon of 12 weeks.

Furthermore, the superiority of the results of the backward simulation in terms of a combined execution of the simulation model can also be shown for a planning horizon of 12 weeks. Accordingly, half of the simulation runs for VWS0 range from 0.66 to 7.86 percent adherence to due dates for a deviation of ±24 hours, while SimBack ranges from 0.94 to 13.98 percent. For a deviation of ±72 hours, the values are 2.54 and 17.72 percent (VWS0) and 3.09 and 31.81 percent (SimBack). In contrast, half of the simulation runs for VWS0 have a mean cycle time between 50.29 and 84.11 days and a mean of 72,36 days, while SimBack measures values between 62.78 and 115.35 days and a mean of 91,39 days.

As a result, the authors achieve a higher adherence to due dates in both experiments, but at the same time record a higher average cycle time. The authors initially attribute this fact to the "simple" execution of the simulation, which is still carried out without further optimization. The transfer of the backward simulation approach by means of the described procedure to a more complex model, however, initially focuses primarily on the time feasibility of promised planning data and on proving the applicability of the proposed solution approach for the automated execution and evaluation of extensive simulation experiments in the context of backward simulation in principle.

5 OUTLOOK

Simulation requires effort and time; even if a preexisting model just needs to be updated with new parameters, there is still the runtime required to run the simulation, see Pappert and Rose (2022). Today's manufacturers must develop production plans that keep inventories as low as possible while meeting quality requirements and delivering on promised delivery dates. One way to address this objective is by optimizing overall planning processes, which require overarching optimization methods, see Jain and Chan (1997) and Laroque et al. (2022). The purpose of this paper was to present an approach for automated execution and evaluation of extensive simulation experiments in the context of backward simulation as a first component of a larger overall concept, see Figure 10.

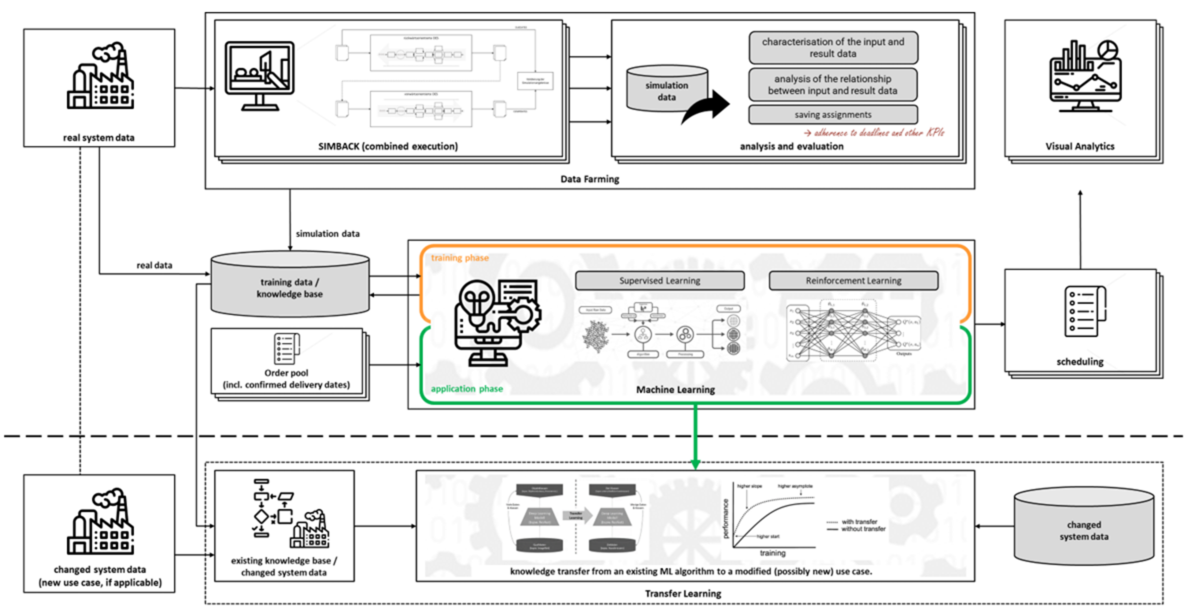

Figure 10: Overall solution concept for a powerful tool to support operational decisions in scheduling and sequence planning.

In addition to an on-going research of questions concerning the methodological approach of backward simulation, for example with respect to critical queue time, and the study of real-world use cases at industry partners, the authors intend, besides transferring the model into the AnyLogic simulation tool, to use targeted data generation in the form of the execution of concrete factor configurations as part of the training phase of machine learning techniques in order to provide a powerful tool for supporting operational decisions in scheduling and sequencing in the semiconductor industry. This is to ensure that the solution approach is immediately applicable to decision makers and to minimize the time and resource requirements associated with the deployment of the techniques.

Finally, the testing of transfer learning should address the difficulty of having to train the machine learning-based decision support and the underlying predictive model from scratch with new industry and problem specific data (simulation and real data) as soon as input data changes significantly and/or similar use cases are to be considered. The need for model adaptation and re-validation, combining data generation through data farming with data analysis, and the resulting time and resource requirements represent a significant research need.

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