Backward-Oriented Decision and Planning Approaches in Production Scenarios: A Systematic Literature Review and Potential Solution Approach

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Abstract. Manufacturing processes are increasingly driven by new product needs, innovations, and cost efficiency. Planning Staff and decision makers face the challenge of achieving fixed production programs and subsequently individual orders in a certain quantity and within a certain period at a guaranteed completion date. A systematic approach to scheduling and tracking resource requirements is necessary to ensure efficient flow of manufactured products. Forward- and backward-oriented planning strategies are most used by manufacturers to meet their demands for existing orders. The current application of such approaches is very time and resource intensive due to the complexity and dimension of the decision and planning problems to be considered; it is difficult to react to short-term changes within the production program. To address this gap, this paper provides a systematic literature review of backward decision and planning approaches in production scenarios and presents a potential over-arching solution approach of a simulation- and machine learning-based decision support combination for operational production planning.

Introduction

Global business, an advancing digital transformation, and the need for on-time production and delivery are defining competitive factors for manufacturers. For production planning and control (PPC), the efficient flow of manufacturing processes is indispensable.

Companies need to be constantly aware of the continuous adoption screws for PPC to establish and maintain an "optimal operating state" and therefore an efficient organization of all manufacturing processes. Uncertainty in PPC and the resulting adjustments can have unexpected repercussions on the performance of production systems and result in monetary and time resources being misused. A permanent (effective) adjustment of PPC also requires flexibility regarding structuring within manufacturing companies to be able to adapt to continuously changing market situations and correlating customer requirements.

Planners and decision makers are faced with the challenge of achieving fixed production programs and subsequently individual orders in a certain quantity and within a certain period at a guaranteed completion date. The success in terms of an efficient flow of manufacturing processes demands a systematic approach to scheduling and tracking of resource requirements.

Orders can be planned in a variety of ways, depending on the specifics of a given company and the characteristics of an order. The most common strategies are forward- and backward-oriented planning approaches [1].

In a series of experiments, the authors have shown that the use of a backward-oriented application of material flow simulation models (SimBack) can be a powerful tool for operational production planning, see [2][3]; however, the current usage of such approaches is also very time-consuming and resource-intensive due to the complexity and dimension of the decision and planning problems considered. In addition, it is difficult to react to short-term changes within the production program.

The authors intend to provide an extended solution approach to the given problem. Before, a systematic literature review on applications of backward decision and planning approaches in production scenarios was conducted.

This includes identifying applications of backward scheduling and backward simulation, as well as implementation challenges. We intend to answer the following research question for production scenarios: “What applications of backward scheduling and backward simulation exist in the field of production planning and control?”.

To answer these research questions, we give a short definition and delimitation of the terms backward scheduling and backward simulation in Section 1, followed by the applied review methodology in Section 2. Section 3 presents the results of our analysis. Section 4 addresses the potential of simulation models for targeted data generation and evaluation (data farming, cf. for example [4]) as well as their application for further optimization of target values, which is rarely used today, and presents a potential overarching solution approach of a machine learning-based decision support for operational production planning based on the extension of the methodological SimBack approach to generate a scheduling by backward simulation to a targeted data generation and evaluation based on the approach of data farming. Finally, a conclusion is given in Section 5.

1 Terminology

1.1 Backward Scheduling

Scheduling is a continuous decision-making process that involves scheduling tasks over time periods. The goal is generally to optimize one or more objectives. This can be used in manufacturing and services industries, as well as other industries where demand changes almost daily [5].

The procedures of a forward and backward scheduling can be described, which serve as solution procedures for scheduling and a correlating scheduling logic. The schedule logic is the process of organizing activities into a predictable and repeatable order. Scheduling steps often include assigning times, establishing priorities (priority control), prioritizing resources from highest to lowest priority and tracking progress towards completion, among others [6].

Forward scheduling is a process that sets deadlines for each work task and moves from a certain starting point (date) to complete the work within a specified period, with no waiting times between tasks. In contrast, backward scheduling is a technique for determining the latest possible start date of individual orders based on pending completion dates. This procedure is particularly useful for scheduling orders promised to customers with guaranteed completion dates.

The primary advantage of backward scheduling is that orders are not manufactured until the latest possible date. This allows for a capital commitment to be minimized, which in turn minimizes downtime from disruptions in production. However, there is always a risk that a disruption cannot be absorbed by the production process [7].

Manual scheduling procedures, which include forward and backward scheduling, provide a good basis for decision-making according to the insertion of a given production program and detect possible delays of individual orders. However, changing the scheduling framework such as by short-term insertions is usually complicated.

1.2 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 [8][9]. Gutenschwager et al. [10] 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-oriented simulation (DES) can handle much more complex models.

Models for discrete event-oriented 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-oriented 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-oriented simulation is suitable in general and in connection with an input of a concrete production program in particular – to consider feasibility of concrete production program as well as adherence by firms to completion and/or delivery dates promised in advance, see [3].

Discrete event-oriented simulation models are used individually or in combination with heuristics in the context of simulation-based optimization to study forward-time decision and planning problems.

One approach of discrete event-oriented simulation with respect to time-backward decision and planning problems has been described in the literature as backward simulation and concretizes a reversal of the flow logic of the simulation along with the implemented control and priority rule procedures and the resulting backward execution of the same.

According to Jain and Chan [11] and Laroque [12], 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 [11]. For a validation of the resulting solution set, 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).

2 Research Methodology

This paper provides a systematic overview of existing applications of backward-oriented decision and planning approaches in production scenarios, following the five-step approach developed by Denyer and Tranfield [13].

2.1 Question Formulation

Any research requires a decision about its focus. Relating to the authors' research interest and their research work towards backward simulation, the authors want to address the question related to the applications of backward scheduling and backward simulation: “What applications of backward scheduling and simulation exist in the field of production planning and control?”.

2.2 Selection of Database and Definition of Search Strings

The authors conducted a keyword search in journal and conference papers, keyword lists, and abstracts where the authors classified their work in backward decision and planning approaches, thus excluding works where the terms backward scheduling or backward simulation (or backward termination or backward planning) were not used. As shown in Figure 1, the search strategy consisted of two major steps: first, the identification of all possible papers using the search terms; then, filtering out all those papers that had no relevance in terms of the focus of this literature review.

In the first step, relevant keywords were selected with respect to the aim and scope of our literature review.

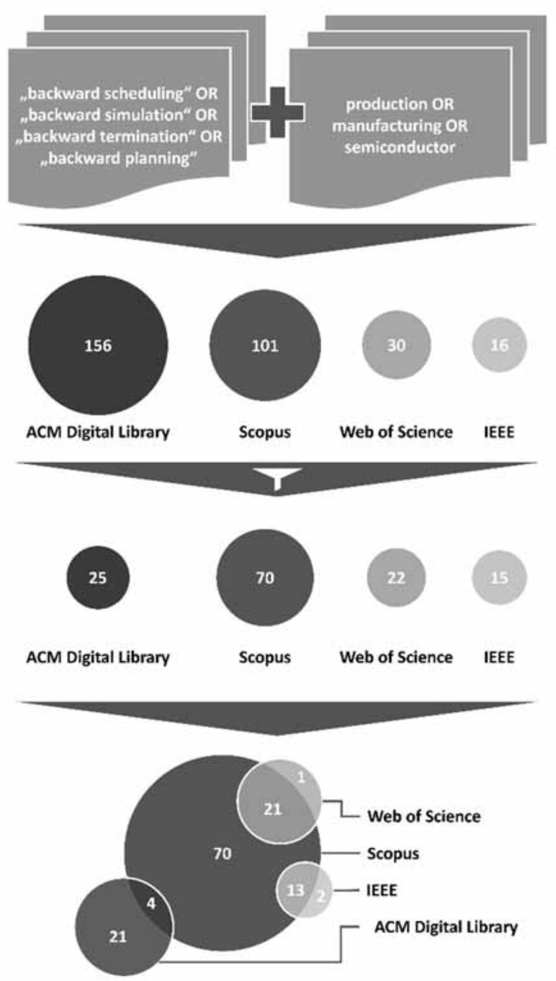

Figure 1: Search process and total number of papers.

These keywords can be seen in relation to backward decision-making approaches and in relation to the concrete context. The keywords were then constructed as a search string with the operators OR and AND between them: (("backward scheduling" OR "backward simulation" OR "backward termination" OR "backward planning") AND (production OR manufacturing OR semiconductor)).

The keyword semiconductor is most important for the solution approach proposed later, as it represents the most important research area explored by the authors over the last few years. They have focused on developing a methodical approach to generate a scheduling by backward simulation considering stochastic model influences in semiconductor manufacturing.

For this study, the authors chose the ACM Digital Library (ACM-Association for Computing Machinery), Scopus, Web of Science, and IEEE Xplore (IEEE – Institute of Electrical and Electronics Engineers) databases to collect scientific papers.

Only scientific papers published online that were written in English before the end of August 2022 were included. Figure 2 shows the growth in the number of relevant publications from the first paper identified in this study, from 1982 to 2022.

2.3 Article Selection and Evaluation

Denyer and Tranfield [13] note the importance of transparency in conducting systematic reviews, which they explain by citing a set of explicit selection criteria that they use to assess each study found and see if it does address the review question. In a first step, as already described in Section 2.2, the authors used a manual abstract screening to filter out all papers that were not relevant to the focus of this literature review. The accepted 94 papers were then screened by full text according to the following criteria: full text accessibility and thematic focus on backward decision and planning approaches in production scenarios. Applying the full text accessibility criterion reduces the total to 54 papers from 1989 to 2022, which are subsequently processed using a KNIME workflow.

The KNIME workflow processes abstracts and full texts of remaining papers and breaks the text into fragments. These fragments are subsequently combined in pairs as N-grams, which are the result of breaking a text into fragments and allows for the following in section 2.4, that papers and linking studies can be related to each other.

In this step, the pairwise summary of the individual fragments as N-grams offers the opportunity to assess the suitability of a paper according to the thematic focus of backward decision and planning approaches in production scenarios. Accordingly, the N-grams can be specifically summed up per paper, in this case, for example, based on the occurrence of the term backward; a more specific consideration of papers based on their numbers can be made.

It should be noted that a low number does not automatically equate to a low relevance of papers for analysis.

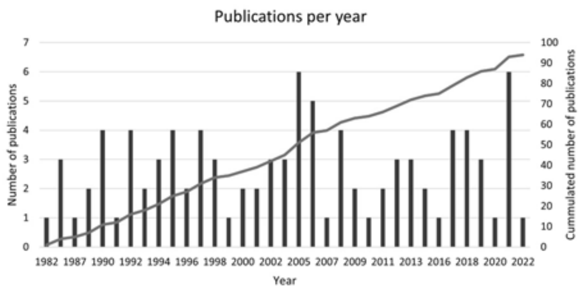

Figure 2: Number of publications per year and cumulated number of publications.

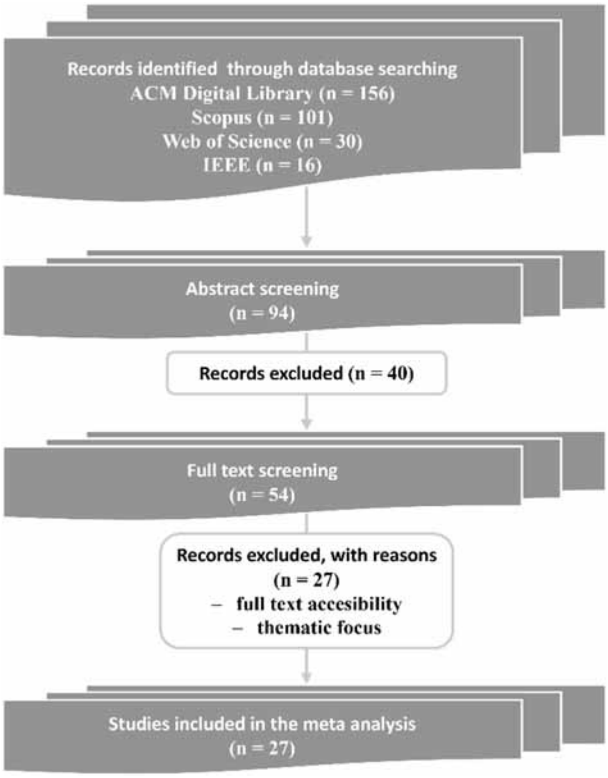

Figure 3: PRISMA flow diagram. The PRISMA flow diagram for the systematic review detailing the database searches, the number of abstracts screened, and the full texts retrieved.

The resulting systematization of the term backward* was further narrowed by a more specific consideration of abstract and full text, resulting in 27 papers for the meta analysis, see Figure 3.

2.4 Analysis and Synthesis of Results

The data analysis and synthesis stages of research begin with the collection of relevant sources. The aim of analysis is to break down individual studies into constituent parts and describe how each relates to the other. The aim of synthesis is to make associations between the parts identified in individual studies, see [13].

In this step, a deeper content analysis of the 27 identified core papers and the results of the literature review were synthesized to consider similarities and differences within and between two highlighted backward decision and planning approaches in production scenarios. The results of this step revealed that 12 papers focused on backward scheduling while 15 papers focused on backward simulation.

2.5 Evaluation of the Results

The results of the analysis and synthesis of the 27 core papers identified in the literature review are organized below in Section 3 according to the formulated research questions.

3 Review Analysis

Most of the reviewed papers on production scenarios and scheduling falls into the (here relevant) category of problem solving, with the goal of finding an improved solution approach for a specific production scenario that can deal with high cost, time, and quality pressures as well as planning uncertainties and/or unforeseen events.

3.1 Backward Scheduling in Production Scenarios

In the first paper (within this consideration), Agrawal et al. [14] propose a solution approach for scheduling the production of large assemblies and using a mate-rials requirements planning system with the goal of manufacturing products on time with minimum lead times and low production costs. The proposed solution approach includes an effective lead time evaluation and scheduling algorithm. Detailed backward scheduling is used to achieve the goal of minimizing lead times. Following up on this, Lalas et al. [15] presented a hybrid backward scheduling method for discrete manufacturing environments and evaluated it through several relevant performance indicators in a typical textile industry. The method applies a set of transformation relationships to transform a finite capacity forward scheduling method that can employ different allocation strategies into its backward counterparts. In contrast, Chen et al. [16] propose a solution to the problem of resource-constrained scheduling using particle swarm optimization. Specifically, the authors propose a rule for local delay search and a rule for bidirectional scheduling that are designed to facilitate the search for a global minimum and, further, a minimum amount of time. In the case of the bidirectional planning rule for particle swarm optimization, the authors propose a combination of forward and backward scheduling to expand the search range in the solution space and obtain a potentially optimal solution.

Kamaruddin et al. [17] evaluate the effectiveness of forward and backward scheduling in a job shop and a cellular layout. They compare the performance of both scheduling approaches, finding that backward scheduling in the job shop layout has lower average lead time, lower delay, and higher labor productivity than forward scheduling under all conditions.

In contrast, forward scheduling in the cellular layout has lower average lead time, lower delay, and higher labor productivity than forward scheduling under all conditions.

Chen et al. [18] develop an advanced planning and scheduling system to automatically generate production schedules for a colour filter factory with multiple lines. Both a forward and backward scheduling approach are used to balance the workload and control capacity losses by considering sequence-dependent setup times. In contrast, Hanzálek and Šůcha [19] study a lacquer production planning problem that is formulated as a resource-constrained project planning problem with general time constraints. They propose a parallel heuristic to solve it. This heuristic uses a temporal symmetry mapping that allows for simple construction of a schedule in the backward time orientation. Following up on this and to deal with the increasing size of wafers and demand for production in semiconductor manufacturing, Wang et al. [20] present a periodic scheduling algorithm for single-arm cluster tools with multitype wafers and shared processing modules. They derive analytical expressions for schedulability testing using a modified backward scheduling strategy. Accordingly, the backward strategy is the most widely used and efficient strategy for single-arm cluster tools.

Kalinowski et al. [1] likewise focus on the scheduling problem of minimizing lead time but refer to job store class systems and production orders arising there. Their proposed method supports both forward and backward scheduling, using an additional backward pass to calculate the latest possible release date of a given production order. In a further paper [21], the authors consider the problem of scheduling in flexible manufacturing systems considering additional resources and discuss both forward and backward scheduling strategies as well as serial and parallel scheduling schemes. Following on from this, Suryadhini et al. [22] apply backward scheduling to the batch scheduling model they developed to achieve the goal of minimizing the expected average lead time for a three-stage flow production. The batch scheduling model is thereby proposed for such a flow production along with an algorithm to solve it.

Finally, Viady et al. [23] consider a specific use case from textile production and aim to minimize the prevailing scheduling problems by reducing bottlenecks at workstations and excessive quantities. To solve the problem, the authors propose the drum-buffer-rope method and the Campbell Dudek and Smith (CDS) algorithm, applying backward scheduling to minimize waiting times and control work in process.

The result of this research is a reduction in lead times and, at the same time, a reduction in delays. In contrast and in the context of material requirements planning, Seiringer et al. [24] proposed a multistage and multipart production system with a rolling planning horizon, random customer demands, lead times, and machine setup times. The objective of their simheuristic algorithm was to optimize total cost; backward scheduling counted as one step in this optimization process. The results demonstrate that the proposed approach is promising for MRP systems under uncertainty conditions.

3.2 Backward Simulation in Production Scenarios

The authors themselves have repeatedly published application studies in the field of backward simulation in recent years [2][3]. The presented results based on a real-world use-case from semiconductor manufacturing show in a very practical way, that the methodical approach for generating a production schedule by backward simulation works under the given specifics, while stochastic influences can be considered. Already in Scholl et al. [25], the authors describe how they applied a backward-oriented simulation approach in their research on semiconductor manufacturing and identified restrictions and limitations.

However, the first research (within this consideration) has been done by Jain et al. [26]. The authors describe an application of advanced concepts of artificial intelligence in conjunction with simulation modelling and state-of-the-art computer hardware for effective real-time factory control. This application proves that disciplines such as AI and simulation modelling can be used synergistically for a practical purpose. The authors employ the concept of backward simulation to construct reliable schedules.

On the other hand, Ying and Clark [27] proposed a deterministic simulation to determine order release times in the forward or reverse direction. They developed a bidirectional algorithm that includes a series of forward and reverse simulation runs. A backward simulation run determines potential order release times; if these are all nonnegative, the algorithm modifies them to determine order release times for the subsequent forward simulation run. A final forward simulation run determines order completion times. The experimental results show that the bidirectional algorithm results in significantly improved mean lead time and that it can improve mean delay in some cases.

Having previously introduced in detail the concept of backward simulation as a means of determining a required state based on a desired target state [28], Watson et al. [29] address the challenge of order call scheduling for a customer-based production facility, which is characterized by the interfacing problems among order processing, capacity planning and production scheduling. The authors state that conventional order-call planning strategies often result in infeasible plans and make it difficult to manage customer orders. They discuss an approach called resource scheduling based on queue simulation, which simulates a queue in a manufacturing environment by using backward bill-of-material explosion logic like material requirements planning except that it uses a queue simulation model of the plant.

The approach proposed by Jain and Chan [11] to determine lot release times based on backward simulation has been highly cited in the literature, but it does not lead to improvements in a highly complex semiconductor manufacturing scenario. In their paper, the authors describe the approach, its implementation, and limitations found in the more complex scenario.

Chong et al. [30] propose a planning approach that includes one forward and one backward run using discrete event simulation. In the first run, bottlenecks are identified, and in the second run, strategies to reduce the load on those bottlenecks are used. Following up on this, Werner et al. [31] focus their research on the aspect of optimizing the process flow and calculating exact release dates for lots. This five-step procedure combines methods from scheduling rules, heuristic optimization, and analytical calculations. The basic principles highlighted are applicable not only in the semiconductor industry but also in other industries.

In Mejtsky [32], a metaheuristic algorithm for simulation optimization is described and applications of the algorithm to traveling salesman and job store scheduling problems are presented. To account for due dates, the author applies backward simulation and a pruning rule. In contrast, Zhai et al. [33] presented a special planning model based on simulation technique and genetic algorithm for precast production with two critical resources. The authors developed three simulation approaches with different simulation heuristics and directions, which were then compared using their resource and production schedules. A satisfactory resource and production schedule was produced by applying the critical precast component rule and bidirectional simulation.

Moreover, Dori and Borrmann [34] propose a combination of forward and backward simulation, addressing the extension of the discrete-event simulation method to include the calculation of buffer times. To determine the buffer times, the authors believe that it is important that the order of task execution is the same for both forward and backward simulation. Therefore, an extension of the simulation concept is presented that controls execution order. The authors illustrate application by means of a comprehensive case study.

Ju et al. [35] consider the application of backward simulation to analyse shipbuilding production and show how a shipyard's planning process can be improved. The authors' developed planning system, based on backward simulation, could be connected to an existing advanced planning system for ship construction. A major advantage of this system is that data input and preparation work for running simulations are simple; therefore, compared to forward simulation, backward simulation can be performed faster for different conditions and many cases, and by selecting best results from those simulations, production plans could be improved.

Finally, Okubo and Mitsuyuki [36] propose a method for modelling and representing the complex data sets of an entire factory structure. They prove that backward simulation is an efficient tool for meeting a given production program with guaranteed completion dates at short lead times. Moreover, they show that the effectiveness of their method and the validity of their production plan are confirmed by using actual factory processes and real data.

4 Potential Solution Approach

In the semiconductor industry, production systems and processes have an above-average level of complexity compared to other industries and will continue to gain complexity, see [37][38][39]. Recent developments in the areas of product diversity, smaller batch sizes and a more rapidly changing product range are documented by increased interconnections between plants due to automation. Possible dependencies relevant for planning result from limited plant capacities, stochastic processing, changeover, waiting and transport times, preventive mainten-ance, setup changes or dynamic time and/or capacity restrictions in queues or along several production stages [9].

The manufacturing technologies used in the semiconductor industry are considered particularly sensitive and involve complex local control logics.

Depending on various characteristics defined in advance, individual production batches do not run through linear process sequences, but rather circular process sequences and up to 700 individual steps, see [3][39]. Individual production batches are sometimes processed several times under cleanroom conditions via special equipment (re-entry cycles). Failure to comply with planning rules often leads to relevant rejects of intermediate and end products that must be compensated for at short notice by additional infeeds [3].

In order to ensure competitiveness, today's manufacturers must develop production plans that keep inventories as low as possible while meeting quality requirements and delivering on promised delivery dates. In addition, they must increase throughput and overall equipment effectiveness. Approaches to achieving these goals include optimizing overall planning processes, which require overarching optimization methods, see [3][11].

While application studies on backward simulation methods have appeared continuously over the years, promising results are described in Laroque et al. [2][3] according to a methodological approach to generate a scheduling by backward simulation under the specifics of the semiconductor industry and considering stochastic influences. The application of several simulation models and a series of experiments shows that backward simulation can be a powerful tool for operational production planning. However, backward simulation methods can be very time-consuming and resource-intensive depending on the complexity and dimension of the decision-making and planning problem under consideration and the interfacing issues; thus, highlighting a need for research in this area. In addition, the underlying data within the methodological approach to generate a scheduling by backward simulation remains largely unchanged so far (in terms of further optimization). Accordingly, potentials in terms of targeted data generation and evaluation as well as application of resulting findings for further optimization remain largely unexplored at present.

Such a targeted data generation and analysis can be understood as data farming and should efficiently and effectively increase the amount of data and furthermore the information concerning a decision and planning problem to be considered and connecting questions and enable the derivation of recommendations for action, see for exam [4][40]. According to Lendermann et al. [9], under the condition of a valid modelling, huge amounts of data have to be generated and processed in the sense of a forward as well as in the sense of a backward execution of a simulation model, in order to be able to make high-quality statements about the simulated system by a sufficiently careful experiment design (Design of Experiments, DoE). The extension of a backward simulation in the sense of a combined design by the approach of data farming shall considerably increase the informative power of the simulation study to be performed and at the same time address the difficulty to include the dynamics and stochastic of production systems and processes sufficiently accurately.

The described combination presents difficulties when implementing this procedure repeatedly from scratch for a new and/or adaptable planning horizon (in the case of additional and at the same time sometimes short-term infiltrations). This procedure is associated with a considerable expenditure of time, as well as the associated question of economic benefit. Moreover, sufficient knowledge of methods and/or procedures mentioned is assumed, which means that this procedure is sometimes not directly applicable for decision-makers.

Mönch et al. [41] states that executing concrete factor configurations, for example by simulation, can be part of the training phase of machine learning methods, see [9]. Machine learning as a subfield of artificial intelligence describes approaches that enable technical systems to extract and expand knowledge from training data and/or experience values (historical data) to solve an existing problem better than before [42].

In the semiconductor industry, discrete event simulation models and machine-learning methods are being used to develop self-learning algorithms that control and monitor production processes.

This approach is primarily concerned with the development of decision and planning algorithms addressing only temporally forward decision-making problems, see [43][44][45][46][47]. For the investigation of temporally backward decision and planning problems in a sense of scheduling and sequence planning, little research has been conducted so far. A need for research concerning ordering concrete production orders emerges for contract manufacturing within the semiconductor industry, where the development in last decade has been above all regarding an intensification of global enterprise and continuing digitalization. These changes have led to an increasing demand for semiconductors; therefore, challenges arise for the industry. The signs point to growth; therefore, it is necessary for companies in the value chain to adjust their research and development capacities, production facilities and material purchasing to this development, see [48].

The authors intend to address the difficulties surrounding the adherence to promised delivery dates and other performance indicators by developing a methodical approach for generating a scheduling by backward simulation to a target-oriented data generation and evaluation based on an approach called data farming. As in previous studies [2][3], in contrast to the known research, stochastic influences will be considered to obtain more robust schedules.

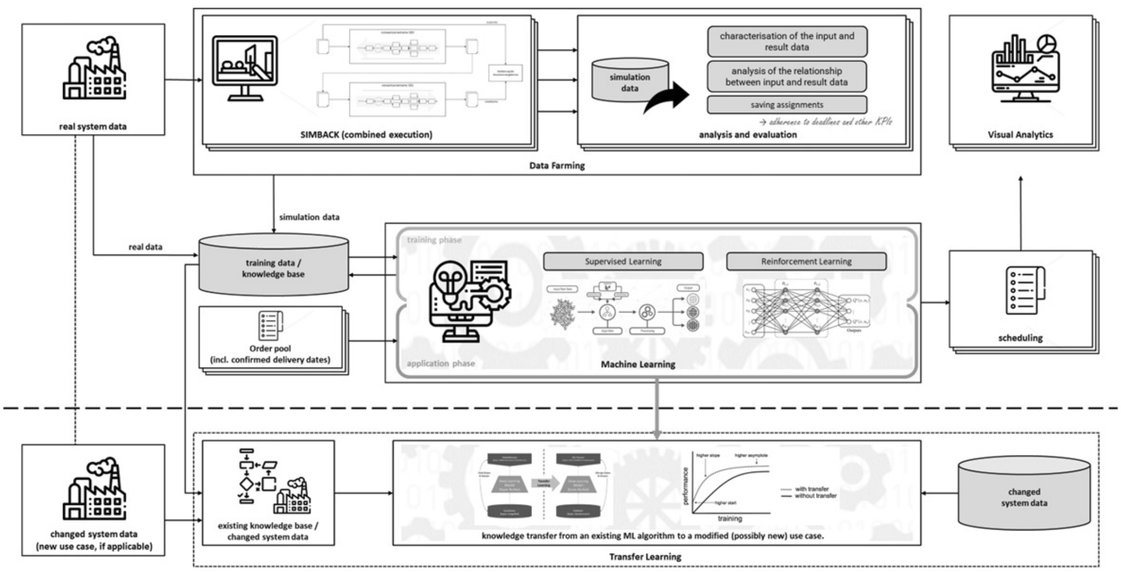

Figure 4: Solution approach.

They intend to use their resulting set of data as part of a training phase for machine learning methods, which will subsequently provide a powerful tool for scheduling and sequencing decisions in semiconductor manufacturing. This will ensure immediate applicability of the developed solution approach for decision makers and minimize substantial amounts of time and resources tied up in methods. Figure 4 illustrates the (envisioned) solution approach described here.

This results in various sub-objectives, which will be explained in the following:

4.1 Model Development and Validation

The developed method will be evaluated on various realistic use cases, including a model of a semiconductor industry. Specifically, it is planned to select at least one realistic system for evaluating the method's ability to emulate dynamic aspects of semiconductor manufacturing – for example, stochastic processing, changeover, waiting and transport times, control, and priority control procedures (also in the sense of characteristic re-entry cycles) or time or capacity constraints in queues or along several production stages. For example, this could be one of the Semiconductor Manufacturing Testbeds (SMT2020), see [49].

4.2 Data Generation and Analysis

A comprehensive mapping of the impact space corresponding to the system under consideration is required to generate sufficient data for the method of data farming and the combined execution of a simulation model by means of forward and backward simulation described in the previous section. This raises a variety of issues with respect to the scope and relevance of individual system, input, and result data for further use.

First, it has to be conceptually investigated which system data are of importance for the later development and implementation of a decision support based on machine learning in the mentioned problem space. This can be followed by a characterization of relationships between input and result data. Finally, the storage of mappings with respect to a statement regarding the adherence to promised delivery dates and further selected performance metrics is to be performed.

As described in the previous paragraph, concrete parameter configurations using simulation models and the amount of data generated by data farming address the challenge in production planning and control to be able to fall back on a comprehensive data stock and a sufficient quality of the same.

Accordingly, an extensive experimental design is necessary for each model to increase the amount of data efficiently and effectively and furthermore the information concerning the system under consideration according to its complexity and dimensionality. In view of this, suitable methods from statistical experimental design must be reviewed and selected and adapted for application in this work.

4.3 Technical Implementation

The objective of this sub-objective is to develop and implement a decision support system based on machine learning for operational production planning. To achieve this objective, the sub-objective first deals with the technical implementation of data generation in the context of a targeted data generation by the method of data farming and simultaneously focuses on data management as well as analysis and evaluation of resulting data. For this purpose, suitable simulation tools for combined execution of simulation model and connecting experiment design must be selected in advance. Following on from this, suitable procedures such as extensive data analysis and evaluation and machine learning must also be researched, adapted, and embedded in uniform framework.

The prototypical implementation of the machine learning based decision support for a use case from the semiconductor industry shall test different methods of ma-chine learning (especially methods of supervised and reinforcement learning) regarding the business benefit and prove the feasibility in principle of the elaborated concept.

4.4 Transfer Learning

This sub-objective addresses the difficulty 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 change significantly and/or similar use cases are to be considered. The necessity of model adaptation as well as new model validation, linking data generation by the method of data farming and data analysis and the resulting time and resource requirements again highlight a considerable need for research.

Transfer learning as a method of deep learning deals with approaches based on so-called convolutional neural networks (CNN) to use the model trained on one use case as input for another (related) use case. Transfer learning can thus result in a reduction of the required amount of data (training data or experience) and the time needed for the training phase of machine learning methods, or an increase in the predictive performance and faster convergence of the model, see [50][51][52][53].

This sub-objective tests the method of transfer learning in the context of the concept elaborated and a modification of the considered use case from the semiconductor industry. By successfully implementing the method, possibilities arise to prove not only that it is feasible, but also that it has economic benefit compared to conventional production planning and scheduling mechanisms. Accordingly, once prediction or planning models have been generated, they can be adapted to related applications by using corresponding data sets.

5 Conclusion

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 [54]. 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 [3][11]. The purpose of this paper was to provide a systematic literature review on applications of backward decision and planning approaches in production scenarios.

The present work demonstrates that backward decision and planning approaches already are of high importance within production scenarios. There are differences between the industries; semiconductor production is often mentioned in connection with the method of backward simulation; accordingly, some application studies can be found in this industry. However, backward scheduling and backward simulation methods can be time-consuming and resource-intensive depending on the complexity and dimension of decision making and planning problems. Accordingly, the authors have identified a need for research in this area. In addition, cur-rent methodological approaches to generate scheduling by backward simulation remain largely unchanged so far (in terms of further optimization). Thus, potentials for targeted data generation and evaluation as well as application of resulting findings for optimization remain largely unexplored at present.

The proposed solution approach is intended to help exploit the findings highlighted in the systematic literature review and to address existing challenges related to the implementation of backward decision and planning approaches.

Furthermore, the proposed solution approach is intended to further develop the backward simulation method towards a targeted data generation and analysis based on the data farming approach. The use of the resulting set of data as part of the training phase of machine learning methods and thus the provision of a powerful tool (application phase) as an operational decision support for scheduling and sequencing in the semiconductor industry shall subsequently ensure the applicability of the developed solution approach for immediate decision makers and minimize a considerable time and resource requirement linked to the methods.

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