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Predictive-Reactive Scheduling to Increase Robustness of Production Systems

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***Abstract*—In order to enhance the robustness and flexibility of production systems and improve their responsiveness to unforeseen events, it is essential to devise appropriate strategies. This paper aims to develop and evaluate a predictive-reactive scheduling method to increase the robustness of production planning and control. As disruptions can often be anticipated, but not always prevented, a scheduling method that combines predictive planning and reactive control reduces the impact of such occurrences on the production system. In order to achieve this, a real-world use case is introduced, and the relevant disruptions are identified. To address the predictive aspect of the methodology, an allocation problem and subsequently a sequencing problem are first solved using heuristics and mathematical optimization in order to schedule the jobs. Reactive scheduling strategies are then developed and implemented into a discrete event simulation model for the purpose of evaluating the improvement of the results. The results demonstrate a significant enhancement in production planning, as evidenced by more balanced processing times and a sufficient buffer for rescheduling. Therefore, this method enables the generation of a robust and cost-minimized production plan. By implementing the rescheduling strategy for production control, the impact of disruptions are minimized, as evidenced by the obtained key figures which serve as a robustness indicator.**

***Index Terms*—Robustness, Production Disruption, Simulation, Automated Production Planning and Control, Advanced Manufacturing**

I. Introduction

Volatile market conditions, unpredictable fluctuations in demand, raw material and energy prices are just a few examples of possible challenges companies must navigate in today's rapidly changing and globalizing world. Furthermore, the modern production landscape faces a multitude of production disruptions which must be overcome in order to succeed [1]. Disruptions can occur in any context and have a variety of effects. Therefore, it is important for every area of a company to be aware of them, plan for them in advance, and react to them quickly when they occur. It is essential to consider that disruptions can occur both internally, such as the breakdown of a production machine, and externally, such as supply bottlenecks due to political or economic crises in other countries [2]. These disruptions can have a significant impact on the company and production, affecting the achievement of its goals [3].

The challenges faced by production companies are numerous, complex, and interdependent. To succeed, companies must not only be highly flexible but also able to make their production systems robust and adaptive [4]. In this context, it is increasingly important to develop new strategies that enhance the robustness of production processes and systems. This is because they form the foundation for coping with uncertainties and achieving sustainable competitiveness. The objective of this paper is to develop a method that enhances the robustness of production systems in the areas of production planning and control. This will contribute to the sustainable success of a company. The predictive-reactive scheduling method comprises two parts.

Firstly, disruptions should be anticipated and included in the planning at an early stage. Therefore, the aim of predictive planning is to generate a robust and feasible production schedule. The term 'predictive' refers to the fact that planning is based on predictions and forecasts. This can be achieved by analyzing historical data, using models, algorithms, or expert knowledge. Predictive scheduling is a planning method that optimizes schedules and resources by taking possible future events, conditions, and uncertainties into account. This approach is especially valuable in dynamic and stochastic environments where factors such as machine breakdowns, quality issues, or raw material delays can impact the production [5].

Secondly, disruptions should be reacted to as their occurrence cannot be prevented in many cases. The objective is to minimize the effects of disruptions and their impact on the performance of the production system [6]. Reactive scheduling or rescheduling refers to the process of adjusting and updating a planned schedule by changing the sequence or planned times due to an imminent or already occurred deviation from the planned values. This is typically caused by unexpected events, such as disruptions [7]. Therefore, the plan is executed in a simulation model and adapted in response to changing environmental conditions. The knowledge acquired is then promptly applied to the real-world production system. Reactive scheduling is particularly relevant in the area of production control. For this reason, constant monitoring of production processes and data updates are necessary [8].

II. Use Case

This paper presents a use case that was developed in collaboration with a multinational manufacturing company located in Bavaria. The production process is large-scale and involves prefabrication, final assembly using six parallel assembly lines, and subsequent packaging processes, storage, or direct dispatch.

The assembly lines are identical in their basic structure and consist of the same number of processing stations. Each order passes through each processing station of a line with a constant cycle time each for a continuous material flow. Because it is spatially and temporally bound, the production is called continuous flow production [9]. In the basic structure a parallel flow shop scheduling problem (PFSP) has to be solved, but the assembly activities vary depending on the assembly line. Therefore, not all orders can be produced on every line, as some features can only be assembled on specific lines. Consequently, any order that includes such features must be scheduled on the corresponding line.

The number of employees required varies from order to order, as each order passes through each processing station but is not processed at every station. At the start of each shift, the products with the most features are processed first, while the less complex variants are assembled towards the end of the shift. As a result, the number of employees required is highest at the beginning of a shift and decreases as the shift progresses. The work is carried out in two shifts, over a five-day week.

Production planning generates a fixed plan for the next ten days. If this plan is interrupted by a disruption, the production planner will manually decide how best to deal with the situation and resolve it.

This process requires a great deal of experience and decision-making, but subjective evaluations should be excluded. Different planners may arrive at different results due to the complexity of the decision-making process [4]. Therefore, a holistic approach for the predictive production planning and the reactive production control in the event of a disruption is developed. This concept will serve as the basis for the function of a simulation model that can independently recognize, categorize, and predict faults and deal with their effects, so that a planner can use it as a supporting tool for his decisions or to compare different plans and solutions [10].

III. State of the art

Various approaches to the predictive-reactive scheduling method exist in the literature. However, these approaches differ based on the application situation, production type, or implementation structure. This overview briefly presents selected approaches with similar framework conditions or methods fitting to the use case of this paper, which form the basis for the self-developed procedure.

The solution of an identical parallel machines flow shop problem is addressed by Duenas and Petrovic [11], Mahajan [12], Tighazoui et al. [13] and Yin et al. [14]. This approach can be applied to the present case of identical parallel assembly lines. However, the complexity of this use case is significantly increased due to the constraint that each order contains information on which lines it may be produced. Consequently, a simple transfer of the previous approaches is not possible.

In addition, there are various approaches to the optimization goal. The most common optimization goal is to minimize makespan. Other sub-goals are often pursued and combined. Duenas and Petrovic [11], Li et al. [15], Mahajan [12], Tang et al. [16], and Wu et al. [17] all pursue the minimization of makespan, and thus it is also used as one of the optimization goals for the present use case.

Even the considered disruptions differ in the various papers. As an overview, Vieira et al. [6] identified the most common types of disruptions that occur in production. These include machine failure, urgent job arrival, job cancellation, due date change, delay in the arrival or shortage of materials, change in job priority, rework or quality problems, over- or underestimation of process time or employee absence.

Numerous approaches exist in the literature for solving complex planning problems through the use of predictive-reactive scheduling. None of the approaches in the literature can be directly adopted to solve the problem of this work in a way that is suitable for the use case at hand. These approaches mostly focus on either the economic objectives i.e., the minimization of makespan or concentrate on developing an indicator for robustness. The innovation of this approach lies in its combination of these two elements implemented into a single objective function which aims to create a schedule that is simultaneously cost-minimized and robust. The method is developed for a PFSP with an additional constraint to special line restrictions.

IV. Predictive Scheduling

Due to the restriction that each order may only be produced on specific lines, the total orders are distributed as evenly as possible across the various assembly lines using a heuristic. The greedy heuristic is employed for this purpose to solve the allocation problem. Once the orders have been scheduled in a manner that minimizes the discrepancy in processing times across the lines, it becomes evident that the total processing times (TPT) of the various assembly lines may still differ. If the number of orders that are allowed to be produced on one assembly line during the specified planning period is less that of the other lines, the resulting TPT will be lower, regardless of the approach employed to address the allocation issue. However, the differences in the TPT can be utilized as a time window for reactive scheduling at a later stage and are therefore advantageous as they contribute to robustness in the event of a disruption.

The subsequent stage in predictive scheduling is to resolve a sequencing problem. Once the orders have been allocated to the individual lines, they should be scheduled in a cost-minimizing and simultaneously robust sequence. Given the multiplicity of company objectives, such as on-time delivery or set-up costs, some of which are in conflict with each other, this sequencing problem is not straightforward to solve.

Therefore, mathematical optimization is employed to define a basic model that can be utilized to schedule orders in a robust and cost-minimized way. To this end, relevant cost factors are initially defined, which, in the context of the present use case, encompass demand costs d_{i}, setup costs s_{i}, worker costs w_{i}, and material costs m_{i}. For each cost factor, a weighting factor wf is introduced to later adapt the optimization to different use cases reflecting individual preferences. The total costs of a production plan cpp_{i} are therefore calculated as the sum of the aforementioned cost factors, as presented in (1). Optimization is carried out as a minimization of the total costs of the resulting production plan from the sequence of scheduled orders.

$$cpp_{\text{i}} = wf_{\text{d}} * d_{\text{i}} + wf_{\text{s}} * s_{\text{i}} + wf_{\text{w}} * w_{\text{i}} + wf_{\text{m}} * m_{\text{i}} \quad (1)$$

The demand costs d_{i} are calculated as the absolute value of the difference between an already scheduled order j and its possible successor $j+1$, totaled over all orders J, as presented in (2). Here, the difference between the order and the possible subsequent order is calculated. In accordance with the requirement to minimize the cpp_{i}, the order for which the difference and the resulting demand costs d_{i} are the lowest is then selected from the orders not yet scheduled. Therefore, in each iteration, the order with the smallest cost difference in relation to its already scheduled predecessor is scheduled.

$$d_{\text{i}} = \sum_{j=1}^{J-1} |d_{\text{j}} - d_{\text{j+1}}| \quad (2)$$

Following the scheduling of each order, the sum of all differences is then calculated. This total extends from order $j = 1$ to order $J - 1$, ensuring that the difference is calculated for all orders included in the schedule. As it is also possible for negative terms to arise due to the specified data and the type of calculation, the absolute value is calculated in each case. By calculating the absolute values, negative terms are considered in the same way as positive terms. This enables the calculation of the demand costs across all orders, which subsequently serve as one cost factor in the objective function.

The remaining cost factors are calculated in accordance with the aforementioned principle by the equations (3) for the setup costs, (4) for the worker costs and (5) for the material costs.

$$s_{\text{i}} = \sum_{j=1}^{J-1} |s_{\text{j}} - s_{\text{j+1}}| \quad (3)$$

$$w_{\text{i}} = \sum_{j=1}^{J-1} |w_{\text{j}} - w_{\text{j+1}}| \quad (4)$$

$$m_{\text{i}} = \sum_{j=1}^{J-1} |m_{\text{j}} - m_{\text{j+1}}| \quad (5)$$

The manner in which the cost factors are calculated depends on the specific use case. In the use case of this paper, the deviations from the scheduled delivery date are incorporated into the demand costs. For the setup costs the given product type is used and to calculate the worker costs, the required number of workers of each individual order is used.

To ensure that the cost factors are included in the objective function equally, they must be normalized to the value range of $[0, 1]$. To express individual preferences of the cost factors, the weighting factors wf are used.

The advantage of this definition of the cost model is its simplicity and flexibility. Depending on the specific circumstances, all factors influencing the resulting costs of the schedule can be defined on a problem-specific basis and then assigned to the respective cost factor. Therefore, the model can be extended and adapted to diverse scenarios very easy. This model enables the generation of a cost-minimized and robust production plan for the predictive scheduling.

V. Reactive Scheduling

In order to complete the predictive-reactive scheduling method, a concept for the step of reactive scheduling or rescheduling in the area of production control is developed in this section. The objective is to minimize the effects of disruptions by having a solution ready in the event of a disruption. The aim is not necessarily to eliminate the disruption as quickly as possible, as this is often beyond control. Instead, the focus is on finding alternative courses of action that enable the production system to maintain its functionality despite the disruption.

Reactive scheduling occurs as a sequence of action steps, which can be modeled as a flowchart using the event-driven process chain (EPC) notation. A flowchart is a graphical representation of nodes and edges that abstractly represents the theoretical sequence of a process, including entry options, subprocesses, and work steps. The advantages of a flowchart are clarity, logical representation, and simple expandability [18].

As different disruptions are crucial in every production and in every use case, the initial step is to identify the relevant disruptions. This can be accomplished through the use of historical data and by conducting interviews with experienced employees. In this particular use case, the three most significant factors are machine breakdown, employee absence, and material shortage.

Once the relevant disruptions have been identified, an action strategy is defined for each type of disruption. These strategies are executed as soon as the disruption occurs. The action strategies serve as the foundation for the simulation model, which represents the production as a digital twin. During the simulation process, the specific type of disruption is automatically identified, and the corresponding action strategy is executed as a consequence.

The output of the simulation model is the updated production plan in response to the disruption that has occurred. Due to the simulation model's reference to reality, the rescheduled plan can be implemented directly or used as decision support for the production planner. The aim is to use simulation to anticipate disruptions on the one hand and to enable a rapid response in the event of a disruption on the other.

To illustrate the concept in concrete terms, Fig. 1 depicts the sequence of a process chain in the event of a machine breakdown. Once the disruption has occurred, it is first identified and classified. If the disruption is identified as a machine breakdown, the subsequent steps in the process chain are processed automatically. As this is a continuous flow production process, the entire production line comes to a standstill. The parts that have already passed through the faulty machine are still fully produced, but no further parts can pass through the faulty machine. Consequently, the line will come to a standstill after a certain time.

As there may be orders scheduled on this line that have an urgent delivery date and therefore need to be produced promptly, the first step is to check whether the next order in the production plan for this line can be scheduled on another line. However, certain additional constraints must be taken into account. Primarily, the information in the order data must be checked to see on which lines the order can be produced. This information has already been used in the solution to the assignment problem to initially assign the orders to the lines. If the order cannot be produced on any other line due to its specification, it is skipped and the next order in the production plan is iteratively checked for rescheduling.

In the event that an order is identified for which a transfer to an alternative line is permissible, the system will check whether the TPT of the target line is less than that of the current line. In the phase of predictive planning, it was determined that the production lines have disparate TPTs. This control step is intended to ensure that no rescheduling occurs that would additionally extend a production plan that has already been extended. Consequently, rescheduling to a line whose production plan has a shorter TPT also addresses the issue of imbalanced processing times among the respective lines, as a result of predictive scheduling. In the event that the TPT of the target line is longer than that of the previous line, the order in question is not rescheduled. Instead, it is skipped, and the next order is checked.

If scheduling is still possible due to the TPT, scheduling is carried out according to a selected rule, for example, the earliest due date rule, in the production plan of the target line. This ensures that the delivery date of this order can be met as far as possible despite the rescheduling and that it is not added as the last element in the new plan due to its late scheduling. This is the primary reactive step for this type of disruption. The system then determines whether the disruption has been rectified and, if so, whether the line can resume production. If the fault has not been rectified, the system returns to the start of the process chain and the next order in the original schedule is checked for rescheduling. If the disruption has been rectified, production can continue as normal. The reactive scheduling process has been successfully completed, resulting in a reduction of the disruption's effects and an enhancement of the production system's robustness.

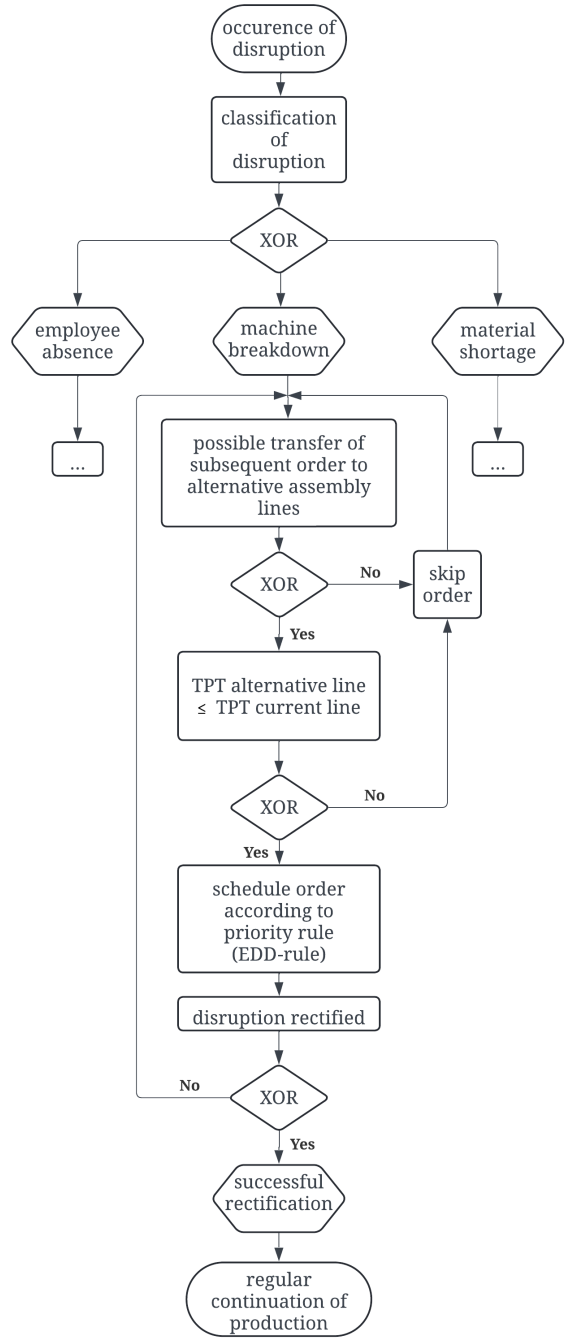

Fig. 1. Flowchart depiction of the logical steps for reactive scheduling in the occurrence of a disruption by using the event-driven process chain notation. The process chains for employee absence and material shortages are not described in detail for reasons of clarity.

The process chains for employee absence and material shortage were developed according to the same principle, but are not shown for reasons of clarity. Should further disruptions arise in the respective use case, these can be modeled analogously. This elaboration and presentation serves either as a guide to action for the responsible decision-maker or as a basis for implementation in a simulation model.

VI. Evaluation

In order to demonstrate the effectiveness of the method developed here and its potential to enhance the robustness of production systems, it is essential to implement it. Due to its mathematical nature, the predictive scheduling can be easily implemented in a programming language such as Python. In predictive scheduling, the original data set of the use case is used, and Python programming is employed to first solve the assignment problem and then the sequence problem in accordance with the developed theoretical concept.

The previous scheduling of orders is done according to the first specification in the data set, on which line this order can be produced, without checking whether another line would be suitable for this order and could possibly lead to better results. Table 1 shows the results of predictive scheduling. After solving the assignment problem according to the greedy heuristic, the results for the TPT, expressed in hours (h), of the individual lines are already significantly more balanced than when they are assigned according to the first line priority from the original data set.

The final two columns illustrate the results of the sequence problem. The values presented are the result of the objective function and are therefore expressed in cost units (cu), as these represent the costs associated with the respective production plan of each assembly line. A scheduling according to the priority indication and then using the earliest due date rule produces significantly higher objective function values than a sequence that employs iterative scheduling with mathematical optimization.

The results demonstrate a significant enhancement in production planning. The more balanced TPTs ensure a more even utilization of all assembly lines, while simultaneously providing a sufficient buffer for rescheduling. This method of predictive scheduling enables the generation of a robust and cost-minimized production plan. Robustness in general, refers to the ability of a system and its processes to maintain its functionality despite the occurrence of disruptions. As there is no concrete value to measure robustness, similar to the approaches from the literature, the difference between the planned and actual values is calculated [19]. The classical efficiency criteria are employed to measure the performance of the developed method, including the makespan, the number of delayed orders according to their delivery date, and the maximum delay.

TABLE I.
RESULTS OF PREDICTIVE SCHEDULING. THE INITIAL COLUMN COMPRISES THE SIX ASSEMBLY LINES. THE SECOND COLUMN PRESENTS THE RESULTS FOR TOTAL PROCESSING TIME (TPT) ACCORDING TO THE PRIORITY INDICATION IN HOURS, WHEREAS THE THIRD COLUMN PRESENTS THE TPT WITH THE GREEDY HEURISTIC. THE FOURTH COLUMN PRESENTS THE RESULTS FOR THE COST OF THE FINAL PRODUCTION PLAN (CPP) IN COST UNITS ACCORDING TO PRIORITY INDICATION, WHEREAS THE FIFTH COLUMN PRESENTS THE CPP ACCORDING TO THE COST FUNCTION.

a. l.	***TPT - prio. ind. [h]***	***TPT - greedy [h]***	***CPP - prio. ind. [cu]***	***CPP - cost func. [cu]***
one	204	131	54.1	21.7
two	151	161	63.6	25.4
three	170	162	55.2	19.4
four	377	203	52.0	13.6
five	132	204	48.0	14.5
six	31	204	69.3	29.7

The final assembly of the use case was recreated in a simulation model in the Plant Simulation software. In order to apply reactive scheduling, the production plan was first executed without disruptions to obtain the planned values. However, as this does not correspond to reality, machine disruptions were incorporated and the results of the defined efficiency criteria were measured again. As expected and illustrated in Fig. 2, these are significantly worse, as production is delayed by the disruptions. The simulation was then run again using the reactive scheduling strategy for machine breakdowns.

The structure of the three diagrams in Fig. 2 is identical. The left bar symbolizes the measurement result of the plan model, without any disturbances. The middle bar represents the measurement result of the disruption model with a total machine downtime of almost 20 hours, which can occur across the different lines and the entire simulation period. The third bar represents the measurement result of the solution model using the reactive scheduling strategy. As illustrated in Figure 2, although the original plan values cannot be attained, a notable improvement in the results can be achieved in comparison to the model without a reactive scheduling strategy.

By implementing the rescheduling strategy for production control, the effects of the disruptions that occur are minimized and, as a result, the deviations in the measured values are lower than in the simulation run without a reactive scheduling strategy. This reduction in the deviation in the measured values is used as a robustness indicator in order to be able to make a statement regarding the increase in the robustness of the production system. Therefore, the evaluation indicates the potential of the developed method and its contribution to enhance the robustness of a production system against disruptions.

VII. Conclusion and Future Work

The predictive scheduling with the combination of heuristics and mathematical optimization for production planning and the reactive scheduling with simulation for production control lead to a promising method to increase the robustness of production systems.

Future work will focus on expanding the simulation model. The more disruption types the simulation model recognizes and corresponding action strategies it comprises, the better the applicability and the greater the closeness to reality. A further research topic could be to ascertain the methodology of the simulation model to identify and categorize different disruption types.

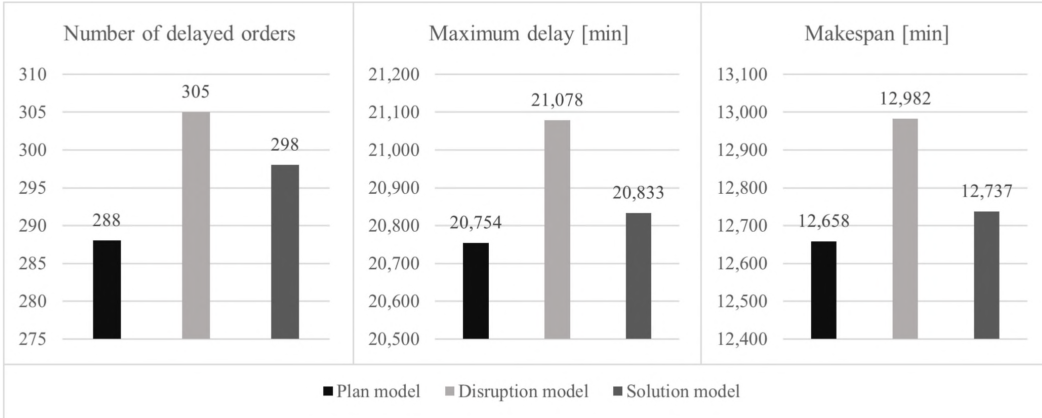

Fig. 2. Evaluation of the obtained key figures including the number of delayed orders, the maximum delay of an order, and the makespan. The key figures were measured after running the simulation model in an ideal world, then after implementing the machine breakdowns, and finally after running the simulation model with the rescheduling strategy, which improved the results despite the disruptions.

In this paper, the question of how a method of predictive-reactive scheduling can increase the robustness of a production system is answered. The theoretical concept shows the transparency, flexibility, and expandability of the method. The implementation proves the potential of the developed concept by using the data of the real-world use case.

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