Increase of Robustness on Pre-optimized Production Plans Through Simulation-based Analysis and Evaluation

Christoph Laroque
Heinz Nixdorf Institute
University of Paderborn
Paderborn, Germany
laro@hni.uni-paderborn.de

Robin Delius
Heinz Nixdorf Institute
University of Paderborn
Paderborn, Germany
robin.delius@hni.upb.de

Jan-Hendrik Fischer
University of Paderborn
Paderborn, Germany
jhfischer@gmail.com

Dennis Horstkämper
University of Paderborn
Paderborn, Germany
dhorstkemper@gmail.com

***Abstract*—We propose the use of the material flow simulation to evaluate the robustness of a production plan, which was created and optimized with no respect to unforeseen derivations. Since the necessary probabilities for machine failures and similar operational events on the floor can easily be integrated in the simulation model, in order to analyze, how initial plan performs in these situations. The influence of unforeseen events in daily production cannot be modeled within mathematical optimization without consuming large amounts of computation time. We show a possible way to use simulation to evaluate and enhance a production plan. We illustrate the developed process using a real-world use-case of medium complexity and can show, that simulation is able to evaluate the robustness of a given pro-optimizes production plan.**

Keywords: material flow simulation; robustness; production planning; mathematical optimization

I. MOTIVATION

Even after overcoming the global economic crisis tremendous requirements exist within the daily operation of a production facility and its supply chain. Fluctuating demands are leading to less adaequate forecast data and the need to lower capital commitment is leading to the necessarily of designing robust production planning models [1],[5],[6]. It is always the intention to be able to serve all demands in due time while causing minimal costs.

Several uncertainties exist within the production planning process. On the one hand, many unforeseen events can take place: machine failures, missing materials, changed sales demands or ill employees are only a small subset of possible examples. On the other hand, it is simply impossible to include all factors that might occur into the planning process in the first place. Therefore, planning methods are always based on different models of a production structure, which are an abstraction of reality themselves. It is the responsibility of the production planner to decide which factors he wants to take into the account when creating his models. He always has to find a compromise between the detail level of the model (and therefore its significance) and the solvability of the optimization problem which is created on its basis. The lot sizing and scheduling problems that are used within production planning are usually already np-complete even in their simplest form [15]. Therefore, one cannot guarantee to be able to find acceptable solutions in a timely manner while using modern operation research techniques. Thus, we have to find a solution to include the aforementioned uncertainties within the production planning process without limiting its solvability significantly. We connect a mathematical optimization model with a down streamed material flow simulation for this purpose. While we always assume optimal conditions within the mathematical optimization model, we are including the uncertainties in the simulation process. This allows us to analyze whether a production plan is able to perform well creating an acceptable monetary solution under these changed conditions or not. We create a sensible scheduling using rule-based machine controls within the simulation. In addition, we are able to create automatic or manual modifications of the plan and can evaluate these as well using additional simulations. It is easily possible to develop a more robust production plan with these tools.

Simulations usually are used to verify the solutions of an optimization problem. However, the aim of our research is to replace parts of the optimization process with simulation methods to receive solutions with an acceptable quality on a timely matter. First, we solve a mathematical optimization problem with standard solver software like IBM ILOG CPLEX [17]. Figure 1 shows the general optimization and simulation process.

After regarding the necessary State-of-the-Art in Section II, we describe the production model and the corresponding optimization models in Section III. It is possible to include uncertainties in the planning phase within the mathematical optimization process. We briefly discuss these methods in Section IV. To generate a more robust production plan based upon a given near optimal plan we propose a procedure which generates and evaluates a number of scenarios with the help of off-line simulations to create a new plan. We explain the transfer of the optimization solutions into the simulation process in Section V. To cover a broad spectrum of stochastically possible scenarios; several replications of the stochastic simulation based upon the production structure are performed. This way we are able to cover a wide field of possible scenarios for machine failures and other events.

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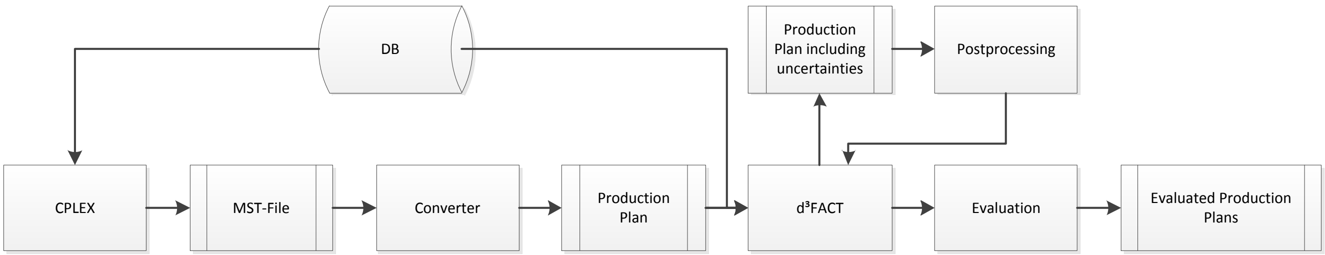

Figure 1: General Structure of presented concept

The production schedules are logged and afterwards evaluated on the base of costs and robustness. A rule-based machine control is used, to try to reduce possible production losses when intermediate products were not assembled in due time. An additional post-processing can be used to maintain further robustness increasing actions. The effect of these actions can be evaluated using further simulations. We present these processes in Section VI. We finally evaluate the outcome of our work using a case study. Additionally, we give a conclusion (Section VII) and an outlook towards further possibilities and improvements for this approach.

II. STATE OF THE ART

An ideal environment, free from external influences as used in most scheduling approaches is normally not given when processing a production plan. Production settings are subject to influences from human and machine failures. Additional resources and materials might not be available in due time and new demands often have to be taken into account on a short-term notice. A comprehensive overview about the execution of production plans under uncertainties is given by Aytug et al. [2]. They develop a taxonomy to classify uncertainties, to be able to classify numerous facets of disturbances within operational procedures. These are characterized by four dimensions:

- Cause (e.g., machine failure)
- Context (e.g., materials have not been delivered)
- Effect (postponed starting times)
- Inclusion (reaction upon interruptions, either predictive or reactive) [2]

These aspects illustrate uncertainties within the production planning process. The effect of disturbances and interruptions depends upon the robustness of the scheduling. Schneeweiß [15] gives a basic definition of a robust plan: A plan is robust, when it is insensitive against random environmental influences. Based on this expression one cannot find any quantitative measurements however. Scholl [16] expanded upon this definition. We mainly consider two of the criteria he developed: If a plan is always valid, no matter what environmental influences may effect it, it is called “total validity robust”. One cannot assume to reach this level in practical applications though. Therefore, one is able to analyze the validity robustness in greater detail instead of using a binary value. One could analyze the amount of broken model restrictions or also weight them after their importance. Within production planning, it is especially important to stay within the machine capacities and to adhere to given deadlines. We can consider the objective function of the planning models as the result of a production planning process. Therefore, one can define the criteria of result robustness: A plan is result robust, when its result only differs in a minimal way from the original plan when random environmental influences occur. However, a good result for one scenario may often lead towards a bad result for another scenario. Additionally result and validity robustness conflict with each other: a higher validity often causes higher costs.

Simulations can fulfill two roles within robust production planning: on the one hand, one can use a simulation to simply assess and evaluate the robustness of a plan to confirm the validity of other approaches to create robust production plans. On the other hand they can be used to create robust production plans to include uncertainties.

Aytug et. al [2] identified three main approaches in prior literature to create robust production plans: completely reactive procedures, robust scheduling and predictive-reactive scheduling. Completely reactive procedures only take action when disturbances in the production process already occurred. They sort and filter all jobs given to the current machine and continue with the job that appears to be the best based on this evaluation.

Robust scheduling approaches instead are creating plans, which minimize the effects of disturbances within the production procedure. Therefore, a plan for a worst-case scenario is created. Such a plan aims to be able to be processed in many different scenarios without greater difficulties. Both of these approaches share the issue, that available capacities will not be used to their full extend.

A large amount of research happens within the area of predictive-reactive scheduling. First, a plan for the whole planning horizon is created. This plan will be adapted later on. This can happen in a periodic fashion, on the occurrence of new events or in combination of both methods. In practice, these hybrid approaches are mostly used [12], [7].

Simulations are a standard tool to evaluate the robustness of production plans. This can be done based upon different target measures. Honkomp et al. [10] compare a basic deterministic simulation with multiple stochastic replications. To measure the robustness they use metrics that either compute the relation between the average objctive function of the stochastic simulations and the deterministic objective function or calculate the standard deviation of the stochastic simulations towards the best deterministic objective function. Apart from cost analysis, Pfeiffer et al. [13] also consider the plan efficiency and stability. This is also done in the overview about rescheduling approaches. Usually one obtains simple efficiency measurements (e.g., delays, backlogging amounts and production times). One can also evaluate these values visually [8]. Plan changes caused by stochastic events are processed to optimize the efficiency values. However, effects of changes within the scheduling are not taken into account within these approaches. Instead of optimizing the efficiency values one might also aim to create plans that only differ minimal from the original plan. A framework to evaluate different techniques to generate robust production plans has been developed by Rasconi et al. [14].

III. PRODUCTION MODEL

To receive meaningful results we base our work on a close to reality production model with a corresponding complexity. Leaned upon a company in the supply industry of average size the model contains 21 machines with a general production structure, meaning that converging, diverging and linear substructures appear. Some of the 44 products can be produced on several machines in a parallel matter. This may possibly lead to different production and setup times as well as costs. 11 products with external consumer demands exist in total. Based on this assumption, a high degree of freedom exists, when a concrete production plan shall be created. Figure 2 shows the overall machine plan and material flow of the production model.

Typically, two different optimization models are used to create a production plan. Initially we calculate the lot sizes using a Multilevel Capacitated Lotsizing Problems (MLCLSP) based upon macro periods. Subsequently one creates a plan based upon micro periods using a Discrete Lotsizing and Scheduling Problem (DLSP) to determine exact production timings. As a result, the order in which the machines process their corresponding lots is decided.

A. *Lotsizing*

To determine the production amounts for each given period we use a MLCLSP in this paper. The basic version of the MLCLSP, as described by Tempelmeier and Helber [9] develops a cost optimal multiperiod production plan based on given demands, production costs, setup costs, inventory costs and machine capacities. For this purpose the optimization problem tries to take advantage of possible synergy effects that occur when production lots for several demands are combined, creating less need for setup processes. In contrast, this might create capital commitment and inventory costs when products are created in an earlier period. Therefore, a compromise between these factors has to be found. The model considers machine capacities in particular. Each machine can only be operated for a limited amount of time per period, for example for one or several working shifts. This does force an inventory increase.

The MLCLSP is a model based on macro periods. Therefor it only determines which amounts of which products are produced on which machine in every given period. The model explicitly does not determine a lot scheduling. To reproduce dependencies between different products lead times are used. If a product needs another product from an earlier production level as an input, it has to be produced in an earlier period. A production of intermediate products is triggered whenever a final product is created. A bill of materials is used to determine the needed amounts.

The MLCLSP we are using contains several enhancements over the basic models used in most literature. Several additional constraints are used to comply with the complexity of real production planning. Additionally to the standard model, we allow backlogging for products that have a direct external demand. Products can be manufactured on several machines in a parallel matter. We include transport lots and the machine capacities are determined upon a flexible work shift model. The mathematical formulation of the used model is as follows:

Model MLCLSP:

Minimize O = $\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{t=1}^{T}(s_{kj} * \gamma_{ktj} + h_k * y_{kt} + p_{kt} * q_{ktj} + bo_{kt} * i_k + b_{jt} * pc_{jt})$

Under the Constraints:

$$y_{k,t-1} + q_{k,t-1} - \sum_{i \in N_k} a_{ki} * q_{it} - y_{kt} + bo_{k,t+1} - bo_{kt} = d_{kt} \quad \forall k \in K, \forall t \in T \quad (4.1.1)$$

$$\sum_{k \in K_j}(tb_{kj} * q_{kt} + tr_{kj} * \gamma_{ktj}) \leq b_{jt} \quad \forall j \in J, \forall t \in T \quad (4.1.2)$$

$$q_{kt} - M * \gamma_{kt} \leq 0 \quad \forall k \in K, \forall t \in T \quad (4.1.3)$$

$$q_{kt}, y_{kt}, c_{ktj} \geq 0 \quad \forall k \in K, \forall t \in T \quad (4.1.4)$$

$$y_{k0} = 0;\ y_{kT} = 0 \quad \forall k \in K \quad (4.1.5)$$

$$\gamma_{ktj} \leq avail_{kj} \quad \forall k \in K, \forall t \in T, \forall j \in J \quad (4.1.6)$$

$$\gamma_{ktj}, s_{jt}^0, s_{jt}^1. s_{jt}^2 \in 0,1 \quad \forall k \in K, \forall t \in T, \forall j \in J \quad (4.1.7)$$

$$q_{ktj} = c_{ktj} * cont_k \quad \forall k \in K, \forall t \in T, \forall j \in J \quad (4.1.8)$$

$$bo_{kt} \leq bomax_k \quad \forall k \in K, \forall t \in T \quad (4.1.9)$$

$$b_{jt} = 0 + s_{jt}^0 * 480 + s_{jt}^1 * 960 + s_{jt}^2 * 1440 \quad \forall j \in J, \forall t \in T \quad (4.1.10)$$

$$s_{jt}^0 + s_{jt}^1 + s_{jt}^2 = 1 \quad \forall j \in J, \forall t \in T \quad (4.1.11)$$

In the objective function the sum of setup-, stock-, production-, backlog and personal costs are minimized. The following constraints enforce the creation of a valid production plan which fulfills external demands in due time whenever possible.

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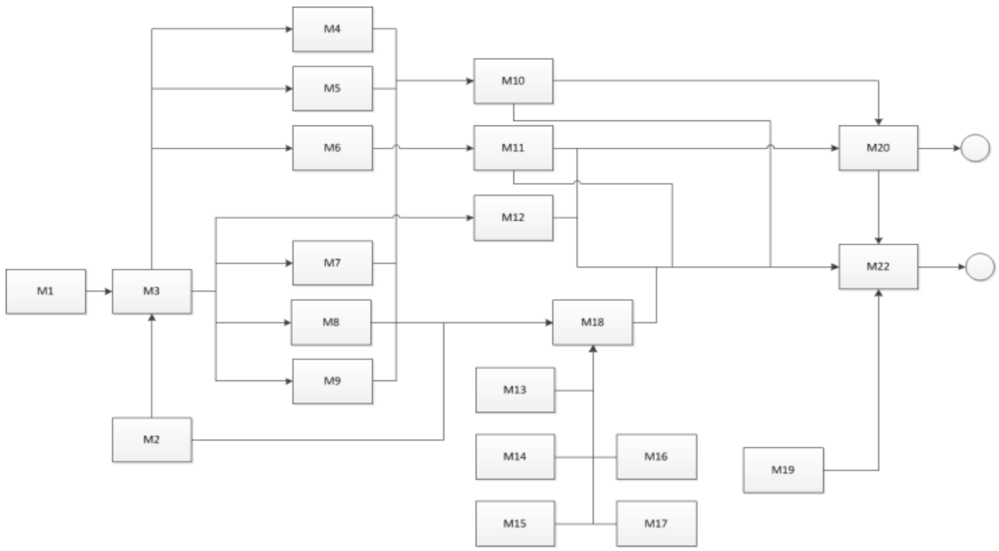

Figure 2: Machine Plan

Constraint 4.1.1. creates a balance between external demands on one side and production- stock and backlog amounts as well as secondary demands on the other side. To be sure that intermediate products are assembled before the final product is created, products must be created a day before the secondary demand takes place. Machine capacities are taken into account in constraint 4.1.2. It is only possible to perform a limited amount of production and setup activities within a single period. Using constraint 4.1.3. ensures that one can only produce a product on a machine when a machine is was set up for that product.

Additionally constraint 4.1.6. ensures that machines can only produce products that they can be set up for. Constraint 4.1.8 expresses that production lots always have to be a multiple of transport lots. Within constraint 4.1.9, maximum backlog amounts for each product are defined. This way we can ensure that demands for intermediate products cannot be backlogged. The constraint 4.1.10 and 4.1.11 determine the amount of working shifts used for a machine in a certain period. The other constraints are used to design meaningful bounds to the variables, for example, stock amounts always have to have a positive value.

Variables and constants meanings:

a_{ki}	Direct demand coefficient of products k and i
b_{jt}	Available capacity of resource j in period t
d_{kt}	Primary demand for product k in period t
pc_{jt}	Personal costs for resource j in period t
h_k	Stock expense ratio for product k
i_k	Penalty costs for backlogging of product k
J	Amount of Resources (j= 1,2,…,J)
K_j	Index set of operations performed by resource j
M	Big number
N_k	Index set of followers of product k
p_{kt}	production costs of product k in period t
q_{ktj}	Production amount of product k on resource j in period t
c_{ktj}	Amount of containers of product k processed by resource j in period t
$cont_k$	Container size/Transport lot size for product k
s_{kj}	Setup costs for product k on resource j
T	Length of planning horizon measured in periods (t=1,2,…,T)
tb_{kj}	Production time for product k on resource j
tr_{kj}	Setup time for product k on resource j
y_{kt}	Stock for product k at the end of period t
γ_{ktj}	Binary setup variable for product k on resource j in period t
bo_{kt}	Backlog variable for product k in period t
$bomax_k$	Maximal backlog amount for product k (always 0 for intermediate products)
$s_{jt}^0, s_{jt}^1, s_{jt}^2$	Binary variables used to calculate the amount of used working shifts

B. *Scheduling*

Using a DLSP one can assess a plan based upon micro periods to determine exact production timings. The solutions of the MLCLSP can be used as parameters for the DLSP. This way one can create a complete machine scheduling plan. A basic version of the DLSP can be found at Fleischmann [11]. The production amounts within a period that have been determined using the MLCLSP can be used as external demands for the DLSP. Periods within the DLSP are chosen as the smallest meaningful unit, for example the smallest common denominator of setup- and production times. The MLCLSP includes lead times; therefore, it is not needed to take dependencies between production levels into account. Hence, we can solve the DLSP for each machine individually. This means that the solution times are rather short. The problem complexity is appropriately low. We do however not include a DLSP within our work, as we use a rule-based machine control to create a scheduling plan within the simulation in an even shorter amount of time.

IV. FUZZY PARAMETERS IN THE MODEL CREATION

Fuzzy parameters and uncertain information can be reproduced using stochastic methods inside the model classes we described earlier. Ideally, we already know exact probabilities for possible events in advance. Where applicable we can use appropriate prognosis methods to estimate this probabilities. Otherwise, we can only use a normal or similar distribution.

The stochastic optimization tries to find a solution that is the best for all possible combinations of parameters. Finding a solution for these models already is an np-hard problem for sharp levels of information. Finding a solution for a stochastic problem is an extremely time consuming task. Fuzzy parameters might even lead to a state explosion, meaning that an exponentially rising amounts of possible parameter combinations exist. The overwhelming amount of combinations cannot be used to create a valid solution. This situation gets even more complicated, as we use a multiperiod, multilevel production structure. A problem in early periods or on a low level can lead to even more problems in later periods or levels. In many situations, one cannot find a solution that is applicable for all possible situations. Therefore, one cannot assume that that it is practical to include uncertainties in the planning process using stochastic optimization methods. Even when such a solution exists, it is unlikely that it can be found within a reasonable amount of time.

Most stochastic optimization approaches are based on three different methods. Multilevel stochastic models with compensation are based upon Dantzig [6]. Decisions on one level are made at an early point of time and fixed for all following levels. We consider a huge amount of possible events; therefore, we would have to model a corresponding amount of model levels. Stochastic programs with probabilistic constraints date back to Charles and Cooper [4]. Within these models, the breach of constraints is permitted for certain parameter combinations. One can only find proper solutions for this type of models when it is possible to transform the models into an equal deterministic model. Additionally, the expressive value of the model can be reduced due to the loosened constraints. Bellman [3] introduced stochastic dynamic programming. Based upon a decision tree a backward chaining is used to conclude the ideal choice at the decision situation. All this approaches share the issue that they can only be solved efficiently, if the amount of possible scenarios can be reduced to a certain amount. However, when looking at a real production problem many decisions are possible. Therefor we have to find different methods to include uncertainties within the production planning process.

V. INTERFACES TO THE OPTIMIZATION SOFTWARE

To be able to simulate the results of an optimization, the solution data has to be preprocessed in order to prepare the data for the simulation model. CPLEX can export a XML-based file-format, which contains the mathematical programming solution for all variables of the problem. The Converter module reads the file line by line, whereas each line represents a variable. We mainly need two decision variables to be able to simulate the plan: The production variable q_{ktj} determines the products that are produced on a certain machine in a given time period. Additional data like production- and setup times as well as costs can be read from the database based on this production lots. Because a work shift model has been included in the mathematical optimization, every machine can have a different capacity in each period. Therefore, we also have to take the variable b_{jt} into account, which describes these capacities. As we included lead times within the MLCLSP, all needed intermediate products should be available at the beginning of a new period. This means that there are no special requirements for the machine scheduling. We are able to schedule the lots in the same order as they appear within the exported XML file. The real scheduling and date safeguarding will be done within the simulation process. Based upon the given data we are able to calculate all needed information in a deterministic fashion. For example, we are able to calculate the stock or backlog amounts via a difference of production amounts, demands and secondary demands. Thus, we have all information needed to control the simulation procedure. These calculations are also needed to evaluate the simulation results. Therefore, it is a sensible approach to calculate these values for the original plan instead of importing every information from the mathematical model.

C. *Simulation*

The simulation model is implemented using the discrete event simulator d³FACT developed by our workgroup, Business Computing, esp. CIM. The extensible Java API provides a high-performance, petri-net-based material flow component [1].

The production plan information is first transferred towards the simulation logic. During the initialization of the simulation model, all machines are loading their fixed schedules for the complete planning period. It holds for each machine, which products in what amount have to be produced in each period. Furthermore, it holds the planned durations for the maintenance, production and setup processes. The lot release order is fixed and stays so, even in the case of blocked lots due, to late secondary demands. All released lots are stored in a FIFO-Queue, to be processed in their incoming order. At the beginning of each new period, all planned lots are enqueued and the production cycle starts. Prior to nearly any lot, a setup is intended for rigging the machine. If planned, a routine maintenance of the unit is performed after a given amount of work pieces.

If multiple products or machines demand the same intermediate product, a Fork is needed to control the material flow. It stores and routes the tokens as needed towards the point of consumption. The built-in buffer stores the tokens until a machine starts a job and signals its demand. The fork uses a FIFO-Queue to handle the incoming requests and to minimize the mean waiting time for supply. The machine uses a strict FIFO-Queue for lots to dispatch. In this naïve version, even a blocked lot with unfulfilled secondary demands waits until its demands are met. If all lots for a period are finished, the shift ends and the next jobs are dispatched in the next period.

Under certain circumstances, it is possible that in case of unmet secondary demands and fully loaded periods, lots are pushed into the following period. In this case, the moved lots are scheduled prior to the regular lots to dispatch the longer waiting jobs first. Because the planning methods calculates with one day lead-time it is easily possible that delayed lots are blocking further following demands.

D. Uncertainties in the production planning process

The production schedule execution is typically affected by unforeseen interruptions und disturbances. In the simulation model, maintenance, cycle, and setup times are considered stochastically influenced, due to their high influence on the overall flow shop production process and their deterministic usage in the production-planning model. Material shortages, which arise from supplier unreliableness, are not taken in account and all materials are assumed of as supplied in time.

The maintenance, cycle and setup times that are incorporated in the formulation of the production-planning problem, are forming the lower bound for the process execution and are modeled in the simulation.

The stochastic influences are modeled with two parameters. On the one, hand the likeliness of an increased process time and on the other hand the amount of the deviation. The probability that the planned process time varies, is modeled with a uniform distribution, whereas for the duration a normal distribution is used. Ideally, one is able to use historical data to determine the probabilities for each machine individually; however, this is not possible in a hypothetical model.

E. Rule-based machine control

To be able to improve the production plan within the simulation we are using a rule-based machine control. We are allowing a machine to change its own scheduling plan. As a day of lead-time is included in our planning process, this should not have a negative effect on later production levels. One possible rule that we also implemented appears, when a machine is unable to produce a lot because the secondary demands cannot be met. In this case, the machine logic tries to find other lots for this period, which do not need the missing intermediate products. When such a lot exists, it is processed first while the original planned lot will be processed later. This way, we are able to ensure an even utilization of the given machine capacities. Additionally we reduce the danger of possible backlog amounts. This way we increase the validity robustness of the production plan. Another possible decision rule concerns setup carryovers. If production lots of the same product exist in successive periods, it is sensible to change the scheduling in a way, which allows this product to be produced in the end of the first period and in the beginning of the second period. Therefore, the need to setup the machines for both production lots is not applicable anymore. If one introduces a setup, carryover into the mathematical optimization highly increased solution times may occur. The discussed rule-based mechanisms however only lead towards a small increase in processing time within the simulation process. Additional rules can always be applied in a model specific fashion.

F. Evaluation

The evaluation calculates performance figures for the validity and result robustness. For measuring the validity robustness, we compare the objective value of the simulated plans with the objective value of the original plan from the mathematical optimization. A comparison of single cost values is also possible, like evaluating the influence of capital commitment costs. A plan is considered validity robust, when it does not violate any of the optimization models restrictions. The model we use does allow backlogging however. Backlogging always incurs penalty costs, which also influence the result robustness. However, one cannot assess the influence of delivery dates that could not be met, as it might lead to the loss of a customer in the extreme cases. Therefore, it is sensible to protocol every appearance of backlog amounts.

Important information considers the machine load factors. It can happen that the planned or even the maximum capacity of a machine is not sufficient to produce all lots allocated to it. These events are protocolled and evaluated separately as well. This allows for the search of admissible alternatives.

G. Post-Processing

Within the post-processing component, we are able to use additional simulation external methods to generate an improved production plan with an increased robustness based upon the simulated production plan. An increase of validity however usually creates increased costs. Therefore, we cannot assume that increased validity robustness also correlates with high result robustness.

The simplest way to increase the robustness of a plan is to extend the given capacities where possible. Our model is based on a possible three-shift production. Generally, one tries to avoid using all three shifts to avoid high personal costs during nighttime. By courtesy of the simulation we can however estimate the increase of robustness when considering the introduction of additional shifts. This allows the production planner to decide whether the additional costs are justified or not. One possible way to do this automatically is to calculate the average of the production timings after a higher number of simulations. Afterwards we can determine the average machine load factor and decide upon the amount of needed work shifts.

Another possible way to increase the robustness of the production plan is to move several lots into an earlier period, when this period contains larger capacity reserves. This process is considerably more complicated, as secondary demands also have to be fulfilled in due time. Therefor one cannot simply review available capacities for the final product. One also has to check whether available capacities for the production of all needed intermediate products exist, which often is not the case when the overall machine load factor is constantly high. Additionally an earlier production causes further inventory and capital commitment costs. Thus, this way often is not an opportune choice. In general, it lies in the responsibility of the production planner to decide which amounts of cost increases he accepts to increase the validity robustness of his production plans. All production plans that are created within the post-processing can be simulated and evaluated again. The production planer consequently can access all information he needs to come to a corresponding decision.

VI. RESULTS

We executed several simulation runs based upon the production plan created by the mathematical optimization, using a planning horizon of 56 periods with a dynamic demand structure. We assumed a failure rate of 10% for each machine. The corresponding processes were prolonged by a standard deviation of 15% and 30%. Table 1 shows several performance indicators in a comparison of simulations with a naïve and rule-based machine control, in particular focusing delays for final products... We calculated the average values of 100 simulation runs. The rule-based machine controls objective function costs are considerably lower than the costs caused by the naïve machine control. It is noticeable that less final parts get delayed when using the rule-based machine control. Therefore, the ability to supply is increased and lower delay penalty costs occur. These also explain the lower objective cost values.

TABLE 1: COMPARISON BETWEEN DETERMINISTIC (D), RULE-BASED (RB) AND NAIVE (N)MACHINE CONTROL

Standard Deviation	Sim-Type	Objective Function	Delayed Final Products (Absolute)	Delayed Final Products (Relative)	Delay Penalty Costs	Stock Costs
	D	2.769.282,95 €	2.769.282,95 €	2.769.282,95 €	2.769.282,95 €	2.769.282,95 €
15%	RB	3.944.976,12 €	3.944.976,12 €	3.944.976,12 €	3.944.976,12 €	3.944.976,12 €
	N	4.211.949,84 €	4.211.949,84 €	4.211.949,84 €	4.211.949,84 €	4.211.949,84 €
30%	RB	4.355.206,90 €	4.355.206,90 €	4.355.206,90 €	4.355.206,90 €	4.355.206,90 €
	N	4.670.432,31 €	4.670.432,31 €	4.670.432,31 €	4.670.432,31 €	4.670.432,31 €

However, a deterministic simulation of the production plan without stochastic influences shows that no penalty costs occur. The deterministic objective function value is correspondingly low. The rule-based machine control causes an improvement in result robustness as well as validity robustness. Table 2 shows the corresponding evaluation metrics by Honkomp et al. [10].

TABLE 2: METRICS BY HONKOMP

Standard Deviation	Sim-Type	$S.D./OF_{DB}$	$\overline{OF}/OF_{DB}$
15%	Rule-Based	40,00%	1,42
	Naive	40,09%	1,52
30%	Rule-Based	42,90%	1,57
	Naive	44,40%	1,69

The first column represents the relations between the standard deviation of all objective function values of all stochastic simulation runs and the objective function value of the deterministic simulation. A lower value indicates that disturbances and environmental influences have less impact on the ability to supply. The second column represents the relations between the objective function values of stochastic and deterministic simulations. The value shows the cost increase caused by the disturbances and directly shows the result robustness. Normally, a higher robustness is gained by increased costs. However, the inclusion of penalty costs into the objective function value causes lower cost for the more robust plan.

Another reason for increased costs are the personal costs. The simulation showed that more working shifts have to be introduced to be able to satisfy customer demands. The original plan was using working shift per day. The resulting plans when using either simulation method mostly used two or three shifts. The rule-based machine control delays 13% less products beyond the planned capacity restrictions, therefore needing less working shifts and causing less personal costs as well. When analyzing the problems within the production process one needs to find out where a possible bottleneck occurs. During the simulation we protocol all occurrences of backlog amounts and the connected machines, products and periods. For further analysis we can determine which products are delayed most as shown in figure 3.

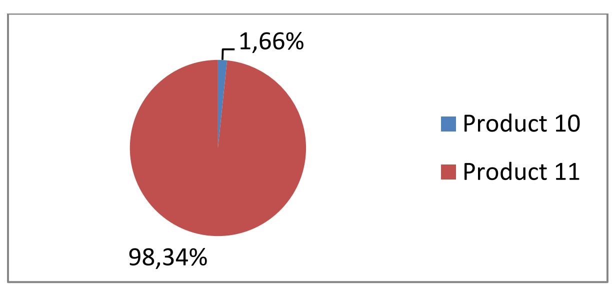

Figure 3: Delayed Final Parts according to products

Surprisingly, most delays are caused by one final part. This is an obvious sign that the production capacity for this part might not be sufficient. Alternatively, production capacities for needed intermediate products might be insufficient. This can be found out by analyzing internal delays for the intermediate products. Table 3 shows the absolute and relative internal delays for both simulation types averaged over 100 simulations. We define internal delays as the amount of intermediate products that couldn't be produced in the planned period.

The usage of the rule-based machine control also shows an improvement when considering the internal demands. Despite not leading to direct revenue losses due to unmet demands, internal delays can cause costs when changes in the production plan have to be made. These costs aren't implicitly included into our production model, but it is in the interest of the production planner to reduce these costs as well. When considering the internal delays per product we are able to find out that product 10 and product 11 are based on the same intermediate product. This product possesses several internal delays, which influence the production of the final products. We were able to find the bottleneck in our production model and can take action to reduce the impact of this issue.

TABLE 3: ANALYSIS: ACCUMULATION OF INTERNAL DELAYS

Standard Deviation	**Sim-Type**	**Internal Delays (Absolute)**	**Internal Delays (Relative)**
15%	Rule-Based	10194,38	1,81%
	Naive	11172,92	1,99%
30%	Rule-Based	16172,68	2,88%
	Naive	17266,10	3,07%

VII. CONCLUSIONS

We have shown in this paper that a material flow simulation can be used to analyze a production plan created in a mathematical optimization and to evaluate its robustness. It is easily possible to read the results of an optimization process, to transfer this data into our simulation framework. We are able to simulate the plan including probabilities for unforeseen events and fuzzy information. The results of the simulations can be used to find possible weak spots in the given plan. In several cases, we might be able to fix these weak spots through automatic post-processing or with manual changes. The effect of these changes can also be evaluated using additional simulation runs. Therefore, a production planner can decide whether he wants to implement these changes or not. Performing a large number of simulations is substantially faster than running another instance of the optimization problem. In the end, we recommend this approach for practical and economic usage.

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