Increase of Robustness of Production Plans using a Hybrid Optimization and Simulation Approach

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 Horstkemper
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. 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 either large amounts of computation time or requiring domain specific techniques, which increasingly decrease the maintainability of a model. 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 pre-optimized 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 adequate forecast data and the need to lower capital commitment is leading to the necessarily of designing robust production planning models [1], [5], [6]. Major objective is always 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 the 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. We show that the applying uncertain information to a simple stochastic optimization model yields either unacceptable solutions or unacceptable solution times. Thus, we have to find a way to include the aforementioned uncertainties within the production planning process without limiting its solvability significantly. Using advanced stochastic optimization techniques is out of the question: Special techniques, like the Benders Decomposition [22], are based upon the specific structure of certain optimization model. As production systems underlie a constant change however, the model needs to be able to be adapted constantly. Additionally efforts made in applying such a model for a certain production system cannot be reused, as two production systems and therefore the corresponding optimization models are seldom identical or even similar [23]. To create an approach, which allows for easy maintainability, sufficient solution quality including uncertain events and practical solution times we connect mathematical optimization models with a down streamed material flow simulation. 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 can improve upon scheduling decisions using rule-based machine controls within the simulation, reacting to changes in the production systems environment. 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 this toolset.

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 manner. First, we solve a mathematical optimization problem with standard solver software like IBM ILOG CPLEX [17]. The solution generated by the optimization is represented by a mst-file, will then be converted into a machine readable production plan, which is used as an input for the simulation environment d³fact. Within this environment we can evaluate the performance of a plan against environmental influences. Additionally, we can create production plans, which are optimized for a certain scenario, meaning a distinct combination of different influences, and use several of these plans to create a new production plan within a post-processing software. This plan shows an increased performance in any scenario, which we can proof by simulating and evaluating it again. Figure 1 shows this 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 discuss these methods in Section IV and analyze the corresponding solution quality and solution times. 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 offline 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.

The production schedules are logged and afterwards evaluated on the base of costs and robustness. A rule-based machine control is used 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.

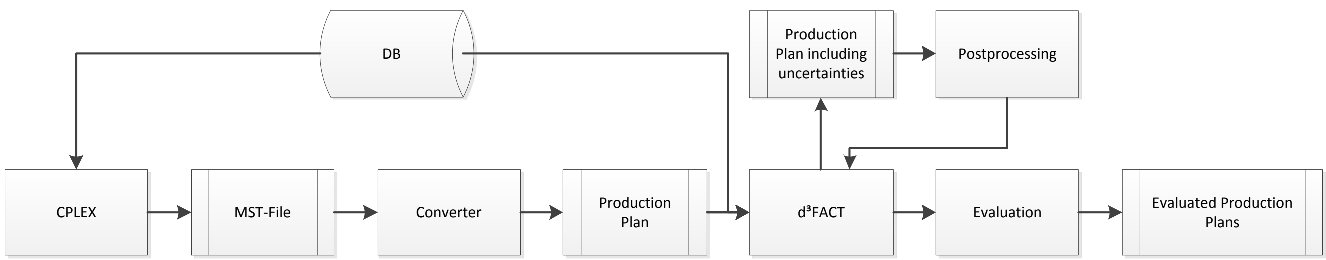

Figure 1. General Structure of presented concept

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 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 objective 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].

Our work is based on well known optimization models. 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 Lot-Sizing and Scheduling Problem (DLSP) to determine exact production timings. As a result, the order is decided, in which the machines process their corresponding lots. We use a MLCLSP based on the formulation of Tempelmeier and Helber [9] and a DLSP based on the formulation of Drexel and Kimms [24]. These models can be combined in a hierarchical manner, relying on the formal description of hierarchical problems of Schneeweiß [35]. Several efforts have been made to include uncertain events into the formulation of these models. Additionally, special solution methods have been applied to these formulations. For example Gupta and Maranas as well as Bakir and Byrne propose a two staged model to include demand uncertainties [25][26]. Demand uncertainties are also analyzed by Chen and Chu [27]. They do however propose an adapted Lagrangian Relaxation approach to solve this problem. While demand uncertainty is a problem mostly approached in operative planning processes, more uncertainties obviously arise in tactical and strategic planning problems, which are spread about considerably longer timeframes. Three main classes of uncertainty, which were analyzed in scientific literature, are classified by Tajbakhsh et al. [28]: stochastic lead times, as they were discussed by Dolgui et al. [29] or Gurnaki and Gerchak [30], uncertainties in supply quality as considered by Radhoui et. al. [31] and uncertainties in purchasing prices. Our work however is only considering uncertainties in the operational production execution level.

All aforementioned stochastic optimization approaches to include uncertainties do not take the model life cycle, as described by Forgione [32], into account. Literature and research typically do focus on creating and implementing better and more sophistic solution methods to find better solutions to increasingly complex optimization models in a shorter timeframe. However, they do not consider the maintainability of such models, which is a key part of a models life cycle and by far exceeds its deployment time if economically used [33]. Other researchers, like Sundaram and Wolf also note, that businesses demand optimization models to be adaptable for changes within their companies. This led to the introduction of Enterprise Model management Software, which however has not been used to include uncertain planning processes as of now [34]. Nevertheless, this demand lets us to conclude, that special complex solution methods for advanced stochastic models will not receive a broad acceptance in businesses and therefore are not applicable for real world problems.

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. We can classify the model into 13 different levels, which could be used to decompose the problem. 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. We create a lot-sizing and scheduling by the combined usage of the Models MLCLSP and DLSP.

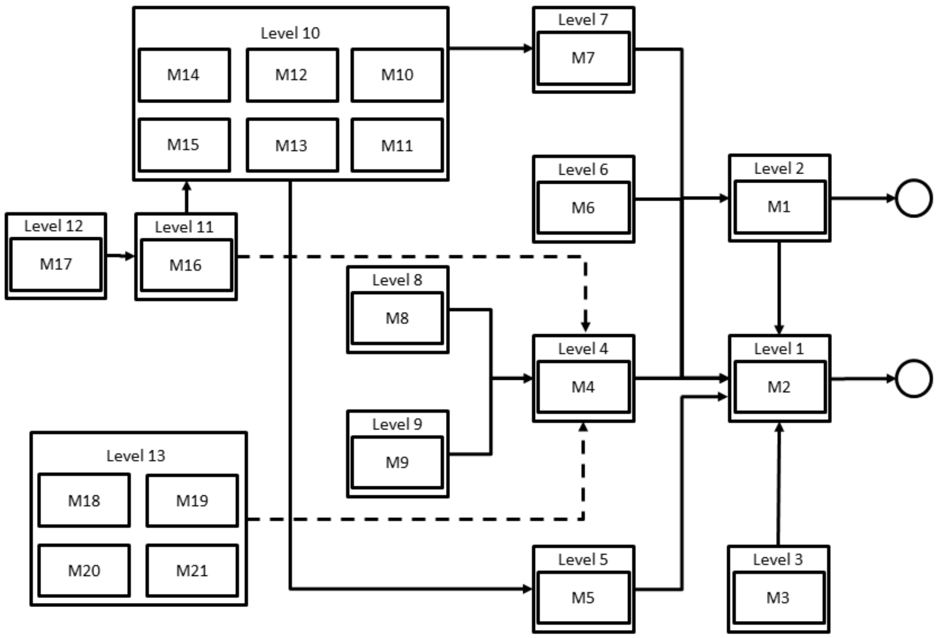

Figure 2. Machine Plan

A. Deterministic Lotsizing Problem

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 multi-period 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, meaning multiple actions can be done within one time period. Therefore 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. Backlogged demands do however create extraordinarily high penalty costs, as the consequences of unsatisfied demands can be as severe as the loss of a customer. Products can be manufactured on several machines in a parallel matter. We include transport lots, forcing the production of certain parts in given batch sizes, and the machine capacities are determined upon a flexible work shift model. Late and Night shifts cause additional personal costs. Also, productions on Saturdays and Sundays lead to increasing costs. We do this to reflect the increased worker salaries at this time.

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:

$y_{k,t-1} + q_{k,t-1} - \sum_{i\in N_k} a_{ki} * q_{it} - y_{kt} + bo_{k,t+1} - bo_{kt} = d_{kt}$	∀k ∈ K,∀t ∈ T	(4.1.1)
$\sum_{k\in K_j}(tb_{kj} * q_{kt} + tr_{kj} * \gamma_{ktj}) \leq b_{jt}$	∀j ∈ J,∀t ∈ T	(4.1.2)
$q_{kt} - M * \gamma_{kt} \leq 0$	∀k ∈ K,∀t ∈ T	(4.1.3)
$q_{kt}, y_{kt}, c_{ktj} \geq 0$	∀k ∈ K , ∀t ∈ T	(4.1.4)
$\gamma_{ktj} \leq avail_{kj}$	∀k ∈ K , ∀t ∈ T, ∀j ∈ J	(4.1.5)
$\gamma_{ktj}, s_{jt}^0, s_{jt}^1. s_{jt}^2 \in 0,1$	∀k ∈ K , ∀t ∈ T, ∀j ∈ J	(4.1.6)
$q_{ktj} = c_{ktj} * cont_k$	∀k ∈ K , ∀t ∈ T, ∀j ∈ J	(4.1.7)
$bo_{kt} \leq bomax_k$	∀k ∈ K , ∀t ∈ T	(4.1.8)
$b_{jt} = 0 + s_{jt}^0 * 480 + s_{jt}^1 * 960 + s_{jt}^2 * 1440$	∀j ∈ J,∀t ∈ T	(4.1.9)
$s_{jt}^0 + s_{jt}^1 + s_{jt}^2 = 1$	∀j ∈ J,∀t ∈ T	(4.1.10)
$\sum_{k\in K_j} \omega_{ktj} \leq 1$	∀j ∈ J,∀t ∈ T	(4.1.11)
$\omega_{ktj} \leq \gamma_{k,t-1,j}$	∀k ∈ K , ∀t ∈ T, ∀j ∈ J	(4.1.12)

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

In the objective function the sum of setup-, stock-, production-, backlog penalty 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.

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. Thus, it is enforced, that demands can be either satisfied by production and inventory amounts, or that appropriate backlog penalty costs are applied. 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. This day of lead time is needed, as the MLCLSP does not create an exact scheduling. 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. Constraint 4.1.3 ensures that one can only produce a product on a machine when a machine was set up for that product beforehand.

Additionally, constraint 4.1.5 ensures that machines can only produce products that they can be set up for. Constraint 4.1.7 expresses that production lots always have to be a multiple of transport lots. Within constraint 4.1.8, maximum backlog amounts for each product are defined. This way we can ensure that demands for intermediate products cannot be backlogged. The constraint 4.1.9 and 4.1.10 determine the amount of working shifts used for a machine in a certain period. Constraints 4.1.11 and 4.1.12 are used to allow for a setup carry-over between different periods. This way, a machine only needs to be set up once, when a product is produced in several consecutive periods. The other constraints are used to design meaningful bounds to the variables, for example, stock amounts always have to have a positive value.

B. *Deterministic Scheduling Problem*

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] or Drexel and Kimms [24]. 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. We adapted the basic DLSP formulation to use a similar notation as our MLCLSP model. We did not include additional enhancements into our DLSP, as most major decisions were already done at the level of the MLCLSP. The mathematical formulation of the DLSP is as follows:

Model DLSP:

Minimize O = $\sum_{k=1}^{K}\sum_{t=1}^{T} s_k * \gamma_{kt} + h_k * y_{kt}$

Under the Constraints:

$$y_{k,t-1} + q_{kt} - y_{kt} = d_{kt} \qquad \forall k \in K, \forall t \in T \qquad (4.2.1)$$

$$tb_k * q_{kt} + y_{kt} * tr_k = b_t * \delta_{kt} \qquad \forall k \in K, \forall t \in T \qquad (4.2.2)$$

$$\gamma_{kt} \geq \delta_{kt} - \delta_{k,t-1} \qquad \forall k \in K, \forall t \in T \qquad (4.2.3)$$

$$\sum_{k=1}^{K} \delta_{kt} \leq 1 \qquad \forall t \in T \qquad (4.2.4)$$

$$q_{kt} \geq 0 \qquad \forall k \in K, \forall t \in \qquad (4.2.5)$$

$$y_{kt} \geq 0 \qquad \forall k \in K, \forall t \in \qquad (4.2.6)$$

$$\gamma_{kt}, \delta_{kt} \in (0,1) \qquad \forall k \in K, \forall t \in \qquad (4.2.7)$$

Variables and constants meanings:

b_t	Available capacity in period t
d_{kt}	Primary demand for product k in period t
h_k	Stock expense ratio for product k
q_{kt}	Production amount of product k in period t
s_{kj}	Setup costs for product k
T	Length of planning horizon measured in periods (t=1,2,…,T)
tb_k	Production time for product k
tr_{kj}	Setup time for product k
y_{kt}	Stock for product k at the end of period t
γ_{kt}	Binary setup variable for a setup process of product k in period t
δ_{kt}	Binary setup variable for a setup state of product k in period t

The objective function is used to minimize the sum of setup and inventory costs. We use the DLSP to solely define a scheduling and not a lot-sizing. Therefore, it is not needed to include production and personal costs within this model.

Constraint 4.2.1 is the inventory equation, expressing that demands have to be fulfilled by production and inventory amounts. As the DLSP is solved on a per machine basis, we do not take secondary demands into account. Additionally, backlog amounts are not represented, as we do not allow backlogging within the scheduling problem. Constraint 4.2.2 ensures that a bucket is either filled by a production process or by a setup process. As the DLSP is following a "All or nothing" principle for micro periods, a period capacity either gets completely used by a process, or is not used at all. In conclusion, a setup-carryover must be possible. Constraint 4.2.3 is included for this purpose. To ensure that only one setup state can occur at any given moment, Constraint 4.2.4 exists. The other constraints are used to design meaningful bounds to the variables. For example, production and inventory amounts always have to be positive.

C. *Combined Lotsizing and Scheduling*

To create a complete production plan including lot-sizing and scheduling decisions, we use the models MLCLSP and DLSP combined in a hierarchical planning compound. This combination can be based on the common schema for hierarchical planning problems, which was described by Schneeweiß [35]. He considers two different planning problems as shown in Figure 3: on the top level, a planning problem is making decisions, which have to be considered by the bottom level problem. Therefore, the decisions by the top level model create a decreased room for maneuvers for the bottom level model. The models MLCLSP and DLSP can clearly be used as a top level and bottom level problem in this fashion.

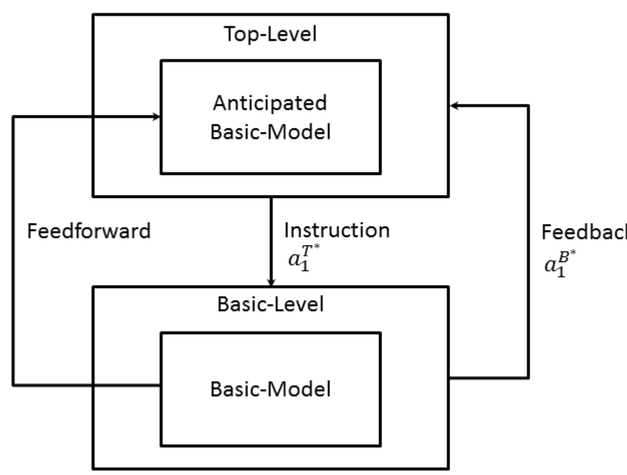

Figure 3. Hierarchical Planning Schema

The Top level tries to anticipate the decision made by the bottom level. Typically a reduced set of information about the bottom level decision problem is used. This amount of information is called “Feed forward”. If all information was used and an exact anticipation of decisions of the bottom level was done, one would solve the complete bottom level problem within the top level problem. A distinction of the planning models would thus be pointless. Decisions of the top level problem can form “Instruction”, which are given to the bottom level problem and have to be considered by it. This does however mean that the top level problem can make decisions that lead to situations within the bottom-level problem that cannot be solved sufficiently. In this case a manual or automatic Feedback process has to take effect, which causes a new planning process at the top level under an adapted anticipation of the bottom level models decisions.

Applied to our mathematical models, this means that the MLCLSP determines, which products shall be produced at what date. The production and setup times used by the MLCLSP are identical to the times used by the DLSP. Therefore the capacity usage can be exactly anticipated. Both models also only allow for the usage of one setup state at the same moment. Theoretically a lot determined by the MLCLSP could be produced in the form of two different lots. However, setup costs would occur twice in this case – therefore the model DLSP avoids this situation and the amount of setup processes is also correctly anticipated by the MLCLSP. Variable bounds and setup carryover constraints are also identical in function in both models. The MLCLSP therefore anticipates all decisions by the DLSP correctly, and the “Feedback” functionality is not needed when combining these models. The “Instruction” process is needed however. The variable outputs for production amounts in the MLCLSP are transferred to the input demand Parameter for the DLSP. The values can be transferred one by one, but the periods need to be adjusted, as the models operate on different time models. We assume that the demand applies at the last micro period within the DLSP that belongs to the according macro period within the MLCLSP. The amount of micro periods per macro period are determined by the amount of work shifts within the MLCLSP and therefore forms another “Instruction”. The different time models also account for the need to separate the models in the first place. Including micro periods within the MLCLSP would vastly increase the decision room and prolong solution times without increasing the solution quality. The correct anticipation of most of the DLSP’s decisions however allows us to exclude a lot of the information needed within the MLCLSP, leaving us with a very simple and fast to solve formulation of the DLSP.

IV. Stochastic Optimization Approach

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 a 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 multi-period, 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.

A. *Stochastic Optimization Techniques*

In literature and research, several approaches to include uncertainties into an optimization model exist. The simplest version is to create a deterministic substitute value model [36] [37]. The stochastic influences will be replaced by a deterministic value, for example by calculating the mean of the value throughout a finite set of scenarios. The expressiveness of such a model is rather limited, because edge cases with tremendous influences will not be handled at all [20]. This model class still is applicable in practice though, as it can be used to calculate minimum needed buffer times.

A more complex version of stochastic optimization models are fat solution models [38]. In this model, class one tries to find a solution that is applicable to a number of finite scenarios, and creates a solution that is ideal within this constraints [39]. The occurrence of edge cases, for example an extremely prolonged set-up time, can cause huge issues: solutions must always adhere to the worst case scenarios. Therefore, it is hard to find a valid solution for this model type. Finding good solutions is almost impossible within most mid to large size problem classes using this modeling technique.

Most sophisticated 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 a seemingly infinite amount of decisions is possible.

B. Setup Of Test Cases

To test our assumption, that stochastic optimization models cannot be used to generate good solutions in a timely manner when including uncertainties, we created several simple stochastic optimization models. The production schedule execution is typically affected by unforeseen interruptions und disturbances. In our test models, 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. However, scrap parts can also occur during the in-house production. We also include this possibility of uncertain behavior. When scrap parts are produced, the appropriate lot sizes must be expanded to compensate.

The stochastic influences are modeled with two parameters. On the one, hand the likeliness of an increased process time or an occurrence of scrap part production 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.

First, we created a deterministic substitute value model. The variable amounts are derived from different test sets, and a ceiling modeling is used to keep the integrity of the integer inventory restriction. As expected, the resulting solution times differ only slightly from a purely deterministic optimization model. In comparison to the original plan, slightly more parts where produced in all lots and slightly more working shifts were applied.

Secondly, we created a Fat Solution model. We use this model class within our MLCLSP similarly as before: for each scenario, the setup times, production times and production amounts are altered via stochastic factors. We are unable to find any solutions using this approach. The inventory balance equation cannot be fulfilled, as the production amounts are different in each scenario. Therefore, the inventory and backlog amounts cannot be equal throughout the scenarios.

Lastly, we created a two staged stochastic optimization model with simple compensation. Inequalities of the model are accepted in some edge cases, but penalty costs apply to keep these occurrences low. Indirectly, we already include such penalties in our model, as we allow backlogging. To formulate a two staged model with simple compensation, we must simply allow different inventory and backlog amounts per scenario. Backlogging of a demand is an opportune business decision: sometimes demands simply cannot be fulfilled with the given production capacities. When a demand is backlogged until the end of the planning horizon, one even might consider ordering those parts externally through an alternative supplier or subcontractor. We can make the problem solvable by making the inventory and backlog variables scenario specific. A similar compensation cannot be done for capacity constraints though: while backlogging is an opportune business decision one cannot prolong a working day beyond the 24 hour mark. Therefore, we kept the capacity constraints in the fat solution format.

We ran the optimization process with 10 and 100 scenarios and for the different amount of machines/production levels to determine the problem sizes we can solve using this method. We cancelled the optimization runs if we either found a solution with a gap below 10% or weren't able to find such a solution within 3 hours. Tables 1 and 2 show the results of our test runs.

Obviously, we are unable to find good solutions in medium or big problem sizes, as they appear in practice. Additionally, the high penalty costs for identified solutions make it appear, that these solutions do not suffice for the creation of a sensible plan. Considering this solutions and our argument that we are not able to use much further advanced stochastic optimization methods, because we cannot guarantee their maintainability, leads us to conclude that a different approach is needed to tackle this problem. Therefore, we propose an approach combining a deterministic optimization with a down-streamed simulation.

TABLE 1. SOLUTIONS FOR 10 SCENARIOS

Model-type	Mean Value			Two Stage with Compensation		
# of Levels	Solution Time (m:s)	Solution Value (€)	GAP (%)	Solution Time (m:s)	Solution Value (€)	GAP (%)
1	00:01	809,644	1.76	00:06	850,455	3.97
2	02:01	3,923,725	1.52	03:20	4,847,523	1.05
3	00:43	3,983,490	2.62	04:44	4,910,212	1.31
4	04:11	3,958,611	1.04	06:56	5,528,856	9.93
5	105:09	5,085,347	9.34	180:00*	156,516,563	17.3
6	166:28	5,969,908	9.32	180:00*	143,278,724	87.3
7	180:00*	6,417,375	13.5	180:00*	246,840,729	21.5
8	180:00*	14,445,652	58.7	180:00*	172,457,779	85.7
9	180:00*	14,323,895	25.0	180:00*	196,765,403	81.5
10	180:00*	14,378,925	24.53	180:00*	190,311,820	76.6
11	180:00*	76,451,461	84.8	180:00*	171,081,633	72.4
12	180:00*	113,678,019	89.50	180:00*	119,017,009	54.9
13	180:00*	842,996,612	85.6	180:00*	195,472,374	71.3

TABLE 2. SOLUTIONS FOR 100 SCENARIOS

Model type	Mean Value			Two Stage with Compensation		
# of Levels	Solution Time (m:s)	Solution Value (€)	GAP (%)	Solution Time (m:s)	Solution Value (€)	GAP (%)
1	00:01	843,109	5.65	02:17	866,438	5.75
2	00:22	3,910,988	1.25	180:00*	1,768,362,646	99.72
3	00:37	3,986,675	0.72	180:00*	1,768,362,646	100
4	02:59	3,945,480	2.71	180:00*	1,768,311,953	100
5	04:11	5,085,347	10	180:00*	1,768,235,686	97.6
6	180:00*	6,414,774	14.5	180:00*	1,768,366,685	97.3
7	180:00*	6,307,645	11.0	180:00*	1,768,312,876	97.3
8	180:00*	7,134,935	15.8	180:00*	1,768,313,128	96.9
9	180:00*	15,696,427	28.4	180:00*	1,768,367,156	95.9
10	180:00*	30,413,920	62.3	180:00*	1,768,367,156	95.9
11	180:00*	49,768,107	75.4	180:00*	1,768,367,632	95.4
12	180:00*	273,806,941	95.4	180:00*	1,768,261,632	95.2
13	180:00*	158,961,462	91.9	180:00*	1,768,262,192	95.7

*: No Solution with <10% GAP could be found within a 180 minute timeframe

V. Hybrid approach

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. We sort the lots generated by the MLCLSP in order of the results of the DLSP model to create our initial scheduling. This can be done by analyzing the occurrence of setup process variables γ_{kt}. 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.

A. *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 naive 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.

B. *Uncertainties in the production planning process*

We include the same kind of uncertainties in our simulation as before. These are the failure of machines in the form of prolonged cycle and setup times and the production of scrap parts.

The 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 also using the same two parameters as before. They determine the number of uncertainties that occur, and the strength of their effects.

C. *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.

D. 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.

E. 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 deterministic mathematical optimization, including all 13 planning levels (c.f. figure 2) and 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 3 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, which took less than an hour of time, enabling us to handle real world problem sizes within a timeframe, which is applicable in practice. 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 3. 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 4 shows the corresponding evaluation metrics by Honkomp et al. [10].

TABLE 4. 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 is 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 4.

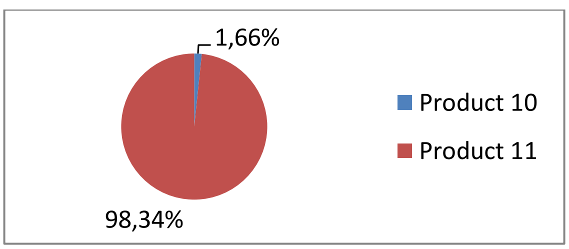

Figure 4. Delayed Final Parts according to products

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 5 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 5. 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. This especially holds true, if we compare runtime of our hybrid approach to the runtime of stochastic optimization methods. We were unable to find applicable solutions in real world sized problems in an acceptable timeframe using stochastic optimization methods and argued that advanced methods of decomposition for increased problem-solving efficiency are not accepted in practice due to their low maintainability. In the end, we recommend the hybrid optimization and simulation approach for practical and economic usage and expect further improvements to be made.

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