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AN EFFICIENT MULTI-OBJECTIVE HYBRID SIMHEURISTIC APPROACH FOR ADVANCED ROLLING HORIZON PRODUCTION PLANNING

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ABSTRACT

This contribution introduces an innovative holistic multi-objective simheuristic approach for advanced production planning on rolling horizon basis for an European industrial food manufacturer. The optimization combines an efficient heuristic mixed-integer optimization, followed by a customized Simulated Annealing algorithm. State-of-the-Art multi-objective solution techniques fail to address highly fluctuating demands in a suitable way. Due to the lack of modelling details, as well as dynamic constraints, these methods are unable to adapt to seasonal (off-) peaks in demand and to consider resource adjustments. Our approach features dynamic capacity and stock-level restrictions, which are evaluated by an integrated simulation module, as well as a statistical explorative data analysis. In addition to a smoothed production, mid-term stock levels, setup-costs and the expected utilization of downstream equipment are optimized simultaneously. The results show a ~ 30 to 40% reduced output variation rate, thus yielding an equally reduced requirement for downstream equipment.

1 INTRODUCTION

The food industry, as part of the *fast moving consuming goods* (FMCG) sector, is characterized by highly fluctuating production volumes over time induced by a combination of varying customer demand, large promotion volumes contributing significant shares of the annual sales volumes, seasonal demand influences and underlying trends. These effects together result in difficult predictions for the planning of the production volumes. Perishable goods – such as food – challenge producers to plan their resources precisely, as the storing durations are limited by an expiry date. In addition, these fluctuations are reinforced within supply chains through slow information dissemination leading to the largest fluctuations on the lowest supply network manufacturing level. This phenomenon is known as the *Bullwhip Effect* (Lödding 2008). Production systems with high demand fluctuations utilize their production facilities unsteadily and have to implement flexibility measures to the detriment of overall productivity. The primary planning goal to counter these disadvantageous effects of volatile demand, is to integrate production smoothing methods in the production planning process, thus minimizing the effects of fluctuating production volumes. Production smoothing, being a complex multi-objective optimization problem with conflicting objectives (Kuhn et al. 2016), allows for lowered flexibility costs and an optimized capacity utilization (Gorman and Brannon 2000). According to trends in fast-changing global markets with increasing product complexity and individualization, quick responsive production systems, capable of delivering adapted planning solutions due to frequent information updates, are demanded for real-world applications (Kuhn et al. 2016; Yavuz et al. 2006). Since flexibility measures (overtime rules, production line layout reconfigurations, …) are cost-intensive, production smoothing is an option to minimize flexibility costs. Within this paper, we present a heuristic mixed-integer optimization approach, followed by Simulated Annealing (SA) for the

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given capacitated Multi-Objective Multi-Product Multi-Period (MOMPMP) production planning problem, with rolling horizon in the context of Production Smoothing.

This paper is structured as follows: Section 2 provides relevant background information about multi-objective optimization problems next to an overview of contributions to practical optimization and modelling approaches in the context of Production Smoothing. Based on the problem description in Section 3, the formalized model is explained in Section 4. Section 5 includes the multi-phase heuristic approach, the subsequent customized metaheuristic, the integrated dynamic simulation module and the corresponding optimization results. Section 6 gives an overview of the methodology on the explorative data analysis and its findings. The conclusion is provided in the final section, including an outlook on further research.

2 RELATED WORK

The class of MOMPMP production planning problems is NP-complete, according to (Karimi-Nasab and Konstantaras 2012), as even the simpler Single-Product Multi-Period (SPMP) problems have been proven to be NP-complete, and thus necessitate problem-specific heuristics or tailor-made metaheuristics to approximately solve problems of this complexity class within a reasonable time. These approaches tend to be the best fit for real-world applications in an industrial environment, due to their quick approximate solution-making process, in contrast to exact (mathematical) optimization approaches requiring simplified models (Wari and Zhu 2016; Yavuz et al. 2006). The latter factor results in limited practical application potential. An extensive literature review of publications on MPMP problems is provided by (Saracoglu et al. 2014) and (Sazvar et al. 2016). A general overview of metaheuristics is given in (Boussaïd et al. 2013). The contribution of (Wari and Zhu 2016) is dedicated to metaheuristics applied in the food manufacturing industry. Recently, more contributions have been published with focus on the inventory planning problem for perishable goods, while previous optimization models were unable to consider inventory and shortage levels appropriately. The best known lean approach to encounter production smoothing, Heijunka Scheduling, tries to harmonize the production process by alternating the sequence between demanding and less demanding products (Korytkowski et al. 2013).

Multi-objective methodological approaches including various mathematical models used in the related literature to deal with the complexity of purposeful search in the given solution space can be classified as

1. *exact methods* like dynamic programming (Yavuz et al. 2006); column generation techniques (Ramos et al. 2018); gradient methods (Gonçalves and Oliveira 2018); decomposition (Zhou et al. 2018) or variable reduction techniques (Hua et al. 2008); mixed-integer-programming (MIP) based algorithms and models (Naber and Kolisch 2014), and
2. *approximate heuristic/metaheuristic algorithms* like greedy heuristics (Yavuz and Tufekci 2007); experimental heuristics (Minner 2009); problem-specific heuristics (Yavuz et al. 2006); metaheuristics; hybrid metaheuristics (Sazvar et al. 2016; Yannibelli and Amandi 2013; Zouache et al. 2018).

Metaheuristics are divided into single-solution based algorithms or *trajectory methods* (Boussaïd et al. 2013) like Simulated Annealing (Tan 2008) or Tabu Search (TS) (Zhou et al. 2018), and population-based methods such as Genetic Algorithms (GA) (Holland 2010), Ant-Colony-Optimization (ACO) (Dorigo and Stützle 2004) and Particle Swarm Optimization (PSO) (Kennedy and Eberhart 1995).

Research in the area of combinatorial optimization has recently experienced a shift towards hybridization of metaheuristics with other optimization techniques (Blum et al. 2011). The focus has changed from algorithm-oriented methods to more problem-specific implementations. Hybridization includes, next to the combination of different metaheuristics (Sazvar et al. 2016; Yannibelli and Amandi 2013; Zouache et al. 2018), combinations with exact algorithms, e.g. for optimal solutions of specific sub-problems, or problem-specific heuristics (Blum et al. 2011). Following these propositions in the context of *production smoothing*, several problem-specific heuristic or metaheuristic solution approaches are proposed to meet the corresponding requirements of a smoothed and cost-efficient production in a reasonable runtime. While (Karimi-Nasab and Aryanezhad 2011) propose a customized Genetic Algorithm, (Yavuz et al. 2006) compared different algorithms to achieve near-optimal solutions having encountered difficulties using an exact approach. In the contribution from (Absi and Kedad-Sidhoum 2007) the authors implement an efficient MIP-based heuristic for the multi-item capacitated lot-sizing problem. The authors in (Juan et al. 2015) define simheuristics, like other simulation-optimization (Sim-Opt) approaches, as an optimization approach using the output of a simulation model as part of the objective function in order to allow a more accurate evaluation of solutions.

Based on these findings, we have developed a customized hybrid optimization algorithm integrating a dynamic simulation, to achieve a realistic evaluation of the forecasted capacity utilization, complemented with a statistical data evaluation. Within our approach a knowledge-based mixed-integer heuristic solution developed together with the application-partner is followed by a subsequent Simulated Annealing optimization. The implemented objective function covers *lexicographically* (Chiandussi et al. 2012) ranked multiple part-goals, each reflecting a specific goal dimension. This function is applied regularly during the metaheuristic optimization serving as an evaluation of the heuristic optimization results.

3 PROBLEM DESCRIPTION

An overview of the case-study process for the presented hybrid simheuristic approach applied on the given MOMPMP production planning problem is shown in Figure 1. The cost- and labor-intensive key production equipment of the bottleneck process (*Salting*) is to be optimized in order to deliver *smoothed* production input volumes for the following downstream processes evaluated by the integrated dynamic simulation module. The main planning task is the creation of a near-optimal, long-term (78 weeks) production plan, considering dynamic and static capacity restrictions covering all (~ 25, depending on the season) production articles of the plant, with a rolling horizon and the following key optimization criteria:

1. Reducing total production volume peaks per planning period for the key production equipment (*Salting*, see Figure 1) with capacity restrictions, within a given planning horizon
2. Reducing production volume peaks per planning period and production article on this key production equipment with capacity restrictions within the given planning horizon
3. Optimizing capacity utilization of this core unit and all downstream production equipment
4. Optimizing stock levels for all product types and periods within a defined time frame
5. Optimizing the amount of required setup processes

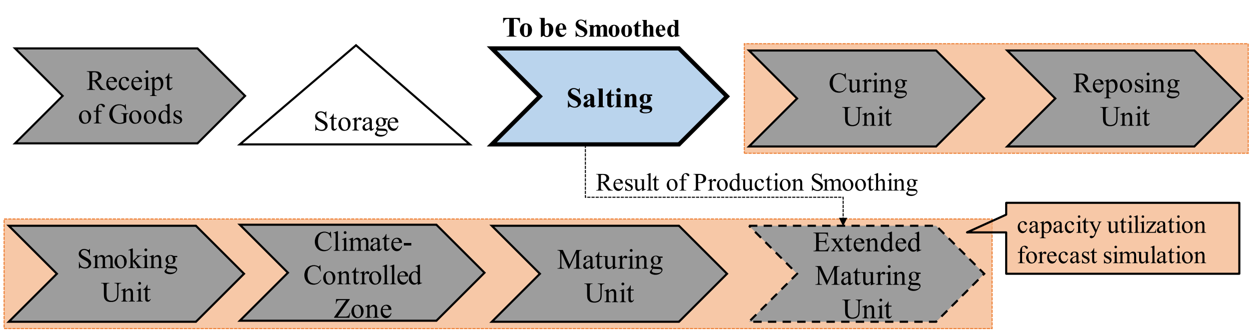

Figure 1: Detailed process value stream including simulation overview.

4 MODEL FORMALIZATION

In the following section, first the notation and the optimization model are formulated, consisting of the objective function and its constraints, followed by explanations. Table 1 provides a summary of the used notation, describing the variables of the objective function (1) and its related constraints listed in (2) – (4).

Table 1: Reference notation.

Notation	Description
Objective function indices and variables	
f, W	Objective function, Weighting vector $W = [\omega_1, \omega_2, \omega_3, \omega_4, \omega_5]$
$\omega_1 - \omega_5, s_1 - s_5$	Individual part-goal weights and scaling factors
i, j, c	Period, product type, capacity
m, n, o	Total number of product types, periods and capacity units
f_1	Part-goal function evaluating the individual production article gradient
f_2	Part-goal function evaluating the total plant production gradient
f_3	Part-goal function evaluating the total capacity utilization gradient
f_4	Part-goal function evaluating the production article stock level gradient
f_5	Part-goal function evaluating the total amount of setup processes
$f_1(q_{ij})$	Production gradient for product type *j* in period *i*
$f_2(q_i)$	Plant production gradient for period *i*
$f_3(cul_{ic})$	Capacity gradient for period *i* on capacity *c*
$f_4(slq_{ij})$	Stock level gradient for product type *j* in period *i*
$f_5(q_{ij})$	Minimum amount of setup processes for product type *j* in period *i*
Constraint variables	
q_{ij}	Production (share) quantity of product type *j* in period *i*
q_{ic}	Total processed production volume in period *i* on capacity *c*
q_{max_i}	Max. allowed product quantity in period *i* (dynamic capacity constraint)
k_{ijl}	Shifted periods of product type *j* and period *i* by *l* periods into period $i - l$
k_{max}	Maximum allowed offset periods for shifted quantities (integer value)

4.1 Objective Function, Part-Goals and Constraints

The optimization model comprises five part-goals that aim at optimizing different production planning measures. This includes part-goals for a smoothed production planning (f_1, f_2), capacity utilization in the multi-stage production (f_3), evaluation of stock levels (f_4) and amount of required setup processes (f_5). The objective function *f* applied in the SA scalarizes the problem by calculating a weighted and scaled fitness value. The scaling is executed using the part-goals of the best solution from the heuristic optimization.

$$\textbf{\textit{Minimize}}\ f(q_{ij}, q_i, cul_{ic}, slq_{ij}) =$$

$$\frac{\omega_1}{s_1}\sum_{i=1}^{n}\sum_{j=1}^{m} f_1(q_{ij}) + \frac{\omega_2}{s_2}\sum_{i=1}^{n} f_2(q_i) + \frac{\omega_3}{s_3}\sum_{i=1}^{n}\sum_{c=1}^{o} f_3(cul_{ic}) + \frac{\omega_4}{s_4}\sum_{i=1}^{n}\sum_{j=1}^{m} f_4(slq_{ij}) + \frac{\omega_5}{s_5}\sum_{i=1}^{n}\sum_{j=1}^{m} f_5(q_{ij}), \quad (1)$$

$$\textbf{\textit{Subject to}}$$

$$\sum_{j=1}^{m} q_{ij} \le q_{max_i}, \quad \forall i \in \{1, \dots, n\}, \quad (2)$$

$$\sum_{c=1}^{o} q_{ic} \le max\_cul_{ic}, \quad \forall i \in \{1, \dots, n\}, \quad (3)$$

$$k_{ijl} \leq k_{max}, \qquad \forall i \in \{1, \dots, n\}, \forall j \in \{1, \dots, m\}. \tag{4}$$

The part-goal functions $f_1 - f_3$ are calculated by absolute differences in the respective gradient magnitudes between all adjacent planning periods within the planning horizon. The part-goal f_3 requires the output from the dedicated dynamic simulation module, in particular the capacity utilization of the orange colored capacities on the downstream processes, see Figure 1. The part-goal f_4 is derived by the gradient difference between the stock-level in the respective period and the desired target stock-level. Part-goal f_5 is a simplified measure for the expected setup costs and estimated by a boolean equation.

4.2 Constraint Handling

The *dynamic* capacity constraint (2) for the respective key equipment formed by q_{max_i} must strictly be fulfilled in each period to generate a valid solution. Constraint (3) checks, whether the number of required racks fits, for each period and process, to the corresponding *static* maximum rack-capacity (max_cul_{ic}) of the associated process. Constraint (4) specifies for each article a specific limit regarding the maximum amount of shifted periods from a respective originate period into another period. These limits are defined both for standard and promotion volumes, thus requiring a separate treatment of each volume dimension.

5 HYBRID SIMHEURISTIC OPTIMIZATION APPROACH

The hybrid optimization approach is designed in two stages: The first stage covers a *knowledge-based heuristic* implementation followed by Simulated Annealing. The intention is to combine the advantages of the deterministic heuristic optimization with the benefits of a stochastic metaheuristic algorithm.

5.1 Heuristic Knowledge-Based Mixed-Integer Optimization

The mixed-integer heuristic, details published in (Kamhuber et al. 2018), features four modular optimization phases. Each of them manipulates the production schedule towards reaching difference part-goals within (1): First promotion and standard peak volumes are minimized by reducing and shifting volumes of peaks into earlier periods and filling gaps (see Figure 2), first considering only $f1$ (article gradients) followed by $f2$ (plant gradient). In case this is not possible, the weekly capacity average is raised. In the next phase, the volumes are rounded tactically to half or full racks according to their ABC classification. Due to the *frozen zone* of volumes being in production the stock levels are optimized within a defined decision window to attain the corresponding target stock level as of the impact window.

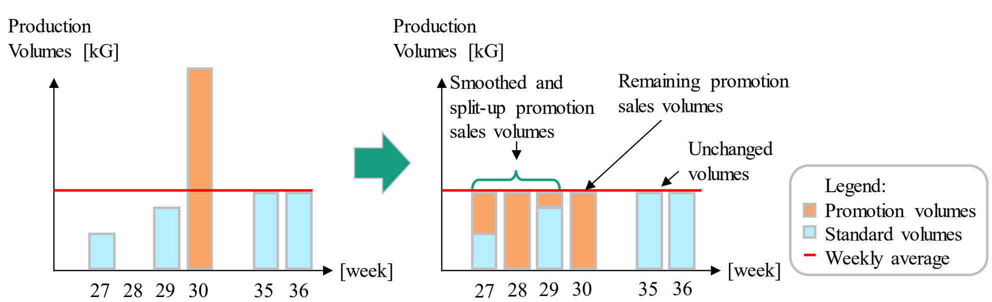

Figure 2: Production smoothing by shifting volumes and filling gaps.

5.2 Metaheuristic Optimization: Simulated Annealing

The metaheuristic optimization complements the prior executed knowledge-based heuristic. Within our approach, a customized SA algorithm was chosen as the metaheuristic due to its successful utilization in simulation based applications (Gendreau and Potvin 2019). After the bulk of the optimization potential has been obtained in the first stage, the metaheuristic is meant to release additional potential for optimization the heuristic was not able to identify. With the stochastic search approach, the intermediate solution is meant to be improved upon quickly, without changing the major characteristics of the existing solution – which fulfills the decision maker's preferences – while still avoiding local optima. The ability to rapidly find better solutions based on an already optimized intermediate solution, without risking to loose desired core characteristics of the heuristic solution, outweighed the ability of e.g. GA to find good solutions in large search spaces, because the initial search space is meanwhile severely restricted.

Simulated Annealing: mimics the annealing process of crystals in materials science by bringing a material from high temperatures gradually down to lower temperatures while accepting a decreasing amount of worse intermediate energy levels in the course of the controlled cooling process (Michalewicz and Fogel 2004). In terms of optimization, the probability to accept worse solutions in early stages of the optimization process is higher than towards the end. This mechanism allows the algorithm to escape local optimal solutions.

Implementation: The Simulated Annealing optimization process in our implementation is supported by a *Guided Local Search* mechanism ensuring that at least the part-goal $f_2(q_i)$, that was not focused purposefully in the first stage, is always improved by creating a modification on the production plan. The algorithm, remembering already shifted production volumes in a mapping, starts by moving forward volumes that previously have not been relocated and iteratively moves on to rescheduling volumes that have already been shifted, in accordance with the corresponding constraint in (4).

5.3 Integrated Dynamic Simulation

As mentioned in Section 4, the part-goal f_3 within (1) requires an evaluation performed by an integrated dynamic simulation module (IDSM). The primary goal of the simulation is to provide a realistic and accurate dynamic capacity utilization forecast (on palette unit level) of the core downstream processes of the plant, marked orange in Figure 1. As illustrated in Figure 3, articles packed on palettes arrive from the corresponding upstream process. The simulation module groups, different articles belonging to the same article group together into one palette, in each period and process, before being processed inside process specific production rooms. Then they advance, according to their individual work schedule, into the next downstream process, where they are regrouped again.

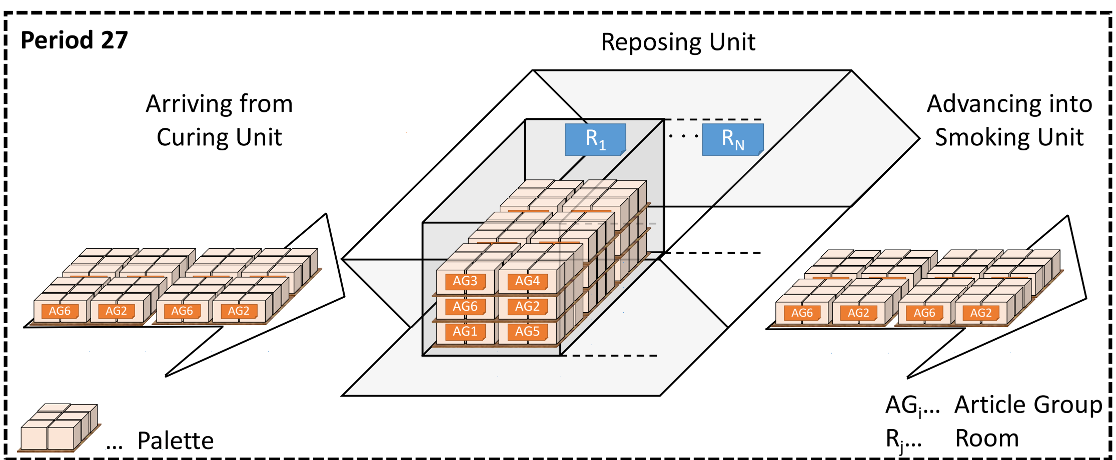

Figure 3: Simulation model details with view on a specific process on palette unit level.

5.4 Optimization Results

The optimization results of the hybrid optimization algorithm presented in the following, are derived from a specific data set (featuring 78 planning weeks from 40/2018 – 13/2020), after having applied a computational study for parameter optimization of the SA. Figure 4 features the normalized global goal optimization results (represented as trends) using the preferred weighting set $W = [1.25, 1.25, 1, 1, 0.5]$ in agreement with the decision maker, next to the individual part-goal results. The multi-phase heuristic approach accounts for about 35% of the global goal optimization. The total capacity gradient (aggregated from five sub-capacity gradients, according to sub-section 5.3) is positively influenced by the optimization of the article gradient. These promising results are achieved by shifting only about 8 – 10% of the annual production volume. However, the smoothing requires the lots to be split into partial lots resulting in 5 – 7% more lots in total, see Figure 4. A detailed view on the progress of the metaheuristic optimization reveals that the *Guided Local Search* mechanism proves very helpful by reducing the plant gradient within a few hundred optimization steps by another 30%, by only deteriorating the article gradient for less than 5%. The results, partially achieved by part-goal trade-offs, have been validated on different data-sets with at least two runs on each data-set and prove to be consistent with the optimization process results in Figure 4. The total goal results of about 40 – 50% are due to the untreated initial manually compiled solution provided by the planner and the efficient combination of two algorithms. An internal benchmark showed that the implemented SA alone, i.e. without the heuristic optimization, was not able to deliver comparable results.

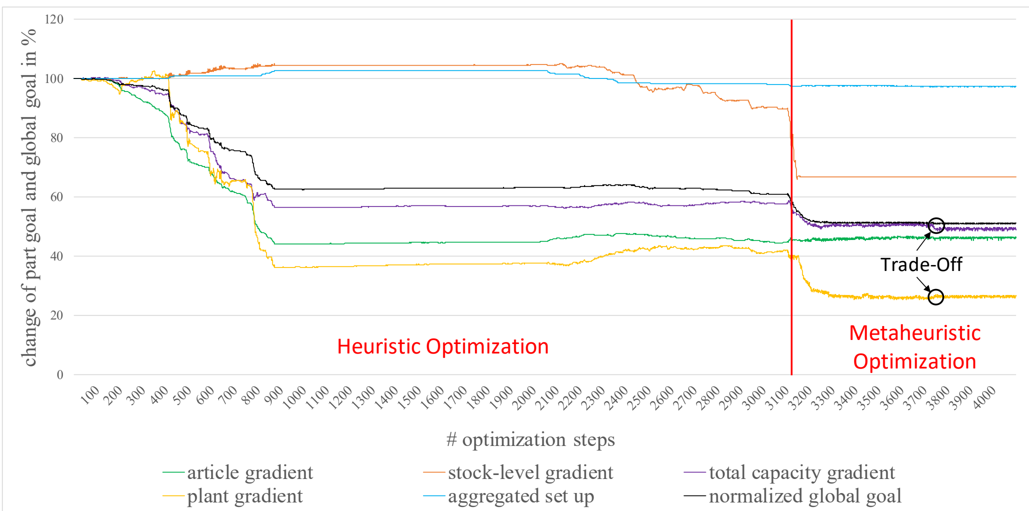

Figure 4: Results of the combined heuristic and metaheuristic optimization.

Varying the four given common initial SA parameters by a grid-search in a computational study results in a final parameter value recommendation, see Table 2. The approach is implemented *efficiently*: Within the heuristic optimization, multiple lot splitting steps can be executed at once, before they are evaluated in terms of their respective constraints (2) – (4). Tests showed that the runtime complexity of the heuristic, metaheuristic, objective function and simulation increase almost linearly with regard to the size of the planning horizon, whereby the most expensive step represents the IDSM. This is a practical performance advantage compared to solely simulation based metaheuristic optimization, whereby the complex simulation, combining discrete and continuous material flow, covers the whole use-case (Sihn et al. 2018).

Table 2: Results of the computational parameter optimization study.

Iterations Per Temperature	Initial Temperature	Frozen Temperature	α (Annealing Rate)
100 – 200	0.0005	0.000005	0.90

6 EXPLORATIVE DATA ANALYSIS

The hybrid simheuristic approach is complemented with an explorative data analysis. The goal is to provide recommendations for continuously improving the master data, in particular minimum and target stock levels, as well as updated ABC classifications based on historic data. The collected as-is stock values from each period, the production forecast volumes and the production confirmations, are used as input. The boxplot in Figure 5 shows the scatter of the stock levels (22 planning weeks from 30/2018 – 52/2018) for each article, as well as minimum, average and target stock level. This plot is the basis for evaluating the stock volatility. For example, the inventory level of article 1 is within range, whereas article 7 shows a surplus stock. The derived recommendation for the latter is to reduce its minimum and target stock level.

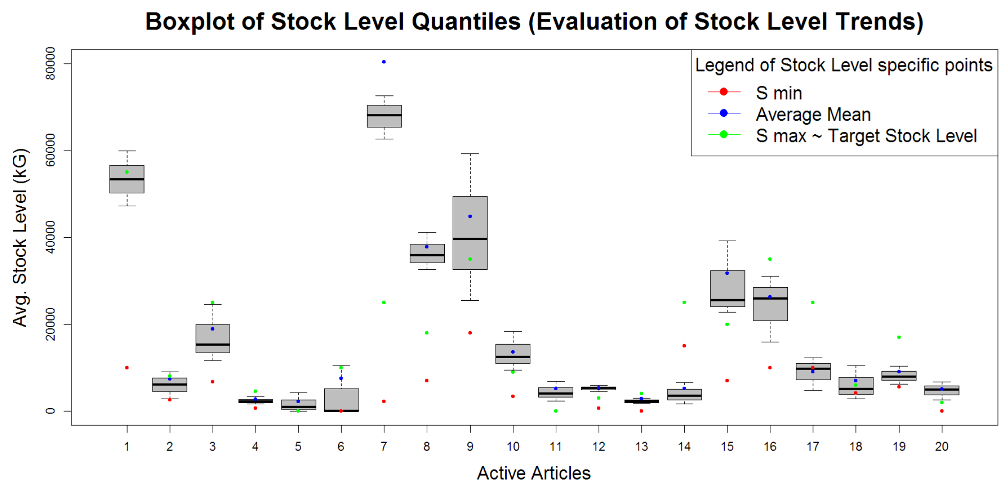

Figure 5: Boxplot for the evaluation of the stock volatility.

As another preliminary result Figure 6 shows a comparison on article level between the static and dynamic relative deviation between the proposed and the as-is production volumes. Moreover it proves the advantage of rolling horizon planning regarding lower production deviations in comparison with a static production plan created once in the past without regular planning related information updates. The proposals differ from the as-is production feedback due to ramp-up of the plant, sourcing strategies and external reasons.

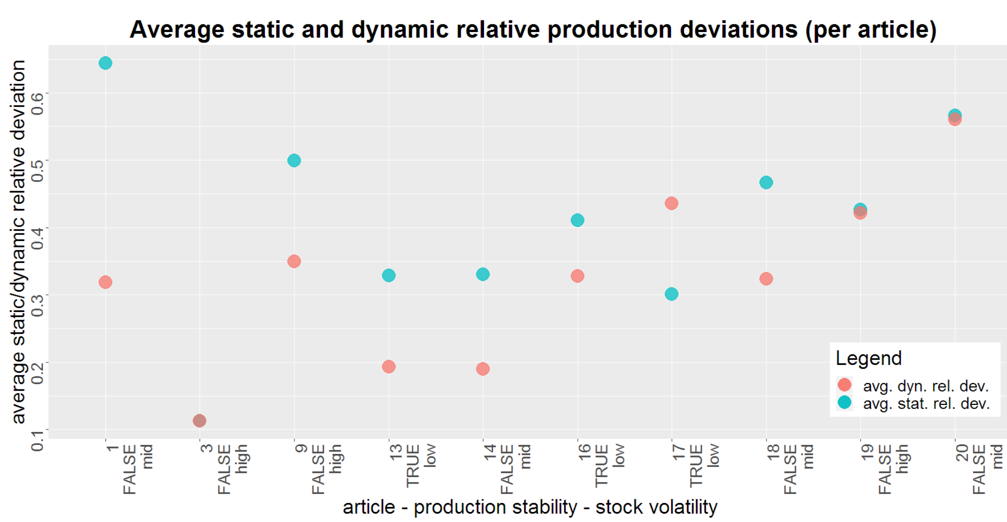

Figure 6: Average static and dynamic relative deviations between production proposal and confirmation.

As a final outcome of the statistical analysis, complemented with a risk assessment of inventory stock based on threshold levels, an overall recommendation for the adaption of the minimum and target stock level values is derived, see Table 3.

Table 3: Overall recommendations based on the explorative data analysis.

Article	Smin	Smax	ABC	Production forecast	ABC recommendation	Inventory risk evaluation	Recommendation (inventory levels)	Recommendation (production stability)	Overall recommendation
1	10050	55000	A	447566	A	OK	K	K	K
2	2680	8000	A	67453	A	OK	K	K	K
3	6700	25000	A	341840	A	OK	K	R10	R10
4	700	4500	B	51425	B	OK	K	K	K
5	0	0	B	24617	B	high inventory level, high risk	L20	K	L20
6	0	10000	A	331457	A	OK	K	K	K
7	2200	25000	A	440377	A	high inventory level, high risk	L20	K	L20
8	7000	18000	A	103656	A	high inventory level, high risk	L20	K	L20
9	18000	35000	A	340918	A	OK	K	R10	R10
10	3350	9000	A	75455	A	high inventory level, mid risk	L10	K	L10
11	0	0	A	21363	C	high inventory level, high risk	L20	K	L20
12	700	3000	C	21304	C	high inventory level, mid risk	L10	K	L10
13	0	4000	A	41586	B	OK	K	L10	L10
14	15000	25000	A	130838	A	low inventory level, high risk	R20	K	R20
15	7000	20000	A	47114	B	high inventory level, mid risk	L10	K	L10
16	10050	35000	A	329122	A	OK	K	L10	L10
17	10050	25000	A	176292	A	low inventory level, high risk	R20	L10	R10
18	4200	6000	A	151732	A	OK	K	K	K
19	5600	17000	A	269876	A	OK	K	R10	R10
20	0	2000	A	28800	B	high inventory level, high risk	L20	K	L20

Legend: [K = Keep inventory levels] [L10/L20 = Lower inventory levels by 10%/20%] [R10/R20 = Raise inventory levels by 10%/20%]

7 CONCLUSION

The global goal optimization results show a production smoothing potential of approximately 40 - 50%, compared with the initial production plan. The total cost saving potential from the production and capacity gradients vary around 30 - 40%. This results in significantly lower investments for production equipment, i.e. fewer necessary production units, in turn leading to reduced investment and operating costs for a new factory as well as improved resource and energy efficiency. Operation costs are lowered by balanced operation times and making use of operators' idle times. These savings are achieved by comparatively very low additional costs for the extended maturing step used for smoothing.

The presented hybrid optimization approach integrates a forecast simulation only for a certain part goal to address the capacity utilization in a realistic manner. The problem-specific heuristic, using dynamic constraints to counter seasonal effects in contrast to existing rolling-horizon approaches (Sampaio et al. 2017), allows for high runtime efficiency being beneficial for rolling horizon optimization. Metaheuristic evaluations are more expensive compared to the *lexicographic* heuristic which is able to perform several optimization steps at once while only checking the constraints without needing to recompute the fitness value. The results of the explorative data analysis enable our approach to optimize the master data related to the mid-term inventory levels.

An outlook on further research includes an extended validation of the results by varying the individual weights during the optimization, as well as a consideration of further downstream packaging processes.

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