Developing a Matheuristic for the Integrated Planning of a Cold Rolling Steel Plant

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Abstract: Steel-producing firms are confronted with the challenge of determining plans that coordinate production processes across a set of processing stages. While several approaches for integrated planning of hot rolling mills have been proposed, the cold rolling process is still poorly investigated. Therefore, we present a model formulation to simultaneously form campaigns of coils in cold rolling steel plants. The model considers multiple processing stages with unrelated parallel machines, sequence-dependent setup operations and order-specific due dates. To solve the model, we propose a matheuristic based on Fix-and-Relax and Fix-and-Optimize that utilizes a production line-based decomposition strategy. The results of a numerical study are presented that replicates the realistic production environment of a real cold rolling plant and a planning horizon of up to 10 days. The proposed matheuristic consistently outperforms a commercial solver in terms of solution quality and time.

Keywords: Campaign Formation, Cold Rolling, Fix-and-Optimize, Fix-and-Relax, Integrated Production Planning, Matheuristics, Steel Production

1. INTRODUCTION

The steel industry is a key sector for modern industrial societies. In Germany alone, it accounts for more than 20 major steel production plants and 10 to 30 percent of intermediate inputs in sectors such as mechanical engineering, vehicle manufacturing, electrical engineering, and construction (Wirtschaftsvereinigung Stahl, 2020). The production of steel products is not only particularly energy-, investment-, and cost-intensive, but is also characterized by an extremely high level of complexity in the combination of continuous and discrete production processes, extreme process conditions, a huge product variety, and volatile market conditions. Typical steel plants consist of several dozen large production lines with very specific characteristics and are capable of producing several hundred tons of products every day from a spectrum of billions of possible product configurations with the highest demands on product quality. To cope with this complexity, steelmaking companies are turning to production management systems. These highly integrated IT systems provide assistance for data-driven planning and control of production by relying on advancements in operations research (OR). Based on these techniques, it is often possible to derive near-optimal plans that address the complexity of the production environment at the level of individual production lines (e.g., Wichmann et al., 2014; Boctor, 2019) as well as processing stages (e.g., Armellini et al., 2020).

Despite these advancements, the integrated planning of steel plants is still poorly investigated. In practice, simplified backward scheduling mechanisms are used to coordinate the order flow, often relying on the expertise of human planners (Guo and Tang, 2019). Optimization is constrained to the level of single production lines. The flexibility needed for this optimization of individual production lines is thereby ensured by high inventories of intermediate products between the processes. This leads to extended total lead times, increased costs and poor delivery accuracies. Against this background, we propose a novel approach for the integrated planning of steel plants. The focus is on the planning of a cold rolling plant with multiple processing stages and parallel production lines for a planning horizon of several days. We formulate a mixed-integer non-linear program (MINLP), which we then linearize to a mixed-integer linear program (MILP), to minimize the costs related to lead time penalties, inventory and setup operations. A matheuristic is developed to solve the model. This heuristic combines a Fix-and-Relax (F&R) approach for finding the initial solution with a Fix-and-Optimize (F&O) approach for the improvement of the solution. A numerical analysis is presented that is based on the typical configuration of a cold rolling plant. The results demonstrate the superiority of the heuristic compared to a state-of-the-art commercial solver for instances of up to 220 orders.

The remainder of the paper is organized as follows: Section 2 reviews the relevant literature. The definition of the problem and its mathematical formulation are given in Section 3. A matheuristic for solving the problem is described in Section 4. In Section 5, the performance of the heuristic is tested using the example of a German cold rolling steel company. Section 6 concludes.

2. LITERATURE REVIEW

The vast majority of planning models for steel production focus on hot rolling plants. Recent reviews of the literature can be found in Escudero et al. (2019) and Özgür et al. (2021). A few planning models for cold rolling plants can be found in the literature, mostly focusing on single processing stages with one or more production lines. For cold rolling, Zhao et al. (2008) and Boctor (2019) have developed planning models and corresponding solution approaches. The scheduling of a continuous annealing line is considered in the work of Mujawar et al. (2012). Tang et al. (2010), Valls Verdejo et al. (2009), and Weiss Cohen et al. (2019) propose planning models for galvanization. Vaez et al. (2020) study the skin pass line. Most of these models are solved using some sort of problem-specific algorithm or "nature"-based heuristic.

Integrated approaches for the production planning of cold rolling plants have only seen a very limited consideration in the literature. The one closest to the model presented in this paper is described in Okano et al. (2004). They develop a problem-specific four-stage algorithm to solve instances for a planning horizon of one month. Further integrated planning models are proposed by Nastasi et al. (2015), with a focus on product quality, Liu et al. (2020), who formulate and solve a mixed-integer quadratic program for a multi-stage production process with exclusive machines at each stage, and Iannino et al. (2021), who outline a MILP for the planning of a cold rolling plant. The model seeks to optimize volume and completion time within a lexicographic solution approach. The results obtained from a commercial solver are discussed in light of two approximate approaches for a planning horizon of one day.

The heuristics proposed by Okano et al. (2004) and Nastasi et al. (2015) are highly problem specific, which limits their applicability in a more general sense. The exact approach of Liu et al. (2020) is more promising in this regard but limited to production systems without parallel lines. The work of Iannino et al. (2021) offers promising potential but misses to report the details of the mathematical formulation and the evaluation. Notably, none of the approaches integrates penalty costs for tardiness.

In an attempt to provide a universal modeling and solution approach that copes with the complexity of real-world cold rolling steel plants, we refer to a solution approach that is based on the matheuristic F&O. The basic idea of matheuristics is to decompose an original problem into smaller subproblems that are solved iteratively while fixing (F&O) or relaxing (F&R) the remainder of all integer variables. Applications of F&O to solve multi-level lot-sizing problems were first studied in Sahling et al. (2009) and combined with F&R in Stadtler and Sahling (2013).

Applications of similar approaches using decomposition strategies to the steel-industry have been reported in Harjunkoski and Grossmann (2001), Xu et al. (2018) and Hong et al. (2022) but are limited to hot rolling plants. We will build on these works and propose a solution approach for the integrated planning of cold rolling plants in the following.

3. PROBLEM SETTING AND FORMULATION

3.1 Problem setting

The cold rolling production processes aim at transforming coils of hot-rolled steel into flat steel with material properties, geometry, coating and due date according to customer specifications. The production process involves multiple stages (Okano et al., 2004; Iannino et al., 2021). While easily extendible, we will focus on the processing stages cold rolling, continuous annealing, skin passing and galvanizing, as these are typical for most industrial processes. At each processing stage, there are parallel production lines with specific properties. Each coil travels through an individual sequence of production lines.

The main challenge for integrative planning, meaning the comprehensive planning of all processing stages and production lines, is the formation and scheduling of campaigns at each processing stage such that the flow of coils and the operations of the production lines are optimized (Okano et al., 2004). A campaign is a batch of coils that can be continuously processed on a specific production line. For campaign formation, the sequential coils have to be compatible with respect to process-dependent parameters. For example, the grades, widths, and thicknesses have to be compatible, in order to allow the welding of consecutive coils into a continuous steel strip for the processes of annealing and galvanizing. In addition, the temperatures have to be compatible for annealing and the type of coating has to be identical for galvanizing. Hence, coils might have to be re-grouped after each processing stage to form new campaigns that comply with the requirements of the next processing stage. Between campaigns, setup operations are required on each production line to adjust the line settings and change worn out rollers. Setup costs depend on the sequence of campaigns, as the difference in the campaigns' process parameters will impact the necessary amount of labor, time and energy needed (e.g., in increasing the annealing temperature).

The decision problem for integrated planning of cold rolled production can thus be divided into three steps:

(1) The formation of campaigns of compatible coils based on their characteristics for each processing stage.
(2) The allocation of the campaigns to the parallel production lines at each processing stage and the scheduling of the campaigns, considering the sequence-dependent setups between the campaigns and the flow of the coils across the processing stages.
(3) The sequencing of coils within the campaigns based on their mutual compatibility.

In the optimization model developed here, only steps 1 and 2 are considered. Step 3 is largely independent of the first two and can be considered as a separate optimization problem (Tang et al., 2010). The arrangement of coils within a campaign has almost no effect on the length of the campaign and the required setup operations before and after the campaign. Moreover, it is assumed that before the completion of a campaign, none of the coils contained in it is further processed in the next process. Therefore, sequence formation has little influence on the overall production flow. We further assume that the specific

settings of the production lines for a campaign (e.g., temperature, coating) are defined by a set of campaign types. All coils have a fixed type for each processing stage and cannot skip any processing stage, i.e., all coils must pass through all four stages in the specified order.

3.2 Problem formulation

We consider a set of coils $i \in I$ with a specific arrival date at the plant r_i, due date d_i, length l_i and type, where the binary parameter $ityp_{itp}$ is set to one if coil i is from type t ($t \in T$) in processing stage p and zero otherwise (see Fig. 1). The coils are produced over a set of processing stages $p \in P$ for a specific processing time w_p. At each stage p there is a set of unrelated parallel production lines $A_p \subset A$ from the set of all production lines $a \in A$. The coils have to be assigned to campaigns $k \in K$ from the set of all campaigns K. These campaigns can contain several coils and can initially be viewed as "empty containers", which are by definition assigned to one of the processing stages ($K_p \subset K$) and production lines ($K_{pa} \subset K_p$). Campaigns can take different types $t \in T$ depending on the processing stage, as indicated by the binary parameter $ktyp_{kt}$. A setup time $u_{tt'}$ is required to change from type t to type t' on a particular production line. Between processing stages the coils have a minimum waiting and transportation time v. Fig. 1 illustrates the decision situation for a plant with four processing stages and two production lines each. The planning horizon is shown as a time line on the x-axis. The coils pass through the processes sequentially with a stock of coils between the processing stages. Both the horizontal sequence of campaigns must be planned for each line, as well as the vertical sequence of coils through each process.
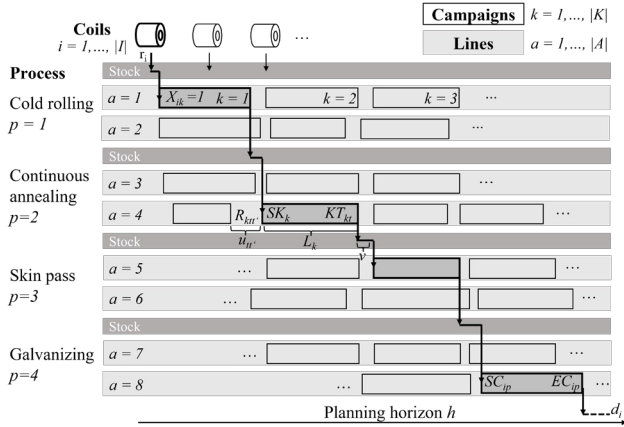

Fig. 1. Overview planning problem for four processes with two lines each

The optimization model can be described as a MINLP as follows. The binary variables $X_{ik} \in \{0, 1\}$ denote the decision of whether to assign coil i to campaign k. The chosen type t for each campaign k is $KT_{kt} \in \{0, 1\}$. For each campaign, a starting time $SK_k \in \mathbb{R}^+$ and a length $L_k \in \mathbb{R}^+$ that is necessary to complete the production of all coils entailed in the campaign are determined. $SC_{ip} \in \mathbb{R}^+$ is the starting time, and $EC_{ip} \in \mathbb{R}^+$ is the ending time of each coil at each processing stage p. From the sequence of campaigns and the chosen campaign types, the setups are derived. Binary variables $R_{ktt'} \in \{0, 1\}$ indicate the need

for a setup between the preceding campaign of type t and type t' of the considered campaign k.

The mathematical formulation is:

$$\min \quad Z = c^d \cdot \left(\sum_{i \in I} \max \left\{ EC_{i, p=|P|} - d_i, 0 \right\} \right)$$
$$+ c^u \cdot \left(\sum_{k \in K, t, t' \in T} R_{ktt'} \cdot u_{tt'} \right) \quad (1)$$
$$+ c^b \cdot \left(\sum_{i \in I, p \in P, p \geq 2} (SC_{ip} - EC_{i, p-1}) \right)$$

s.t.

$$\sum_{k \in K_p} X_{ik} = 1 \qquad \forall i, p \qquad (2)$$

$$X_{ik} \cdot r_i \leq SK_k \qquad \forall i, k \in K_{p=1} \qquad (3)$$

$$SC_{ip} = \sum_{k \in K_p} X_{ik} \cdot SK_k \qquad \forall i, p \qquad (4)$$

$$EC_{ip} = \sum_{k \in K_p} X_{ik} \cdot (SK_k + L_k) \qquad \forall i, p \qquad (5)$$

$$EC_{i, p-1} + v \leq SC_{ip} \qquad \forall i, p \geq 2 \qquad (6)$$

$$SK_{k-1} + L_{k-1}$$
$$+ \sum_{t, t' \in T} u_{tt'} \cdot R_{ktt'} \leq SK_k \qquad \forall k \in K_{pa} \forall a \qquad (7)$$

$$L_k = \sum_{i \in I} X_{ik} \cdot l_i \cdot w_p \qquad \forall p, k \in K_p \qquad (8)$$

$$minl_t \cdot KT_{kt} \leq L_k \cdot KT_{kt} \leq maxl_t \quad \forall k, t \qquad (9)$$

$$KT_{kt} \leq ktyp_{kt} \qquad \forall k, t \qquad (10)$$

$$\sum_{t \in T} KT_{kt} = 1 \qquad \forall k \qquad (11)$$

$$X_{ik} \cdot ityp_{itp} \leq KT_{kt} \qquad \forall i, t, p, k \in K_p \quad (12)$$

$$R_{ktt'} = KT_{k-1, t} \cdot KT_{kt'} \qquad \forall k, t, t' \qquad (13)$$

$$0 \leq SK_k \leq h \qquad \forall k \qquad (14)$$

$$0 \leq SC_{ip} \leq h \qquad \forall i, p \qquad (15)$$

$$0 \leq EC_{ip} \leq h \qquad \forall i, p \qquad (16)$$

$$X_{ik}, KT_{kt}, R_{ktt'} \in \{0, 1\} \qquad \forall i, k, t, t' \qquad (17)$$

The objective function Z (1) minimizes the sum of costs due to tardiness, setups, and inventory holding. In this, tardiness quantifies the positive deviation of the ending time of each coil at the last processing stage from its due date d_i, where d_i can be set to r_i to minimize the total lead times. The time on inventory for each coil is calculated as the time between the finishing of one process and the start of the consecutive one. c^d, c^u, and c^b are the corresponding cost factors. Equation (2) ensures that each coil is assigned to one campaign per processing stage. The earliest starting point for each coil in the first processing stage is defined in (3). Equations (4) and (5) assign the starting time for each coil in each processing stage depending on the campaign. Please note, that this will assign the same start and end time to all coils in the campaign, as we do not consider the transport of partial campaigns. In (6), the vertical order of processing stages and the waiting time between them is ensured while (7) ensures the horizontal

order of campaigns on each production line. The length of a campaign is defined in (8) and limited to a minimal ($minl_t$) and maximal ($maxl_t$) length due to technical or logistical constraints in (9). All coils in a given campaign must be of the same type, and this type is adopted for the entire campaign, as described in Equations (10) - (12). The setup operations depending on the campaign types are considered in (13). Equations (14) - (16) define the value range of the continuous variables, which is between zero and the end of the time horizon h, while (17) defines the binary variables. Equations (1), (4), (5), (9) and (13) are non-linear but can easily be linearized using large-number formulations according to standard techniques. We have used these linear formulations for the numerical study in this paper.

First numerical computations have shown that large instances of the problem cannot be solved to optimality, or at least not in a reasonable computation time. For this reason, a heuristic from the class of matheuristics is developed in the following section.

4. THE PROPOSED MATHEURISTIC

The basic idea of matheuristics is the decomposition of the original problem into several smaller subproblems that can be solved to optimality using standard, exact algorithms in an iterative fashion to generate a solution that is close to the optimal solution (Caserta and Voss, 2010). The proposed matheuristic consists of two phases. The first phase is to generate an initial feasible solution by applying a F&R approach. In the second phase, we use a F&O heuristic to improve the initial solution (see Fig. 2).
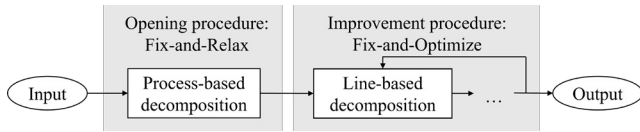
Fig. 2. Heuristic procedure

4.1 Generating an initial solution via Fix-and-Relax

For the F&R heuristic, a process-based decomposition strategy is chosen. The model (1)-(17) is extended by the following constraints:

$$X_{ik}, KT_{kt}, R_{ktt'} \in [0,1] \qquad \forall i,t,k \tag{18}$$

$$X_{ik}, KT_{kt}, R_{ktt'} \in \{0,1\} \qquad \forall i,t,k \in K^{opt} \tag{19}$$

$$X_{ik} = X_{ik}^{fix}, KT_{kt} = KT_{kt}^{fix}, R_{ktt'} = R_{ktt'}^{fix} \\ \forall i,t,k \in K^{fix} \tag{20}$$

The heuristic works as follows: First, all binary variables are relaxed (18). Then, in the first iteration, only the binary variables for the first processing stage are redefined to be binary and optimized together with all continuous variables (19). K^{opt} is the set of campaigns belonging to that processing stage. For the next iteration, the values found for the first processing stage are fixed (20), and the second processing stage is optimized. This is done using the set of campaigns K^{fix}, for which all corresponding variables are fixed to a given parameter $X_{ik}^{fix}, KT_{kt}^{fix}, R_{ktt'}^{fix}$. In

the third iteration, the solutions for the first and second processing stages are fixed, and the third process is optimized. Finally, the fourth process is optimized accordingly. The final solution found is binary in all binary variables and thus is also a feasible solution for the original problem. Algorithm 1 formally presents the procedure, and Fig. 3 illustrates the procedure for four processes with two lines each.

Algorithm 1 Opening procedure with F&R

$K^{fix}, K^{opt} \leftarrow \emptyset$
for $p = 1, ..., |P|$ **do**
    $K^{fix} \leftarrow K^{fix} \cup K^{opt}$
    $K^{opt} \leftarrow K_p$
    solve submodel and determine $X_{ik}, KT_{kt}, R_{ktt'}$
    $X_{ik}^{fix}, KT_{kt}^{fix}, R_{ktt'}^{fix} \leftarrow X_{ik}, KT_{kt}, R_{ktt'} \qquad \forall i,t,k \in K^{opt}$
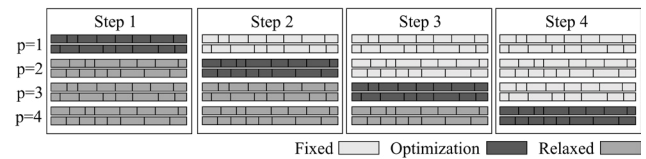**end for**

Fig. 3. F&R heuristic procedure

4.2 Improving the solution with Fix-and-Optimize

The F&O heuristic improves the solution by iteratively solving a subproblem with a limited set of variables while fixing all other variables to the values of the best solution found in prior iterations. Different decomposition strategies can be applied to determine the subproblem. We will focus on line-based decomposition in the following. In each iteration, a set of campaigns $K^{opt} \subset K$ is defined based on the production lines considered. All other variables corresponding to the campaigns $K^{fix} = K \setminus K^{opt}$ are fixed by constraint (20). The lines $a \in A$ for each subproblem could be selected randomly or deterministically. Here, we consider the deterministic selection in increasing order of each line a and its subsequent line $a + 1$ in each iteration (see Fig. 4). Thereby, $|A| - 1$ subproblems are created, each optimizing a share of $2/A$ of the binary variables. Algorithm 2 elaborates the procedure.

Algorithm 2 F&O with line-based decomposition

$K^{fix}, K^{opt} \leftarrow \emptyset$
$Z^{old} \leftarrow Z^{FR}$
$X_{ik}^{fix}, KT_{kt}^{fix}, R_{ktt'}^{fix} \leftarrow X_{ik}^{FR}, KT_{kt}^{FR}, R_{ktt'}^{FR} \qquad \forall i,t,k$
for all $a = 1, ..., |A| - 1$ **do**
    $K^{opt} \leftarrow K_{pa} \cup K_{p,a+1}$
    $K^{fix} \leftarrow K \setminus K^{opt}$
    solve submodel and determine $Z, X_{ik}, KT_{kt}, R_{ktt'}$
    if $Z < Z^{old}$ **then**
        $Z^{old} \leftarrow Z$
        $X_{ik}^{fix}, KT_{kt}^{fix}, R_{ktt'}^{fix} \leftarrow X_{ik}, KT_{kt}, R_{ktt'} \\ \forall i,t,k \in K^{opt}$
    end if
end for

In each iteration, the binary part of the solution is fixed if the newly found objective function value Z is better
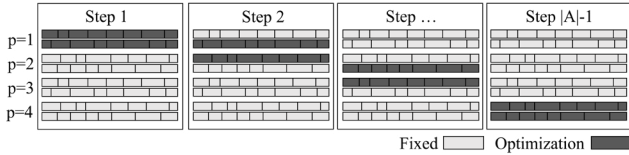
Fig. 4. F&O heuristic with line-based decomposition

than the best one found so far ($Z < Z^{old}$). Otherwise, the new solution is discarded. The line-based decomposition can be iteratively repeated until a termination criterion is met. Either no better objective function value is found after iterating over all lines, the predefined time limit is reached, or the predefined maximum number of iterations is met.

5. NUMERICAL STUDY

In order to evaluate the performance of the heuristic, we refer to a dataset that has been inspired by the case of a German cold rolling company. The production setup includes two parallel lines for cold rolling, three parallel lines for continuous annealing and for skin pass each, as well as five parallel lines for galvanizing. We assume a feasible campaign length between 50-500 coils, process times of 5-10 min depending on the process and setup times of 10-20 min, depending on the campaign types. The number of possible types per process differs from one type for skin pass to 10 types for annealing (corresponding to the temperatures). Furthermore, we assume a planned total lead time of 10 days and a minimum waiting time between processes of 24 h, as in Iannino et al. (2021). The cost rates are chosen to balance the three different objectives in the objective function (approximately 50% of overall costs are for setup operations, 30% for tardiness and 20% for storage).

For the numerical study, three problem classes with increasing size are defined (Table 1). While Class A is a small class with a reduced number of coils and types, Class B resembles the real case with a planning horizon of 5 days and class C with a planning horizon of 10 days. For each class, we solve 12 instances with random orders, varying in size (between 1-20 coils) and product type, and report the mean values of the objective function values, solution times, and the relative deviations in Table 1. For the experiments, we use the programming language *Julia* (Version 1.5.2) and the package *JuMP*. The optimization is done using the *Gurobi* solver (Version 9.1). The experiments are conducted on a computer with an Intel Core i5-8250U four-core processor with 1.60 GHz and 8 GB RAM.

To assess the performance of the proposed heuristic, we refer to a benchmark that utilizes the standard solver *Gurobi*. As *Gurobi* is not able to find a feasible solution for all instances of the largest problem class, the initial solution found by the F&R heuristic is used as a warm start for the *Gurobi* optimization. The solution time for *Gurobi* is limited to 7200 s. The solutions found by the F&O heuristic are compared to that benchmark by calculating the relative deviation as

$$rel.\ deviation = \frac{Z(Heuristic) - Z(Benchmark)}{Z(Benchmark)} \quad (21)$$

For the F&R heuristic, the solution time for each subproblem is limited to 240 s, and the MIP-Gap is set to 18% in order to limit the overall heuristic solution time and to evenly distribute the solution time to the different submodels, which may vary in size and complexity. The solution time limit per subproblem of the F&O heuristic is set to 60 s, the MIP-Gap is set to 5%, and the number of iterations is limited to six, where one iteration refers to the optimization of all production lines and their subsequent lines. These parameters have demonstrated a good compromise for the trade-off between solution time and solution quality.

The results show that the heuristic generates significantly better results for problem classes B and C than *Gurobi*. The advantage of the heuristic increases with problem size. While this comes at the cost of a longer solution time, even in the largest problem class C, the heuristic delivers 36% better solutions than *Gurobi* in less than half the time. This is true not only on average but also if we take a look at the single instances. Fig. 5 shows that for every instance of class C, the objective function value found by the heuristic is lower than the benchmark found by *Gurobi*. In general, we observe that the approach allows the planning of orders for a five-day horizon in approximately 10-15 min and for a 10-day horizon in 20-30 min of solution time.
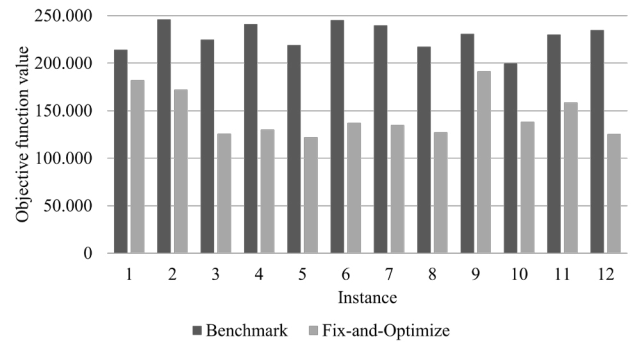

Fig. 5. Comparison of objective values from benchmark and heuristic for all instances of class C

6. CONCLUSION AND FUTURE WORKS

This study shows the relevance and complexity of the integrated planning of cold rolling plants. The proposed approach of combining F&R and F&O heuristics, which have been used mainly for lot-sizing applications so far, shows to be very effective for solving this type of problem. In the numerical study, the proposed heuristic has demonstrated its ability to identify significantly better solution in a shorter time than a standard solver. This finding provides the starting point for many further investigations. Next steps include the testing of different decomposition strategies (e.g., product- or time-based) and their combination within the heuristic, as well as the optimization of heuristic parameters such as subproblem size and selection, MIP-Gaps, time limit and iteration limits, to increase the performance. The coupling with a simulation model of the production setup would enable a test of the robustness and flexibility of the generated production plan under uncertainty and the development of an iterative simulation and optimization approach. Finally, a real industry data

Table 1. Numerical study results

Class	# binary variables	F&R		Benchmark	F&O		
		objective function value	solution time (s)	objective function value (in 7200 s)	objective function value	solution time (s)	relative deviation
A	9.100	13.307	25	12.320	12.321	18	0%
B	28.730	75.478	269	63.861	52.515	986	-17%
C	73.060	247.175	845	230.487	146.337	2.897	-36%

set should be tested to prove applicability to the industry and validate the model's results.

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