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MULTI-OBJECTIVE OPTIMIZATION FOR A SCHEDULING PROBLEM IN THE STEEL INDUSTRY

Viktoria A. Hauder[(a)(b)], Andreas Beham[(a)(c)], Sebastian Raggl[(a)], Michael Affenzeller[(a)(c)]

[(a)] Heuristic and Evolutionary Algorithms Laboratory,
University of Applied Sciences Upper Austria, Hagenberg, Austria

[(b)] Institute for Production and Logistics Management,
Johannes Kepler University Linz, Austria

[(c)] Institute for Formal Models and Verification,
Johannes Kepler University Linz, Austria

[(a)]{viktoria.hauder,andreas.beham,sebastian.raggl,michael.affenzeller}@fh-hagenberg.at

ABSTRACT
Multiple conflicting objectives such as costs versus quality are part of many optimization processes in the area of production and logistics management. Exactly such a case is also examined in this work. For an already existing resource-constrained project scheduling problem, a second objective function, inspired by the steel industry, is taken into account. Together with the presentation of the related mixed integer programming (MIP) and constraint programming (CP) models, the recently developed balanced box method (Boland, Charkhgard, and Savelsbergh 2015) is used to solve this bi-objective optimization problem. Both approaches (MIP and CP) are compared in terms of runtime and solution quality, showing the advantages of using CP.

Keywords: multi-objective optimization, scheduling, balanced box method, steel industry

1. INTRODUCTION
For the successful implementation of real-world logistics optimization problems, more than one objective has to be considered in many cases. In this work, such a multi-objective optimization problem is investigated. The starting point for this examination is the work of Hauder, Beham, Raggl and Affenzeller (2018), where a single-objective scheduling problem of a steel manufacturer is presented. They introduce a resource-constrained multi-project scheduling problem, where one out of multiple alternative production paths has to be selected for the manufacturing of steel lots. The objective is the minimization of the makespan. For the real-world application, however, an additional target criterion has to be taken into account. The company has defined priorities for the selection of the alternative production paths, resulting in a priority function maximization as a second objective (Hauder, Beham, Raggl, Affenzeller 2019b). In order to tackle this multi-objective optimization problem (MOP), the so-called balanced box method (BBM) (Boland, Charkhgard, and Savelsbergh 2015) is regarded. The results of the chosen method are presented for the mixed integer programming (MIP) as well as for the constraint programming (CP) model of the multi-objective optimization problem by solving it with the optimization suite IBM ILOG CPLEX. The achieved solutions are then compared concerning runtime efficiency and solution quality.

The paper is organized as follows. First, related work concerning multi-objective optimization is described in Section 2. Next, the multi-objective industry case models are presented in Section 3. Optimization results are then illustrated in Section 4, followed by concluding remarks and a future outlook in Section 5.

2. RELATED LITERATURE
Many real-world optimization problems involve two or even more conflicting objectives. Typical well-known examples are a maximized quality on the one hand and minimized costs on the other hand. For decision makers, it is very often not easy to prioritize or weight such conflicting goals prior to a necessary optimization process. One possible way out of this challenging target is the generation of all Pareto-optimal solutions, i.e. the set of all optimization solutions in which one objective can no longer be improved without worsening another one (=Pareto-set). Decision makers can then evaluate all generated trade-off solutions and select the one they rate best for their field.
In order to generate the Pareto-set, different heuristic and exact solution methods have already been developed (Bechikh, Datta, and Gupta 2016; Ehrgott 2005). Examples for MOP methods are the weighted sum method (Aneja, Nair 1979; Hauder, Beham, Raggl, Affenzeller 2019b), the ε-constraint method (Haimes 1971) and the non-dominated sorting algorithm (Srinivas, Deb 1994). However, since a full investigation of such methods is outside the scope of this work, the

interested reader is referred to Bechikh, Datta, and Gupta (2016), Deb (2014), and Ehrgott (2005) for a further detailed examination.

One of the most recently developed methods is the balanced box method. This new algorithm for bi-objective optimization problems has been introduced by Boland, Charkhgard, and Savelsbergh (2015). Such as other multi-objective optimization methods, it finds all nondominated points and is described to be very competitive in terms of solution quality and runtime. The BBM is an extension of the Box algorithm (Hamacher, Pedersen, and Ruzika 2007) and always splits the solution space into two parts (bottom and top rectangle). First, the bottom rectangle is searched for a nondominated point by lexicographically optimizing it. Second, the top rectangle is optimized the same way, but already without considering the part which has been identified to be dominated by the first bottom rectangle optimization. This procedure is repeated until all nondominated points are found, always by again splitting the existing boxes and without considering the dominated part of the prior optimization for a speed up of the optimization process (Boland, Charkhgard, and Savelsbergh, 2015).

Project scheduling is known to be a promising modeling approach when limited resources and precedence relations have to be taken into account. The related optimization problem is the so-called resource-constrained project scheduling problem (RCPSP). The basic RCPSP consists of activities which have to be scheduled under consideration of time restrictions, resource constraints and precedence relations (Hartmann and Briskorn 2010). Many real-world applications show that flexibility in the selection of such activities is a necessary extension of this problem (Kellenbrink and Helber 2015; Čapek, Šůcha, and Hanzálek 2012). Hauder, Beham, Raggl and Affenzeller (2018, 2019a) also give two further extensions of the RCPSP where flexibility is considered, based on the work of Tao and Dong (2017). They work on the selection of alternative activities for the production of multiple steel lots in a single-objective environment.

3. MULTI-OBJECTIVE SCHEDULING FOR THE STEEL INDUSTRY

In the following, we first describe the multi-objective problem in detail, including the consideration of a second objective and related additional constraints within a mixed integer programming model in Section 3.1. Thereafter, we present the constraint programming formulation in Section 3.2.

3.1. Steel industry scheduling with multiple objectives: MIP formulation

Our steel industry partner needs an optimized solution for a resource-constrained project scheduling problem allowing flexibility in the selection of activities. This problem arises after the completion of the continuous casting process and ends with customer deliveries. It consists of operations or activities or nodes $i, j \in \{0, \dots, N+1\}$, where nodes $\{0, N+1\}$ represent artificial start and end nodes and all other nodes are real-world activities. Moreover, the subset $L \subset N$ defines the lots and thus, the customer orders considered for the optimization. The adjacency matrix A_{ij} represents the allowed and forbidden connections between all activities. With the flexibility type f_i, flexibility in the selection of alternative production routes is represented. The processing time p_i is defined for every activity and all activities need renewable resources $k \in \{1, \dots, K\}$ with a demand Q_{ik}. We only consider renewable resource capacities C_k, since nonrenewable ones do not exist in the manufacturer´s plant. The time horizon $t \in \{1, \dots, T\}$ gives the maximum planning period. With decision variable y_i, it is decided if an activity is selected for performance ($y_i = 1$) or not ($y_i = 0$) and z_{it} decides if an activity is selected for completion at time slot t ($z_{it} = 1$) or not ($z_{it} = 0$).
The minimization of the makespan is a very well-known objective (Hartmann and Briskorn 2010) and has already been considered in Hauder, Beham, Raggl and Affenzeller (2018). The second goal of priority maximization (Hauder, Beham, Raggl and Affenzeller 2019b) is implemented by the assignment of a priority value $Prio_i$ for the subset P_i which includes all activities with priority values. The higher the priority value is, the more the company wishes to select the corresponding activity and thus, a specific production route. Overall, the presented descriptions result in the following mixed integer programming model:

$$Minimize$$

$$\sum_{t \in T} t \cdot z_{N+1t} \tag{1a}$$

$$Minimize$$

$$\sum_{t \in T} \sum_{i \in P} Prio_i \cdot x_i \tag{1b}$$

$$subject\ to$$

$$y_0 = 1 \tag{2}$$

$$\sum_{t \in T} z_{it} = y_i \qquad \forall\, i \in N, \tag{3}$$

$$\sum_{j \in N} A_{ij} \cdot y_j = y_i \quad \forall\, i \in N, \quad if\ f_i = 0, \tag{4}$$

$$y_j \geq A_{ij} \cdot y_i \qquad \forall\, i, j \in N, \quad if\ f_i = 1, \tag{5}$$

$$\sum_{j \in N} A_{ij} \cdot y_j = y_j \quad \forall\, i \in N, \quad if\ f_j = 2, \tag{6}$$

$$A_{ij}(\sum_{t\in T} t \cdot z_{it}) + (y_j + y_i - 2) \cdot M \leq \sum_{t\in T} t \cdot z_{jt} - p_j \qquad \forall\, i,j \in N, \tag{7}$$

$$\sum_{i\in N} \sum_{\tau=t}^{t+D_i-1} z_{i\tau} \cdot Q_{ik} \leq C_k \qquad \forall\, k \in K, t \in T, \tag{8}$$

$$\sum_{t\in T} \sum_{i\in P} Prio_i \cdot x_i \geq L, \tag{9}$$

$$y_i, z_{it} \in \{0,1\} \qquad \forall\, i \in N, t \in T. \tag{10}$$

Objective (1a) minimizes the overall makespan. Objective (1b) maximizes priority values, i.e. it maximizes the selection of the routes which the company prioritizes the highest. With constraint (2), the production is started and constraints (3) ensure that activities which are selected for performance are exactly finished once. Restrictions (4)-(6) show flexibility possibilities: If an activity is an OR node, exactly one successor must be selected; if an activity is an AND node, more than one successor can be selected. If an activity is an OUT node (=dummy sink node per project), it is guaranteed that no additional nodes of other production routes of the same lot (=project) can be selected. Conditions (7) imply that processing times are met. With constraints (8), capacity restrictions are introduced. Condition (9) serves as a lower bound for the second objective of priority maximization: As for all production routes, a minimum value of 1 is defined in the input, the sum of all priorities must at least correspond with the amount of lots considered for the optimization (since for every lot, one production route has to be selected according to restrictions (4)). Constraints (10) define the decision variables as binary ones.

3.2. Steel industry scheduling with multiple objectives: CP formulation

For the constraint programming model, the formulation, including decision variables and resource utilization, works differently compared to the MIP model. CP in general and also the CP Optimizer of IBM ILOG CPLEX consist of decision variables, functions and expressions for the decision variables, and resource functions (Bockmayr and Hooker 2005; Laborie, Rogerie, Shaw, and Vilím 2018).

For our CP model, we use the decision variable $interval(w_j)$ `optional in 0..T`. It selects one out of multiple alternative activities and decides on the start time of every activity. Moreover, the resource function `cumulFunction` $q_r = \sum_{j\in\mathcal{J}:c_{jr}\geq 0} \texttt{pulse}(w_j, c_{jr})$ decides on the cumulative resource usage of every activity, considering its demand c_{jr}, over time. The resulting optimization model for the BBM implementation is now presented as follows:

$$\text{Minimize} \quad \texttt{endOf}(w_{n+1}) \tag{11a}$$

$$\text{Minimize} \quad \sum_{i\in P} Prio_i \cdot \texttt{presenceOf}(w_i) \tag{11b}$$

subject to

$$\texttt{startOf}(w_0) = 1, \tag{12}$$

$$\texttt{presenceOf}(w_0) = 1, \tag{13}$$

$$\texttt{presenceOf}(w_{n+1}) = 1, \tag{14}$$

$$\texttt{presenceOf}(w_i) = 1 \qquad \forall\, i \in \mathcal{L}, \tag{15}$$

$$\texttt{lengthOf}(w_i) = p_i \qquad \forall\, i \in \mathcal{J}, \tag{16}$$

$$\texttt{endOf}(w_i) \geq D_i \qquad \forall\, i \in \mathcal{L}, \tag{17}$$

$$\texttt{endOf}(w_i) \leq T \qquad \forall\, i \in \mathcal{L}, \tag{18}$$

$$\texttt{alternative}(w_i, \{w_a \in S_i\}) \qquad \forall\, i \in \mathcal{M}, \tag{19}$$

$$\texttt{endAtStart}(w_i, w_a) \qquad \forall\, i \in \mathcal{M}, a \in E_i, \tag{20}$$

$$\texttt{endBeforeStart}(w_i, w_{n+1}) \qquad \forall\, i,j \in \mathcal{L}, \tag{21}$$

$$\texttt{endAtStart}(w_i, w_j) \qquad \forall\, i,j \in \mathcal{A}, \tag{22}$$

$$\texttt{presenceOf}(w_i) = \texttt{presenceOf}(w_j) \qquad \forall\, i,j \in \mathcal{A}, \tag{23}$$

$$\sum_{i\in P} Prio_i \cdot \texttt{presenceOf}(w_i) \geq L, \tag{24}$$

$$q_r \leq C_r \quad \forall\, r \in \mathcal{R}. \tag{25}$$

Objective (11a) minimizes the overall makespan and the objective (11b) maximizes the priority values. Constraints (12)-(14) guarantee the start and end of the whole production cycle. Restrictions (15) ensure the production of all lots. With conditions (16), the processing times have to be adhered to. Constraints (17)-(18) forbid early deliveries and restrict the schedule to the overall project horizon *T*. With restrictions (19)-(20), flexibility in terms of alternative routes is presented. Constraints (21) ensure that all lots have to be produced before the production process is finished. Conditions (23) imply the adherence to existing precedence relations and constraints (24) serve as a lower bound for priority values, as already explained for the MIP model. With constraints (25), capacities cannot be exceeded.

4. COMPUTATIONAL RESULTS

Both models and the corresponding balanced box method are implemented in and solved by IBM ILOG CPLEX 12.9.0 on a virtual machine Intel(R) Xeon(R) CPU E5-2660 v4, 2.00GHz with 28 logical processors, Microsoft Windows 10 Education. The runtime (T) is limited to one hour, since this is the limit set by our steel industry partner. The used benchmark instances are the ones presented in Hauder, Beham, Raggl, Parragh and Affenzeller (2019a) and extended in terms of priority values. The values are defined from 1 to 3 and randomly assigned to all lots. The value 1 corresponds with the highest priority and 3 with the lowest one. The test instances consist of 10, 15, and 20 lots. For every lot size, five instances are randomly generated.

In Table 1, CP and MIP optimization solutions are presented. Column 1 gives the lot size and column 2 the number of activities considered for each instance. The third column shows the runtime in seconds; and the "T" indicates that the runtime limit of 3,600 seconds has been reached. In column 4, the amount of non-dominated points found by the CP optimization is presented. Column 5 and 6 follow the same explanation logic, showing the results of the MIP optimization. Bold letters represent the finding of the whole Pareto-set.

Table 1. CP optimization results with the balanced box method.

		CP		**MIP**	
Lots	Activi-ties	**Run-time**	**#Non.-dom.**	**Run-time**	**#Non.-dom.**
	160	2.27	**4**	T	2
	163	15.07	**9**	T	2
10	158	16.79	**10**	T	2
	163	15.82	**11**	T	1
	167	35.11	**9**	T	2
	232	117.30	**6**	T	-
	259	T	12	T	-
15	238	T	12	T	-
	252	2459.26	**12**	T	-
	247	T	19	T	-
	311	T	2	T	-
	340	T	5	T	-
20	319	T	3	T	-
	340	T	1	T	-
	306	T	2	T	-

It can be seen in Table 1 that, with the MIP model, it is only possible to generate solutions for the smallest instance size of 10 lots. For bigger instances, it is not even possible to generate a feasible solution. We assume that the reasons for these findings are two-fold. On the one hand, we have a huge amount of nodes already for the smallest lot size 10 (already more than 150 nodes), resulting in a huge amount of decision variables and constraints that have to be considered by the MIP solver in contrary to the CP solver. On the other hand, two objectives have to be regarded, which also seems to make the problem very hard to solve for the MIP solver.

For the CP solution approach, it can be seen that the whole Pareto-front is easily found for small instances. However, the bigger and thus, the more complex the instances become, the harder it is for the CP Optimizer to find even one non-dominated point. Nevertheless, the optimization solutions show that the CP model is more competitive in terms of solution quality and runtime, e.g. having a runtime of under one minute and all optimal solutions for all instances of lot size 10 in contrary to the MIP approach, where only some optimal solutions are found within the allowed time limit T.

5. CONCLUSION

In this work, a multi-objective optimization of an already existing RCPSP with activity selection flexibility has been presented. By applying the balanced box method, it is possible to generate the full Pareto-set for small instances with the developed CP model in contrary to the MIP approach. However, bigger instances show the limit of this approach for the here presented RCPSP. Future work should therefore concentrate on alternative multi-objective algorithms, as for example the NSGA-II, in order to generate exact solutions also for huger instances.

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AUTHORS BIOGRAPHY

VIKTORIA HAUDER obtained her master´s degree in social and economic sciences with a major in production and logistics management from the Johannes Kepler University Linz, Austria, in 2014. After gaining practical experience as a logistics manager, she has started working as a research associate in the research group HEAL. Her research interests focus on operations research, production planning and logistics optimization, respectively. In 2017, she has started with her doctoral studies with the working title "Integrated Logistics Optimization".

ANDREAS BEHAM received his master's degree in computer science in 2007 and his PhD in engineering sciences in 2019 from the Johannes Kepler University in Linz, Austria, and is a research associate in the Heuristic and Evolutionary Algorithms Laboratory at the research center in Hagenberg. His research interests include metaheuristic methods applied to combinatorial and simulation-based problems. He is a member of the HeuristicLab architects team.

SEBASTIAN RAGGL received his Master of Science in Bioinformatics in 2014 from the University of Applied Sciences Upper Austria, and is a research associate at the Research Center Hagenberg in the Heuristic and Evolutionary Algorithms Laboratory. His research interests include metaheuristic methods applied to combinatorial and simulation-based problems.

MICHAEL AFFENZELLER has published several papers, journal articles and books dealing with theoretical and practical aspects of evolutionary computation, genetic algorithms, and metaheuristics in general. In 2001 he received his PhD in engineering sciences and in 2004 he received his habilitation in applied systems engineering, both from the Johannes Kepler University in Linz, Austria. He is a professor at the University of Applied Sciences Upper Austria and head of the Heuristic and Evolutionary Algorithms Laboratory.