Scheduling the Brazilian OR Conference

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Abstract

In this paper, we show how to efficiently schedule the Brazilian OR conference using a matheuristic approach. The event has traditionally around 300 presentations across a period of 3 to 4 days, and building a schedule for the technical sessions is an arduous task. The proposed algorithm integrates the concepts of iterated local search and simulated annealing with two mathematical programming-based procedures. The idea is to first group the presentations via a clustering procedure, and handle the side constraints in a subproblem via an integer programming formulation. A set partitioning procedure is applied at the end of the algorithm to find the optimal combination of clusters found during the search. We first assess the performance of the method by comparing our results with the dual bounds attained in the literature on two existing sets of artificial instances derived from other two conferences. Next, we executed our approach on the real-life instances derived from different SBPO editions, and compared the solutions with the manual solutions, when available, or with dual bounds found by an exact algorithm from the literature. The results obtained show that the matheuristic is capable of achieving high quality solutions both on the artificial and real-life instances.

1 Introduction

The Brazilian Operations Research (OR) conference, officially called *Simpósio Brasileiro de Pesquisa Operaiconal* (SBPO), is an event organized every year by the Brazilian OR society, formally known as *Sociedade Brasileira de Pesquisa Operacional* (SOBRAPO). SBPO has now reached more than 50 editions, and it is considered the main national OR conference, gathering hundreds of participants, from undergraduate students to practitioners and experienced researchers.

The event follows the format of a typical academic conference by including technical sessions, plenary talks, short-term courses, poster sessions, social activities, and so on, during a period of 4 days. We are particularly interested in solving the problem of scheduling the presentations of technical sessions, which is by far the most challenging task for the organizers. The other activities can be easily scheduled without much effort.

Up to 2018, the problem was solved manually during several days, and finding high quality solutions was viewed as an arduous task. The initiative of addressing the problem using an optimization approach started that year, and it continues to be used to this date. In this paper, we describe in detail the strategy developed for successfully solving the problem.

The scheduling criteria specified by the SBPO organizers fit precisely the generic clustering-based model recently introduced by Bulhões et al. [2020] for *conference scheduling* (CS) problems. Nevertheless, the exact algorithm proposed by the authors was not capable of solving all of the real-life instances (with up to 324 presentations) derived from the referred event to optimality in an acceptable CPU time. Therefore, the main contribution of this work is the development of an efficient matheuristic algorithm that combines the principles of *iterated local search* (ILS) and *simulated annealing* (SA) with two *mathematical programming*-based procedures. The idea is to group the presentations with similar topics in a same session using a clustering procedure based on ILS and SA, and then handle the side constraints in a subproblem via an *integer linear programming* (ILP) formulation. A set partitioning procedure is applied at the end of the algorithm as an attempt to find the optimal combination of clusters found during the search.

We first evaluate the performance of the matheuristic by means of extensive computational experiments on artificial benchmark instances derived from two other conferences, and compare the results obtained by our method with the existing dual bounds produced by the exact procedure devised in Bulhões et al. [2020]. We then compare the results found by our approach on real-life instances derived from SBPO with the manual solutions, or with the dual bounds provided by the exact algorithm, in order to confirm the high performance of the proposed algorithm. Moreover, we believe that the matheuristic devised in this work can be either directly applied or easily adapted to solve a wide range of CS problems.

The remainder of the paper is structured as follows. Section 2 presents a brief literature review. Section 3 formally defines the problem. Section 4 describes the proposed algorithm. Section 5 contains the results of the computational experiments. Section 6 concludes.

2 Related work

The literature on CS dates back more than 30 years. Eglese and Rand [1987] were one of the first to study the problem by trying to maximize the preference of the participants. They proposed a formulation and a two-phase heuristic. Sampson and Weiss [1995] addressed an extended version of the problem by considering the capacity of the rooms. A heuristic procedure was developed by the authors, that was also later used to examine the influence of some factors (e.g., conference length) on the resulting schedule [Sampson and Weiss, 1996]. Le Page [1996] devised a heuristic procedure for a CS problem that aims at minimizing the conflicts of presentations assigned to parallel sessions based on the preference of the attendees.

Thompson [2002] also studied a variant of the model suggested in Eglese and Rand [1987] by assuming the existence of rooms with different capacities, and they put forward a SA algorithm. Sampson [2004] later compared the preference-based CS with other related problems, namely *course timetabling* and *exam timetabling*. The author also modified the original model by Eglese and Rand [1987], and devised a SA approach for the problem. Gulati and Sengupta [2004] developed a heuristic for a extended version of the model presented in Sampson [2004], which incorporated other criteria, namely reviewer evaluations and session times.

Mori and Tanaka [2002], Tanaka et al. [2002] tackled a CS problem with the objective of grouping the most similar works in a same session. The former proposed a *genetic algorithm*, the latter a so-called *self organizing map*, which is based on the concept of unsupervised neural network. Potthoff and Munger [2003] addressed the problem of assigning sessions containing 3 or 4 presentations, defined *a priori*, to time slots. They also assumed that a presenter can perform other roles such as the coordinator (a.k.a. chair) of the session. Therefore, one must ensure that he/she cannot be assigned to parallel sessions. A *mixed integer programming* (MIP) formulation was proposed, which was used to schedule the Annual Meeting of the Public Choice Society of 2001. Potthoff and Brams [2007] later applied the same method to schedule the 2005 and 2006 editions of the same conference but this time considering the availability of the presenters.

Nicholls [2007] implemented a heuristic for a CS problem that attempt to satisfy the preferences of the presenters, whereas Ibrahim et al. [2008] applied combinatorial design results to generate a balanced schedule. Edis and Sancar Edis [2013] proposed a model that tries to optimize two objectives: (i) minimize the number of parallel sessions with presentations of the same topic; and (ii) balance the number of presentations of the parallel sessions. Quesnelle and Steffy [2015] developed a model to minimize attendee preference conflicts that also avoids presentations by a same author to be assigned to parallel sessions. Rahim et al. [2017] implemented a so-called *domain transformation approach* to solve a problem with a similar preference-based objective.

Vangerven et al. [2018] solved a CS problem aiming at maximizing the attendees' preference and minimizing the number of hops, i.e., the number of times a participant has to change rooms to attend a presentation of his/her interest. The authors proposed a three-phase algorithm based on integer programming and heuristics to solve four real-life conferences. Stidsen et al. [2018] addressed the problem of scheduling the EURO-k conferences by solving five MIP models sequentially. The problem has several objectives to cope with the hierarchical structure of the conference.

Finally, Bulhões et al. [2020] proposed a clustering-based approach to model CS conferences in general. The idea is to group the presentations according to their level of similarity and handle the specificities of the conference by means of side constraints. They proposed three exact approaches: (i) a compact integer programming formulation; (ii) an alternative formulation, in which lazy cuts are added on demand in case any of the side constraints is violated; and (iii) a branch-cut-and-price algorithm over a set partitioning (SP) formulation. They reported results for real-life and artificial instances derived from two conferences.

3 Problem definition

Historically, the organizers of SBPO have been grouping similar papers into a thematic session (e.g., "Combinatorial Optimization", "Metaheuristics", etc.), and this format has been well accepted by the participants. Moreover, they usually tend to avoid parallel sessions with similar topics, as well as many sessions of a similar topic to occur in a same day. They also try to avoid papers from a same author to be scheduled in parallel sessions. Other particularities such as presenter's availability are handled *a posteriori*, once a scheduled has been built. The optimization problem defined in this section was modeled exactly as specified by the organizers. We first introduce some notation, and then we formally provide the objective function and constraints of the problem.

We are given the following sets:

- $P = \{1, \ldots, n\}$ – set of papers (or presentations);
- D – set of days;
- H – a set of non-overlapping time slots;

- S – set of sessions;
- T – set of topics;
- A – set of authors;
- $P_a \subseteq P$ – set of papers by author $a \in A$;
- $P_t \subseteq P$ – set of papers associated with topic $t \in T$;
- $T_j \subseteq T$ – set of topics of paper $j \in P$;
- $A_j \subseteq A$ – set of authors of paper $j \in P$.

In addition, we denote by d_s and h_s the day and the time slot of session $s \in S$, respectively; and we define the following additional sets:

- $S_d = \{s \in S : d_s = d\}$ set of sessions of day $d \in D$;
- $S_h = \{s \in S : h_s = h\}$ set of sessions of time slot $h \in H$;
- $S_d^h = \{s \in S : d_s = d \wedge h_s = h\}$ set of parallel sessions of day $d \in D$ and time slot $h \in H$.

Each pair of distinct papers $i, j \in P$ has an associated unrestricted benefit $b_{ij} \in \mathbb{R}$ if both are assigned to a same session. The higher the number of common topics in both papers, the higher the benefit. Each paper has at most three topics. The objective of the problem is to maximize the total benefit, subject to the following constraints: (i) each paper $i \in P$ must be assigned to exactly one session $s \in S$; (ii) a non-empty session $s \in S$ must have at least m_s papers and at most M_s papers; (iii) there cannot be more than one paper $i \in P$ by a same author $a \in A$ assigned to parallel sessions; (iv) there should be at most M_D papers associated with topic $t \in T$ per day; and (v) there should at most M_H papers associated with topic $t \in T$ assigned to time slot $h \in H$ on the same day $d \in D$, regardless of the session.

Constraints (i)–(ii) can be seen as basic constraints, whereas constraints (iii)–(v) are assumed to be side constraints. The last constraint was specifically imposed by the SBPO organizers in order to prevent various papers with the same topic to be scheduled in parallel sessions. The remaining constraints were defined in Bulhões et al. [2020], along with the proof of $\mathcal{NP}$-hardness.

Given a feasible solution, the order of presentations of each session can be arbitrarily defined. The topic of the session is defined as the mode of the topics of the associated papers.

4 Proposed algorithm

The outline of the proposed multi-start algorithm, denoted as HILS, is presented in Algorithm 1. At each of the I_R restarts (lines 6–39), HILS tries to improve the initial solution, generated via a greedy randomized procedure (line 7), by iteratively performing local search (line 13) and perturbation (line 35) moves for at most I_{ILS} consecutive iterations without improvements (lines 12–38).

Algorithm 1 HILS

```
1: Procedure HILS($I_R$, $I_{ILS}$, $\tau_0$, $\alpha$)
2: $f^* \leftarrow 0$    ▷ Objective value of the best feasible solution
3: $s^* \leftarrow \emptyset$    ▷ Best feasible solution
4: $ClusterPool \leftarrow \emptyset$
5: $SolutionMemory \leftarrow \emptyset$
6: for $i := 1$ to $I_R$ do
7:    $s \leftarrow$ GenerateInitialSolution()
8:    $s' \leftarrow s$
9:    $s'' \leftarrow s$
10:   $iter_{ILS} \leftarrow 0$
11:   $\tau \leftarrow \tau_0$
12:   while $iter_{ILS} \leq I_{ILS}$ do
13:      $s \leftarrow$ LocalSearch($s$)
14:      if $s \notin SolutionMemory$ then
15:         $ClusterPool \leftarrow$ UpdateClusterPool($s, ClusterPool$)
16:         $SolutionMemory \leftarrow$ UptadeSolutionMemory(s)
17:         if $f(s) > f^*$ and CheckFeasibility($s$) = true then
18:            $s^* \leftarrow s$
19:            $f^* \leftarrow f(s)$
20:         end if
21:      end if
22:      $\Delta \leftarrow f(s) - f(s')$
23:      if $\Delta > 0$ then
24:         $s' \leftarrow s$
25:         $s'' \leftarrow s$
26:         $iter_{ILS} \leftarrow 0$
27:      else
28:         select $x \in [0, 1]$ at random
29:         if $\tau > 0$ and $x < e^{-\Delta/\tau}$ then
30:            $s' \leftarrow s$
31:         else
32:            $s' \leftarrow s''$
33:         end if
34:      end if
35:      $s \leftarrow$ Perturb($s'$)
36:      $iter_{ILS} \leftarrow iter_{ILS} + 1$
37:      $\tau \leftarrow \tau \times \alpha$
38:   end while
39: end for
40: $s^* \leftarrow$ SP($s^*$, $ClusterPool$)
41: return $s^*$
42: end HILS.
```

Each solution can be seen as a collection of clusters. A cluster contains the presentations of a session. Hence, for each session, there is an associated cluster with a given minimum and maximum limit of papers. The clusters from local optimal solutions are stored in a pool (line 15). Such solutions are also stored along with their respective objective values in a structure denoted as *SolutionMemory* (line 16). In case one of these solutions is found again, the local search is interrupted and the corresponding solution is returned as the current local optimum.

At the end of each local search, the algorithm checks if the solution belongs to *SolutionMemory*. If so, one verifies whether such solution satisfies the side constraints (lines 17–19) using an ILP formulation (see Section 4.1). If so, then the best feasible solution s^* is updated.

The criterion used to select the local optimal solution to be perturbed is based on SA (lines 29–33). Parameter τ is initialized at each restart with τ_0 (line 11), and its value decreases at each iteration according to a factor $\alpha \in [0, 1]$ (line 37). The smaller the value of τ, the smaller the probability (line 29) of accepting a non-incumbent local optimum as the next solution to be perturbed. When the non-incumbent solution is not accepted, the algorithm restores the current incumbent solution for applying the perturbation (line 32).

Finally, at the end of the procedure, the algorithm attempts to find the optimal combination of clusters from the pool with a view of finding an improved solution (line 40). This is done by an exact approach based on *set partitioning* (SP) (see Section 4.2).

4.1 Feasibility checking

Define $\mathcal{C} = \{C_1, C_2, \ldots, C_l\}$ as a collection of clusters from a given solution, from which we can derive the following sets:

- $\mathcal{C}_a \subseteq \mathcal{C}$ – set of clusters containing the papers by author $a \in A$;
- $S_j \subseteq S$ – set of sessions that cluster $C_j \in \mathcal{C}$ can be assigned to.

The amount of papers of cluster $C_j \in \mathcal{C}$ associated with topic $t \in T$ is denoted by Q_j^t. Moreover, let the binary variable x_j^s assume value 1 if cluster $C_j \in \mathcal{C}$ is assigned to session $s \in S$, 0 otherwise. We can write the model for checking feasibility as follows.

$$\text{Min } 0 \tag{1}$$

Subject to:

$$\sum_{s \in S_j} x_j^s = 1, \qquad \forall C_j \in \mathcal{C} \tag{2}$$

$$\sum_{C_j \in \mathcal{C}: s \in S_j} x_j^s \leq 1, \qquad \forall s \in S \tag{3}$$

$$\sum_{C_j \in C_a} \sum_{s \in S_d^h \cap S_j} x_j^s \leq 1, \qquad \forall a \in A, \forall d \in D, \forall h \in H \tag{4}$$

$$\sum_{C_j \in \mathcal{C}} \sum_{s \in S_d \cap S_j} Q_j^t x_j^s \leq M_D, \qquad \forall t \in T, \forall d \in D \tag{5}$$

$$\sum_{C_j \in C} \sum_{s \in S_d^h \cap S_j} Q_j^t x_j^s \leq M_H, \qquad \forall t \in T, \forall d \in D, \forall h \in H \tag{6}$$

$$x_j^s \in \{0, 1\}, \qquad \forall C_j \in \mathcal{C}, \forall s \in S_j. \tag{7}$$

Constraints (2) ensure that each cluster must be assign to exactly one session. Constraints (3) guarantee that at most one cluster is assigned to a session. Constraints (4) avoid papers from a same author to be assigned to parallel sessions. Constraints (5) and (6) impose a limit on the amount of papers from a same topic to be assigned in the same day and time slot, respectively. Finally, constraints (7) define the domain of the decision variables.

4.2 Set partitioning approach

Given a pool of clusters, we can define the following sets:

- C – set of clusters;
- K – set of session sizes;
- C_i – set of clusters containing paper $i \in P$;
- S_k – set of sessions of size $k \in K$;
- C_k – set of clusters that can be assigned to a session of size $k \in K$.

Let b'_j be the benefit of a cluster $j \in C$. Define y_j as a binary variable that assumes value 1 if cluster $j \in C$ is selected, and 0 otherwise. The SP formulation can be expressed as follows.

$$\text{Max} \sum_{j \in C} b'_j y_j \tag{8}$$

Subject to:

$$\sum_{j \in C_i} y_j = 1, \qquad \forall i \in P \tag{9}$$

$$\sum_{j \in C_k} y_j \leq S_k, \qquad \forall k \in K \tag{10}$$

$$y_j \in \{0, 1\}, \qquad \forall j \in C. \tag{11}$$

Objective function (8) maximizes the total benefit. Constraints (9) are the partitioning constraints, i.e., they guarantee that each paper is assigned to exactly one cluster. Constraints (10) impose a limit on the number of clusters of size $k \in K$ that can be selected. Constraints (11) define the domain of the variables.

The formulation given by (8)–(11) is incomplete because it does not include the side constraints. Therefore, we implemented a *branch-and-cut* algorithm with a lazy separation procedure, that is, every time an incumbent solution is found, the procedure verifies its feasibility using the model described in Section 4.1, and add a lazy cut to remove infeasible solutions.

4.3 Constructive procedure

The constructive procedure works as follows. Initially, a random paper is assigned to each cluster. The remaining papers are iteratively inserted in a greedy fashion, more precisely, the best insertion is the one that yields the highest increase in the objective function. After all papers are inserted, the procedure verifies if there are clusters that violate the minimum limit of papers. If so, the papers from such clusters are removed from the partial solution, and the algorithm tries to reinsert them in other clusters. If it is still not possible to build a feasible solution, the papers that could not be reinserted are relocated to a dummy cluster with negative benefit, which is naturally emptied during the local search.

4.4 Local search

Two neighborhood structures are employed during the local search, namely:

- *Relocate* ($N^{(1)}$) – one paper from a cluster is relocated to another one. Only feasible moves are considered;
- *Swap* ($N^{(2)}$) – two papers from distinct clusters are exchanged.

Algorithm 2 presents the pseudocode of the local search procedure. The search is performed in a *variable neighborhood descent* (VND) fashion [Mladenović and Hansen, 1997] (lines 4–16) but with random neighborhood ordering [Subramanian et al., 2010], as opposed to the traditional version that utilizes a deterministic ordering.

Algorithm 2 Local Search

```
1: Procedure LocalSearch($s$, $SolutionMemory$)
2: InitializeAuxiliaryDataStructures()
3: NL $\leftarrow$ InitializeNeighborhoodList()
4: **while** NL $\neq 0$ **do**
5:     Select a neighborhood $N^{(\eta)} \in$ NL at random
6:     Find the best neighbor $s'$ of $s \in N^{(\eta)}$
7:     **if** $f(s') > f(s)$ **then**
8:         $s \leftarrow s'$
9:         **if** $s \in SolutionMemory$ **then**
10:            **return** $s$
11:        **end if**
12:    **else**
13:        Remove $N^{(\eta)}$ from NL
14:    **end if**
15:    UpdateAuxiliaryDataStructures()
16: **end while**
17: **return** $s$
18: **end** LocalSearch
```

Note that every time an improved solution is found, the algorithm checks whether such solution is a local optimum that has been previously visited. If so, the solution is returned because it is known that no further improvements can be performed, thus avoiding unnecessary operations. Furthermore, *auxiliary data structures* (ADSs) (lines 2 and 15) were implemented to enhance the local search efficiency. The algorithm makes use of the *don't look bits* approach [Bentley, 1992] to examine only the moves with potential chance of improvement, disregarding those that one already knows that will not yield better solutions because they have been already evaluated.

Moves are evaluated in amortized $\mathcal{O}(1)$ operations, thanks to the ADSs that store information such as the benefit of a cluster when removing/inserting a paper. These ADSs are initialized and updated in $\mathcal{O}(n^2)$ operations. Therefore, the overall complexity of enumerating and evaluating all moves during the local search is $O(n^2)$, because each neighborhood has size $\mathcal{O}(n^2)$ and each neighbor solution is evaluated in constant time.

4.5 Perturbation mechanisms

One of the following two perturbation mechanisms is randomly selected to be applied after local search, and only feasible perturbation moves are allowed.

- *Multiple relocate* ($P^{(1)}$) – Two clusters are randomly selected and one random paper is relocated from one to another. The procedure is consecutively applied from 2 to 5 times.

- *Multiple swap* ($P^{(2)}$) – Two clusters are randomly selected and one random paper from one cluster is exchanged with another random paper from the other. As in the previous case, the procedure is consecutively applied from 2 to 5 times.

5 Computational experiments

The proposed algorithm was coded in C++ (g++ 5.4.0) and the tests were executed on an Intel® Xeon® CPU E5-2650 2.20 GHz with 128.0 GB of RAM running Linux Ubuntu 16.04.6 Operating System. CPLEX 12.7 and CBC from Coin-OR were used as ILP solvers depending on the scenario. In particular, the latter was adopted in all practical uses of our method due to license issues. Only a single thread was used for each test.

5.1 Instances

Table 1 presents the detailed information of the real-life instances derived from four SBPO editions: 2016–2019. We assume that the value of b_{ij} is determined by the amount of topics in common, in particular, 1, 10 and 100 for one, two and three topics in common, respectively. The papers considered in these instances do not include those associated with special sessions.

Table 1: Characteristics of the real-life instances

	$\|P\|$	$\|A\|$	$\|S\|$	$\|D\|$	$\|T\|$	**Avg.** $\|T_j\|$	**Avg.** $\|P_t\|$	**Avg.** $\|A_j\|$	**Avg.** $\|P_a\|$
SBPO 2016	288	689	93	3	22	1.69	13.09	3.06	0.41
SBPO 2017	324	788	95	3	22	1.82	13.72	3.15	0.41
SBPO 2018	283	709	85	3	22	1.33	12.86	3.21	0.39
SBPO 2019	288	737	91	4	26	1.99	11.07	3.32	0.39

We also considered the artificial instances by Bulhões et al. [2020] that were derived from two other conferences, namely: *XV Latin American Robotic Symposium* (LARS) and from the *Brazilian Logic Conference* (EBL) of 2019. The main difference with respect to SBPO is that constraint (v) was not taken into account by the organizers. In addition, the number of presentations of both events is considerably smaller when compared to SBPO, with 86 for LARS and 93 for EBL. For each of these two conferences, there are 18 groups of 5 artificial instances with the same number of papers.

5.2 Parameter tuning

In this section, we discuss how we tuned the main parameters of HILS, i.e., I_R, I_{ILS}, τ_0, and α. We used a subset of the LARS and EBL instances for the tuning experiments because we could compare the results with the dual bounds reported in Bulhões et al. [2020]. The SP approach was not considered while performing the calibration tests. The parameters were tuned one at a time. We tried different values and assume that one setting is effectively better than the other if there is an average improvement of 0.5% on the solution quality. This is to prevent unnecessary larger CPU times without significant gains.

We first tuned parameter I_{ILS}. In this case, we disabled the SA acceptance criterion and assumed $I_R = 1$. The value of I_{ILS} was set as $max(100, \beta|P|)$, where β is a positive number. We tested three different values for β, namely 1, 1.5 and 2. The most interesting configuration was obtained for $\beta = 1$. Next, we calibrated parameter I_R. Experiments were conducted with four values: 20, 30, 40 and 50 (also disregarding the SA procedure). The results that yielded the best compromise were those found with $I_R = 40$.

Regarding parameter α, we assumed $\tau = 1000$, and tested three different values: 0.4, 0.6 and 0.8. The first setting was the one that led to better results, and thus $\alpha = 0.4$ as adopted. We then tried different values for τ, but we could find a better setting and we therefore decided to set $\tau = 1000$.

5.3 Assessing the performance of the proposed matheuristic on existing instances

Tables 2 and 3 contain the aggregate results obtained on the LARS and EBL instances, respectively. We report the average CPU time in seconds (Avg. Time (s)), as well as the number of optimal solutions found (#opt) for the BCP algorithm, the gap between the best objective value found by HILS and the dual bound achieved by BCP (Best Gap (%)), and the gap between the average objective value found by HILS and the dual bound achieved by BCP (Avg. Gap (%)) [Bulhões et al., 2020]. In this case, CPLEX was used as ILP solver.

The results show that the proposed matheuristic obtained average gaps always smaller than 0.80%. In case of LARS, HILS found 62 of the 67 known optima confirmed by BCP. Regarding EBL, all known optimal solutions were found by our method. Moreover, while the CPU times required by BCP rapidly increase with the size of the instance, HILS is visibly more scalable and yet capable of attaining high quality solutions. The EBL instances appear to be more challenging, demanding on average more CPU time, possibly

Table 2: Aggregate results found on the LARS-based instances

		BCP		HILS			
Instance group	$\|P\|$	Avg. Time (s)	#opt	Best Gap (%)	Avg. Gap (%)	Avg. Time (s)	#opt
1	26	0.4	5	0.00	0.00	1.64	5
2	34	8025.4	3	0.00	0.00	91.15	3
3	43	10870.7	3	0.00	0.47	154.10	3
4	52	63.8	5	0.00	0.00	7.52	5
5	60	14402.8	1	0.25	0.73	275.17	0
6	69	11518.0	2	0.00	0.66	200.88	2
7	77	12844.0	2	0.00	0.00	181.26	2
8	86	2014.2	5	0.00	0.00	58.19	5
9	95	1258.0	5	0.00	0.03	79.71	4
10	103	833.7	5	0.00	0.00	39.41	5
11	112	861.6	5	0.00	0.00	40.29	5
12	120	3172.4	5	0.00	0.00	53.35	5
13	129	8037.4	4	0.00	0.00	74.75	4
14	138	7241.1	5	0.00	0.00	81.94	5
15	146	15417.5	5	0.00	0.00	99.51	4
16	155	14592.6	4	0.00	0.07	118.92	2
17	163	15338.3	1	0.00	0.00	139.11	1
18	172	18000.0	2	0.00	0.02	172.14	2

Table 3: Aggregate results found on the EBL-based instances

		BCP		HILS			
Instance group	$\|P\|$	Avg. Time (s)	#opt	Best Gap (%)	Avg. Gap (%)	Avg. Time (s)	#opt
1	28	0.5	5	0.00	0.00	2.16	5
2	37	8.9	5	0.00	0.00	3.49	5
3	47	69.8	5	0.00	0.00	6.51	5
4	56	3756.8	4	0.00	0.00	7.07	4
5	65	6938.3	4	0.00	0.00	11.17	4
6	74	18000.0	0	0.00	0.80	256.20	0
7	84	11073.8	2	0.00	0.06	137.92	2
8	93	18000.0	0	0.12	0.73	308.80	0
9	102	14414.4	1	0.00	0.19	177.83	1
10	112	11424.2	3	0.00	0.47	173.81	3
11	121	14451.4	1	0.00	0.20	218.06	1
12	130	11110.6	2	0.00	0.75	221.80	2
13	140	14728.6	1	0.00	0.13	201.68	1
14	149	18000.0	1	0.00	0.20	220.84	1
15	158	14969.9	1	0.00	0.00	158.84	1
16	167	15453.3	3	0.00	0.07	160.60	3
17	177	18000.0	2	0.00	0.15	268.31	2
18	186	18000.0	0	0.00	0.00	277.74	0

due to symmetry issues as discussed in Bulhões et al. [2020].

5.4 Results obtained on real-life instances derived from SBPO

Table 4 presents the results found on the SBPO instances of 2016 and 2017. We provide the objective values found by HILS, both when using CPLEX and CBC as ILP solvers, as well as the one achieved by the manual solution. More precisely, we report the best LB (LB_{Best}), average LB (LB_{Avg}), and average CPU time in seconds (Time (s)) for HILS.

Table 4: Results found on the real-life SBPO instances of 2016 and 2017

		Manual	HILS (CPLEX)			HILS (CBC)		
Instance	$\|P\|$	LB	LB_{Best}	LB_{Avg}	Time (s)	LB_{Best}	LB_{Avg}	Time (s)
SBPO 2016	288	718	2733	2693.6	1262.8	2678	2643	1561.8
SBPO 2017	324	1926	5706	5608.3	1928.5	5545	5504.6	2138.9

The results obtained suggest a considerable gain over the manual solution. However, a direct comparison in terms of objective function might not be entirely representative because of the order of magnitude of the values of b_{ij}. Therefore, to better illustrate the benefits of adopting an optimized solution, we decided to compute the number of pairs of papers assigned to a same section with 0, 1, 2 or 3 topics in common, as shown in Table 5.

Table 5: Number of pairs of papers assigned to a same section with 0, 1, 2 or 3 topics in common

		Manual				HILS (CPLEX)				HILS (CBC)			
Instance	$\|P\|$	0	1	2	3	0	1	2	3	0	1	2	3
SBPO 2016	288	10	268	35	1	2	183	115	14	3	188	109	14
SBPO 2017	324	0	336	79	8	9	176	203	35	8	195	185	35

It can be observed that the manual solution assigned papers mostly with only one topic in common to the same session, as opposed to the optimized solutions, in which more papers with more than one topic in common were allocated to the same session. This comparison visibly confirms the superiority of the solution achieved by HILS, regardless of the solver, when compared to the manual solution.

Table 6 shows the results attained on the SBPO instances of 2018 and 2019. In this case, because there were no manual solution available, we ran the BCP algorithm by Bulhões et al. [2020] and report the best UB attained. At first, we imposed a time limit of 12 hours for the exact algorithm for both instances, but since we observed that giving an extra time for the 2019 instance allowed for proving its optimality, we let the method run until its completion for such instance. It is important to highlight that best known

LB achieved by HILS was provided as initial primal bound for the exact algorithm. The table also reports the best LB (LB_{Best}), average LB (LB_{Avg}), best gap (Gap (%)), and average CPU time in seconds (Time (s)) for HILS, considering both CPLEX and CBC as ILP solvers. The value of the percentage gap with respect to the dual bound achieved by BCP was computed as follows: $Gap(\%) = 100 \times [(\text{UB}_{\text{BCP}} - \text{LB}_{\text{Best}})/\text{LB}_{\text{Best}}]$.

Table 6: Results found on the real-life SBPO instances of 2018 and 2019

		BCP		HILS (CPLEX)				HILS (CBC)			
Instance	$\|P\|$	UB	Time (s)	LB_{Best}	LB_{Avg}	Gap (%)	Time (s)	LB_{Best}	LB_{Avg}	Gap (%)	Time (s)
SBPO 2018	283	1398	46800.0	1398	1370.9	0.0	1202.0	1321	1321	5.51	1050.4
SBPO 2019	288	2800	43200.0	2683	2683	4.36	644.0	2683	2524.1	4.36	937.9

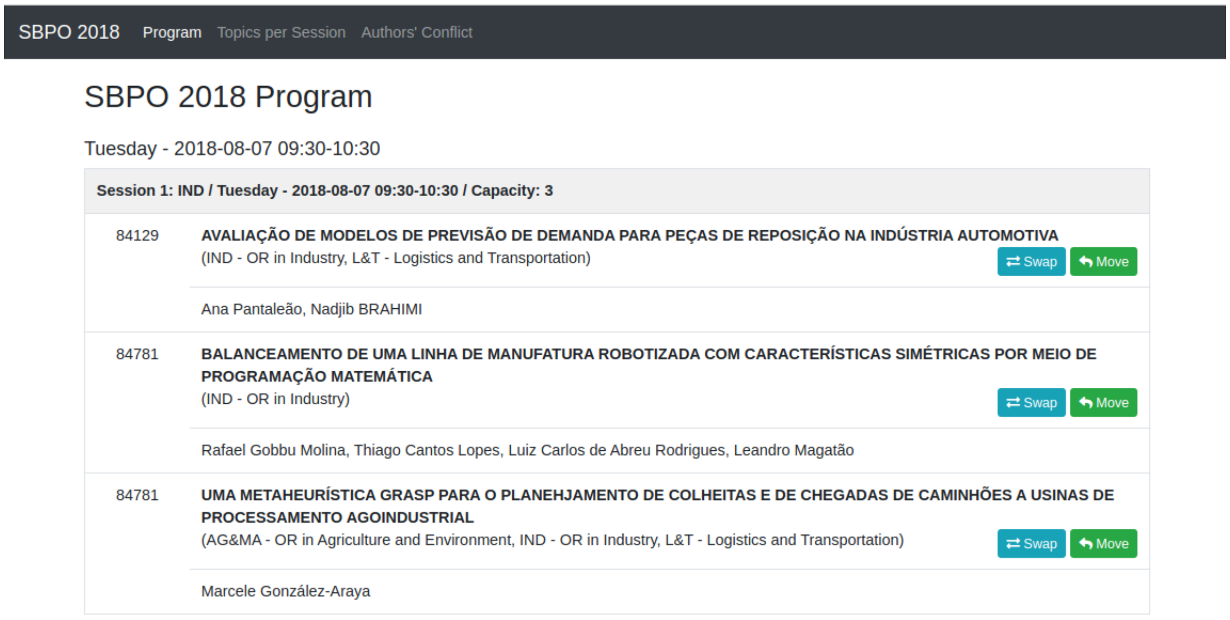
The solutions found using CPLEX were, on average, superior than those by found using CBC, mainly because of the better performance of the former when solving the SP problems. On the other hand, the time required to check feasibility can be considered negligible when using both solvers. When analyzing the 2018 instance, HILS was capable of finding the optimal solution in at least one of 10 executions, whereas on the 2019 instance, both methods attained the same best solution, but the optimality could not be proven by the BCP algorithm.

The SBPO organizers were able to use the HILS algorithm by means of a web interface, as depicted in Figure 1. The system developed not only executes HILS, but also allows the organizers to modify the solutions generated. For example, two presentations can be interchanged between sessions, or a presentation can be moved from one session to the other.

The method also automatically determines the topic of each session based on the most common topic among the papers assigned to that session (see Figure 2). In the solution found on SBPO 2018, only one session had papers without a topic in common, and the final program was almost entirely maintained, with few exceptions of presentations that were relocated due to availability of the presenters. Regarding SBPO 2019, the solution generated by the proposed algorithm was only slightly modified by the organizers to accommodate the needs of some presenters.

6 Concluding remarks

In this work, we addressed the problem of solving the schedule of technical sessions of SBPO, which is considered the main Brazilian OR conference. Given the large amount of presentations (around 300), solving the problem manually is not only a time consuming



SBPO 2018 Program

Tuesday - 2018-08-07 09:30-10:30

Session 1: IND / Tuesday - 2018-08-07 09:30-10:30 / Capacity: 3

84129 AVALIAÇÃO DE MODELOS DE PREVISÃO DE DEMANDA PARA PEÇAS DE REPOSIÇÃO NA INDÚSTRIA AUTOMOTIVA
(IND - OR in Industry, L&T - Logistics and Transportation)
Ana Pantaleão, Nadjib BRAHIMI

84781 BALANCEAMENTO DE UMA LINHA DE MANUFATURA ROBOTIZADA COM CARACTERÍSTICAS SIMÉTRICAS POR MEIO DE PROGRAMAÇÃO MATEMÁTICA
(IND - OR in Industry)
Rafael Gobbu Molina, Thiago Cantos Lopes, Luiz Carlos de Abreu Rodrigues, Leandro Magatão

84781 UMA METAHEURÍSTICA GRASP PARA O PLANEHJAMENTO DE COLHEITAS E DE CHEGADAS DE CAMINHÕES A USINAS DE PROCESSAMENTO AGOINDUSTRIAL
(AG&MA - OR in Agriculture and Environment, IND - OR in Industry, L&T - Logistics and Transportation)
Marcele González-Araya

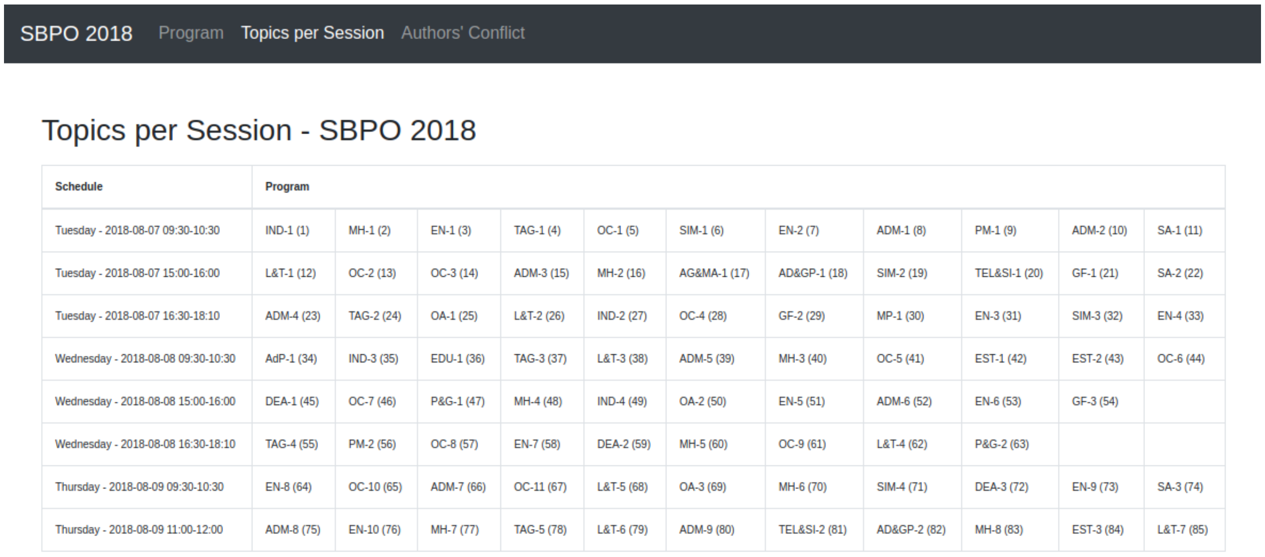
Figure 1: Screenshot of the web system developed for the SBPO organizers. This screen shows the program, as well as buttons that allow the user to perform small changes in the solution.

arduous task, but it can also lead to solutions far from the optimum. Therefore, the use of optimization-based approaches can be very favorable to produce high quality solutions in a reasonable time.

We implemented a matheuristic algorithm that employs the ideas of ILS and SA for clustering the presentations of similar topics in a same session, and an ILP formulation for dealing with the side constraints of the problem. The procedure stores the clusters associated with all local optima found during the search, and at the end tries to find an optimal combination of clusters via a SP-based procedure.

The efficiency of the proposed algorithm was assessed by computational experiments on artificial instances derived from two other conferences that were generated in a previous work. The results obtained were compared with the dual bounds found by an exact algorithm [Bulhões et al., 2020], and it was possible to observe that our matheuristic achieved high quality solutions. We then applied the method on four real-life instances derived from SBPO and compared with the dual bounds attained by the exact algorithm, as well as with the manual solution, when available. The results found were clearly superior than those obtained manually, and the gaps with respect to the dual bounds were relatively tight.

The method presented in this work has been successfully used by the organizers of SBPO since 2018. We project that a large number of conferences can benefit from the



SBPO 2018 Program Topics per Session Authors' Conflict

Topics per Session - SBPO 2018

Schedule	Program										
Tuesday - 2018-08-07 09:30-10:30	IND-1 (1)	MH-1 (2)	EN-1 (3)	TAG-1 (4)	OC-1 (5)	SIM-1 (6)	EN-2 (7)	ADM-1 (8)	PM-1 (9)	ADM-2 (10)	SA-1 (11)
Tuesday - 2018-08-07 15:00-16:00	L&T-1 (12)	OC-2 (13)	OC-3 (14)	ADM-3 (15)	MH-2 (16)	AG&MA-1 (17)	AD&GP-1 (18)	SIM-2 (19)	TEL&SI-1 (20)	GF-1 (21)	SA-2 (22)
Tuesday - 2018-08-07 16:30-18:10	ADM-4 (23)	TAG-2 (24)	OA-1 (25)	L&T-2 (26)	IND-2 (27)	OC-4 (28)	GF-2 (29)	MP-1 (30)	EN-3 (31)	SIM-3 (32)	EN-4 (33)
Wednesday - 2018-08-08 09:30-10:30	AdP-1 (34)	IND-3 (35)	EDU-1 (36)	TAG-3 (37)	L&T-3 (38)	ADM-5 (39)	MH-3 (40)	OC-5 (41)	EST-1 (42)	EST-2 (43)	OC-6 (44)
Wednesday - 2018-08-08 15:00-16:00	DEA-1 (45)	OC-7 (46)	P&G-1 (47)	MH-4 (48)	IND-4 (49)	OA-2 (50)	EN-5 (51)	ADM-6 (52)	EN-6 (53)	GF-3 (54)	
Wednesday - 2018-08-08 16:30-18:10	TAG-4 (55)	PM-2 (56)	OC-8 (57)	EN-7 (58)	DEA-2 (59)	MH-5 (60)	OC-9 (61)	L&T-4 (62)	P&G-2 (63)		
Thursday - 2018-08-09 09:30-10:30	EN-8 (64)	OC-10 (65)	ADM-7 (66)	OC-11 (67)	L&T-5 (68)	OA-3 (69)	MH-6 (70)	SIM-4 (71)	DEA-3 (72)	EN-9 (73)	SA-3 (74)
Thursday - 2018-08-09 11:00-12:00	ADM-8 (75)	EN-10 (76)	MH-7 (77)	TAG-5 (78)	L&T-6 (79)	ADM-9 (80)	TEL&SI-2 (81)	AD&GP-2 (82)	MH-8 (83)	EST-3 (84)	L&T-7 (85)

Figure 2: Screenshot of the web system developed for the SBPO organizers. This screen shows all the sessions and their respective topics.

contributions presented in this research. Future work may include testing the algorithm on alternative scenarios involving different sets of side constraints. In addition, if one wishes to adopt the preference-based policy, one can group the presentations according to the perspective of the attendees. In that case, the value of the benefit of assigning two presentations to a same session will be based on the interest that the participants have demonstrated to attend both of them.

Acknowledgements

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