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Hierarchical Impact: Modeling Organizational Hierarchy in Examination Proctor Assignments

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ABSTRACT

Purpose – This research aims to maintain examination integrity optimizing the proctor assignments under personnel shortages at a vertically organized university.

Design/methodology/approach- In this study, the maturation of a Linear Mixed-Integer Programming model is processed over many iterations of a cyclical evaluation procedure. During these cycles, many of the constraints were reformulated as their flexible versions and the model evolved into a 2-phased multiple objective decision-making (MODM) problem. The subproblems of the overall MODM are tackled with a branch-and-cut algorithm.

Results – By including the middle managers in the model maturation procedure, an optimal allocation of students to the designated rooms and an optimal schedule for the proctoring personnel are obtained. This optimality is defined for the many goals and constraints defined during debates, and the final outcome minimizes the total number of duties, reflects the hierarchy to the planned workload, and maintains in-group fairness.

Discussion – This research is a case study in which workloads for proctors of different hierarchy levels are considered for their compliance with a geometric sequence. The post-application feedback from stakeholders (middle managers, proctoring personnel) implies demand for the inclusion of some additional criteria but approves in-group fairness, acceptability of inter-group workload differences, and optimal management of staff shortage. The proposed formulations add a resource for decision-makers who are dealing with problems with nature.

1. Introduction

A teaching task can simply be decomposed into lecturing and examination. During each semester, the higher education industry produces transcripts that report to what extent of coverage students gained proficiency in each subject. Mid-term examinations and final examinations are organized for each course to measure this proficiency coverage. This multiple-stage process consists of timetabling these exams, room assignments, student assignments, and proctor assignments (Awad & Chinneck, 1998). Maintaining a comfortable and just environment for the exam takers is one of the key factors in the effectiveness of proficiency measurement.

Assigning proctors essentially descends from a broader family of problems named personnel scheduling. Personnel scheduling, in essence, creates rostering timetables that fit problem-specific requirements (Ernst et al., 2004). The personnel scheduling process has 2 phases: data preparation and assigning staff to the slots without any clash. Usually, the staff is clustered in terms of some set of skills that are relatable to the tasks they are assigned to. However, in examination proctor assignment, generally, the staff is assumed homogeneous (for an exception, see Çimen et al., 2022), but the nature of the problem is very time-dependent and complex. Similarities with personnel scheduling include no conflicting duties, meeting workforce requirements for tasks, and consideration of fairness. Studies on proctor assignment root back to Reis & Oliveira (1999). Their conflict-free schedule meeting proctoring requirements for each exam was further expanded by Marti et al. (2000) by the introduction of responsible proctors. This paper refers to the responsible proctors as the course instructors. Later Sağır & Öztürk (2010); and Öztürk et al. (2010) considered fair schedules for the proctors by balancing the workload in terms of quantity. As an addition to these essentials, Al-Yakoob et al. (2010) accounted for undesirable date-times and consecutive assignments. EPA is also referred to as the Examination Invigilator Assignment Problem.

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Hanum et al. (2015) consider a similar case to this research. In their study, the proctor assignments are based on a pre-determined examination timetable, and they, too, employed a multiple-objective decision-making method, goal programming. Another multiple-objective approach is Rosyidi et al. (2019). Their works extend Sağır & Öztürk (2010); and Hanum et al. (2015).

While Hanum et al. (2015); Koide (2015); and Rosyidi et al. (2019) embrace mixed-integer programming approaches, the literature also includes the use of heuristics and meta-heuristics. Çimen et al. (2022) use a constructive heuristic that penalizes the violation of constraints. On the other hand, Taha (2013); Hosny & Al-Olayan (2014); Mansour & Taha (2015) employ metaheuristic approaches like the Bee Colony Algorithm or Genetic Algorithm. For a recent survey on the use of metaheuristics to tackle EPA, see Hosny (2019).

This research provides a novel formulation for the Examination Proctor Assignment Problem (EPA) to tackle a case study in which the shortage of customarily proctoring personnel (teaching assistants) threatens the quality of the examination process by either infeasibility or inefficiency. If the status quo is forced, the teaching assistants may only monitor at most four exam halls at a time, and given a crowded student population with small classrooms in the infrastructure, there are several cases in which more than four exam halls are used at a time. Moreover, for a densely populated classroom, a single proctor may not be able to capture all irregularities or immoralities. Therefore, to maintain the integrity of the examinations, this study entertains the idea of reinforcing the proctoring personnel using the faculty members against customs. Furthermore, to minimize the cultural recoil, along with some justice criteria, a hierarchy in the number of duties in terms of a well-known geometric sequence, the Fibonacci sequence, is employed.

During the model formulation process, the involvement of middle managers enabled an operations research cycle during which the model evolved to become tailor-made. After deploying the optimal solution to the model, feedback was extracted from a stratified sample of personnel.

The study adds to the literature as a novel resource in case-specific constraints and a multiple objective decision-making perspective. The proctoring assignment is a cyclical task repeated for each examination season. Thus, this model enlarges its usefulness beyond a single case study. The proctor assignment task is originally an enumeration task (Mansour & Taha, 2015; Taha, 2013: 2). Providing a fruitful framework for a typically exhaustive task improves the analyst personnel's efficiency.

The rest of this paper is organized as follows: Section 1 explains the raw data structure and its preparation stages: a data preprocessing phase and a pre-optimization phase. Second, the proposed mathematical model is demonstrated. Section 2 illustrates the model output in terms of some critical statistics. In the last section, the findings are interpreted and discussed, along with the contributions' claims.

2. Methodology

The analysis process of this research is threefold. First, the data is preprocessed. Second, a pre-optimization stage is executed, where the formulation is a preemptive goal program of a quadratic mixed-integer program (for a linear formulation, see Bayar & Bayar, 2020). Moreover, the examination proctor assignment problem with some case-specific requirements is modeled as a multiple-objective MIP. In the last stage of analysis, a sense of justness is reflected using a geometric sequence for different levels of stakeholders.

2.1.The Data

In this case study, the research is built on the predetermined examination timetable with designated rooms for each exam. This preceding work is an aggregate plan for the whole school, offering more than 700 courses per semester under different programs and departments. This research succeeds in the aggregate plan of the students' office and aims to plan the allocation of students to the designated exam halls and assign proctors accordingly.

For the department of interest, 87 exams would be proceeded in 128 rooms in 9 9-day timespan. The mean and median values for the number of course enrollments are 68.55 and 64, respectively. The 87 courses are instructed by 46 distinct faculty members, of which two are teaching assistants (TA), and 16 are non-native (originally employed by some other department, school, or university). The department has 4 TAs in total.

The number of simultaneously used exam halls ranges between [1,7], the mean value is 3.36, and 39 times more than four are used at a time. The personnel shortage is clear even when assigning a single TA to each room, which may jeopardize examination integrity. It is trivial to assume that the customary approach to assigning proctoring duties only to the TAs is infeasible. The proctoring personnel was reinforced by the addition of 32 native and two semi-native (part-time) faculty members, but the 14 non-native faculty members were held exempt.

There are several cases where the total seating capacity of the designated rooms does not cover the enrollments. Overall, these seating capacity data are recorded with the emphasis on a sparse examination formation, and thus, minor overbookings are either effectless due to absence or tolerable with some extra effort from the proctors.

2.2.Data Preprocessing

The course instructors and the proctoring personnel are labeled with 0, 1, and 2 indicating native, semi-native, and non-native classes, respectively. The hierarchical levels (TA, Lecturer, Assistant Professor, Associate Professor, and Professor) were also labeled using a one-hot-encoding approach for the proctoring personnel.

For exams with multiple designated rooms, each exam-room combination is considered a distinct exam. Also, up to 3 proctors may be assigned to each room. Thus, proctor-assignable slots are defined for each exam-room-slot combination.

For efficient modeling, a DateTime set, T, which only contains the dates and times, for which at least one exam is timetabled, is defined.

2.3.The Student Allocation Model

A pre-optimization procedure is executed as a follow-up to the data preprocessing stage. This procedure is based on a compromise that dictates one proctor shall be assigned per 40 students per room, and at most three proctors may be assigned to a single exam hall at a time. By this rule, the students taking each class are distributed to designated rooms so that the total number of proctoring duties is minimized, and a tag showing the proctor requirements for each exam-room combination is produced.

$$P1: min \quad \sum_{d,t,r,c \in T} (\alpha_{d,t,r,c}/Rcap_r)^2 \qquad (1)$$

$$P2: min \quad \sum_{d,t,r,c \in T} x_{d,t,r,c} \qquad (2)$$

$$s.t.$$

$$y_{d,t,r,c} - \alpha_{d,t,r,c} \leq Rcap_r \quad , \quad \forall d,t,r,c \in T \qquad (3)$$

$$\sum_{d,t,r,c \in (c = k|T)} y_{d,t,r,c} = Kstu_k \quad , \quad \forall k \in K \qquad (4)$$

$$y_{d,t,r,c} - (41 - \varepsilon) \cdot x_{d,t,r,c} < 0 \quad , \quad \forall d,t,r,c \in T \qquad (5)$$

$$\vec{\alpha} \in \mathbb{R}_+^{|T|}, \qquad \vec{x}, \vec{y} \in \mathbb{Z}_+^{|T|} \qquad (6)$$

$$\varepsilon \ small \qquad (7)$$

The set K is the course-section combinations. The indices (d, t, r, c) are the date-time-room-course combination elements in T. The parameters $Rcap_r$, $Kstu_k$, and ε are the room capacity data, course enrollment data, and a small positive number, respectively (i.e.: 10^{-4}). $\vec{\alpha}$, $\vec{x}$, and $\vec{y}$ are the overbookings, required proctors, and allocated student variables. This model is a preemptive priority goal programming model that is formulated as a quadratic-MIP model. The priority objective (1) penalizes the overbooking, and the second priority objective (2) minimizes the total number of proctoring duties. Equations 3-4 ensure all students enrolled in a certain class are assigned to a designated room, perhaps with some overbooking, while 5 reflects the one proctor per 40 students per room rule. Since students are indivisible, the "$41 - \varepsilon$" notation in (5) helps eliminate some calculation errors. In addition, the domain restrictions in (6) define each variable in the model.

The optimal solution to the student allocations results in a total number of 197 proctoring duties, omitting the upper bound of 3 rules, and a total of 115 overbookings. Since the timetabling and the room assignments are beyond the scope of this research, the best effort is to minimize the overbookings penalizing greater values.

The resultant proctor requirements data range between [1,4] and have a mean of 1.54. Further, the range is corrected to [1,3], replacing the values 4 with 3; thus, the mean value shifted to 1.52, where the total number of proctoring duties is 195.

2.4.The Proctor Assignment Model

Now that the optimal student allocation is available, the 2 stage of the proctor assignments is to assign proctors to necessary date-time-room-course-slot combinations. Many ground rules were cyclically debated in this stage with the middle management. After solving the problem with some state of the model, the outcome was meticulously investigated, and additional goals or constraints were introduced if necessary. This operations research cycle was partially a manual branch-and-cut procedure (Dantzig et al., 1954) with the implementation of lazy constraints shrinking search space on each cycle.

A final version of the model includes the following rules and goals:

- Each proctor may be assigned at most one duty at a time (9),
- For each date-time-room-course-slot combination at most one proctor may be assigned (10),
- Proctor requirements for each instance must be satisfied (11),
- For course-section combinations with at most 40 enrollments, the instructor of the course should be the sole proctor (12),
- Each instructor should be assigned a proctoring duty for their own courses (13),
- For course-section combinations with enrollments over 40, the instructor should not be the sole proctor (14),
- Proctors should not be assigned to two consecutive exams (15),
- Predetermined proctor assignments (16),
- The duties of proctors of a certain field must not clash with the training event (17),
- Semi-native faculty members may only be assigned to their own courses (18),
- Proctors of a certain level are not assigned to the exams of courses instructed by non-preceding level faculty members (19-20),
- Upper bounds to individual totals of proctoring duties are set proportional to members of a geometric sequence (21),
- Proctors of a certain hierarchical level may be assigned a relatable number of duties (22-23)

$$
\begin{aligned}
min \quad & \sum_{c\in C}\sum_{s\in[1,3]}\left(\sum_{h\in H} g_h\cdot h_p\right)\cdot x_{c,s,p} \\
& +\varepsilon\cdot\left(\vec{1}^T+\vec{1}^T\cdot\vec{\alpha}^2+\vec{1}^T\cdot\vec{\alpha}^3+\vec{1}^T\cdot\vec{\alpha}^4\right) \\
& +\varepsilon'\cdot\alpha
\end{aligned}
\tag{8}
$$

$s.t.$

$$
\sum_{c\in\left(\substack{Cdat_c=d,\\ Ctim_c=t}\middle| C\right)}\ \sum_{s\in[1,3]} x_{c,s,p} \le 1 \quad , \quad \forall p\in P,\ \forall d\in D,\ \forall t\in \mathrm{T} \tag{9}
$$

$$
\sum_{p\in P} x_{c,s,p} \le 1 \quad , \quad \forall c\in C,\ \forall s\in[1,3] \tag{10}
$$

$$
\sum_{s\in[1,3]}\sum_{p\in P} x_{c,s,p} \ge Preq_c \quad , \quad \forall c\in C \tag{11}
$$

$$
\sum_{s\in[1,3]} x_{c,s,p} \ge 1-\alpha_c^1 \quad , \quad \forall c\in(Kstu_c\le 40|C),\ \forall p\in(Cins_c=p|P) \tag{12}
$$

$$
\sum_{s\in[1,3]} x_{c,s,p} \ge 1-\alpha_{p,c}^2 \quad , \quad \forall c\in C,\ \forall p\in(Cins_c=p|P) \tag{13}
$$

$$\sum_{s\in[1,3]} x_{c,s,p} \geq 1-\alpha_c^3 \quad , \quad \forall c \in (Kstu_c > 40|C), \forall p \in (Cins_c = p|P) \tag{14}$$

$$\sum_{c\in\left(\begin{matrix}Cdat_c = d,\\ Ctim_c = t\end{matrix}\middle|C\right)} \sum_{s\in[1,3]} x_{c,s,p} + \sum_{c\in\left(\begin{matrix}Cdat_c = d,\\ Ctim_c = t+1\end{matrix}\middle|C\right)} \sum_{s\in[1,3]} x_{c,s,p} \leq 1+\alpha_{p,d,t}^4 \quad , \quad \forall p \in P, \forall d \in D, \forall t \in (t+1 \in \mathrm{T}|\mathrm{T}) \tag{15}$$

$$\sum_{s\in[1,3]} x_{61,s,0} = 1 \tag{16}$$

$$\sum_{c\in\left(\begin{matrix}Cdat_c = 7,\\ Ctim_c < 9\end{matrix}\middle|C\right)} \sum_{s\in[1,3]} x_{c,s,p} \leq 0 \quad , \quad \forall p \in \{19,46\} \tag{17}$$

$$\sum_{c\in(Cins_c = p|C)} \sum_{s\in[1,3]} x_{c,s,p} \leq 1 \quad , \quad \forall p \in P_{SN} \tag{18}$$

$$\sum_{c\in(Cins_c \neq p|C)} \sum_{s\in[1,3]} x_{c,s,p} \leq 0 \quad , \quad \forall p \in (h_p = 0|P) \tag{19}$$

$$\sum_{c\in(h_{Cins_c} > 1|C)} \sum_{s\in[1,3]} x_{c,s,p} \leq 0 \quad , \quad \forall p \in (h_p = 1|P) \tag{20}$$

$$\sum_{s\in[1,3]} \sum_{c\in C} \left(\sum_{h\in H} g_h \cdot h_p\right) \cdot x_{c,s,p} \leq 2\cdot\alpha \quad , \quad \forall p \in P \tag{21}$$

$$\sum_{s\in[1,3]} \sum_{c\in C} x_{c,s,p} - \sum_{s\in[1,3]} \sum_{c\in C} x_{c,s,p'} \leq 0 \quad , \quad \forall h \in (h > h^-|H), \forall p \in (h_p = h|P), \forall p \in \left(\begin{matrix}h_{p'} = h_p,\\ p' \neq p\end{matrix}\middle|P\right) \tag{22}$$

$$\sum_{s\in[1,3]} \sum_{c\in C} x_{c,s,p} - \sum_{s\in[1,3]} \sum_{c\in C} x_{c,s,p'} \leq 1 \quad , \quad \forall p \in (h_p = h^-|P), \forall p \in \left(\begin{matrix}h_{p'} = h_p,\\ p' \neq p\end{matrix}\middle|P\right) \tag{23}$$

$$\vec{x} \in \{0,1\}^{|C|x3x|P|} \tag{24}$$

$$\alpha \in \mathbb{R}_+ \tag{25}$$

$$\vec{\alpha}^1, \vec{\alpha}^3 \in \mathbb{R}_+^{|C|} \tag{26}$$

$$\vec{\alpha}^2 \in \mathbb{R}_+^{|P|x|C|}, \qquad \vec{\alpha}^4 \in \mathbb{R}_+^{|P|x|D|x|C|} \tag{27}$$

$$\varepsilon, \varepsilon' small, \qquad \varepsilon > \varepsilon' \tag{28}$$

For this model, since each date-time-room-course combination is defined as a separate exam, T is replaced with the set of courses C. The remaining sets P, P_{SN}, D, T, and H used in the model are the sets of proctors, semi-native proctors, dates, times, and hierarchical levels, respectively. At most three proctors may be assigned to a single course-room combination. Hence, slot index s loops in the range [1,3]. The remaining indices c, p, d, t, and h indicate courses, proctors, dates, times, and hierarchical levels, respectively. The parameters $Cdat_c$, $Ctim_c$, $Cins_c$, $Kstu_c$, g_h, h_p, h^-, ε, and ε' used in the model are date of an exam, timing of an exam, instructor of a course, total number of enrollment for a course-section combination, assigned geometric sequence member for a hierarchical level, the hierarchical level of a proctor, minimum hierarchical level, a small positive number, and an even smaller positive number respectively.

Besides the previous explanations of the model, some peculiar constraints demand further explanation. In (16), course 61 is a central exam, and the school management undertook the assignment of proctor 0 before the proctor assignment's planning horizon. In (17), proctors 19 and 46 share common research interests, and from day 7 until time 9, they will be joining an academic training workshop. Equations 18-19 share a similar restriction on assignment availability of semi-native and top hierarchy proctors to the only courses they instructed. Equation 22 balances the number of duties for the in-group-hierarchical level, leaving the level preceded by all out. To complete this task, (23) regulates the in-level workload for the remaining level with a difference upper bound of 1 instead of 0. The reasoning for this right-hand-side constant differentiation is the possibility of residuals from the allocation of a total number of proctoring duties required.

The geometric sequence of choice is the famous Fibonacci sequence: $\{\varphi_n\} = \{1, 1, 2, 3, 5, 8, 13, 21, \ldots\}$. Since the model embraces the minimization of a weighted sum of proctoring duties, assigning higher weights to a higher hierarchy is straightforward. Table 1 summarizes the weights for each hierarchical level:

Table 1. Weight for each hierarchical level of the proctoring personnel

	Hierarchical Levels (lower values indicate higher precedence)				
	4	**3**	**2**	**1**	**0**
Weights	$\varphi_2 = 2$	$\varphi_3 = 3$	$\varphi_4 = 5$	$\varphi_5 = 8$	$\varphi_6 = 13$

The Fibonacci sequence is famous for its perceived appeal. This study tests if this appeal applies to the domain of preference elicitation. The 0^{th} and 1^{st} terms of the sequence were not employed as the growth rate starts to stabilize after the transition from the 2^{nd} to the 3^{rd} term.

The resultant formulation contains 4 family of soft constraints (12-15). Along with the minimization of total number of proctoring duties and the minimization of the hierarchical level upper bound multiplier (α), minimization of the deviation variables ($\vec{\alpha}^1, \vec{\alpha}^2, \vec{\alpha}^3$, and $\vec{\alpha}^4$) objectives are aggregated into Equation 8, a weighted sum. Hence, a multiple objective mixed integer model is obtained. The weights $\varepsilon > \varepsilon'$ imply stronger preference in minimizing α over the attainment of goals translated into soft constraint (12-15).

3.Results

The EPA is tackled using the Gurobi version 10.0.3 solver (Gurobi Optimization, 2023) with an academic web license service (WLS) on a Google Colaboratory Notebook[1]. As anticipated from the student allocation model output, the total number of proctoring duties is 195. For the individual number of proctoring duties assigned, please see Table 2.

Table 2. Descriptive statistics for each hierarchical level of the proctoring personnel

	Hierarchical Levels (lower values indicate higher precedence)				
	4	**3**	**2**	**1**	**0**
Mean	19.5	16	9	6	1.67
Variance	0.5	0	0	0	0.52
Range	[19,20]	[16]	[9]	[6]	[1,3]
Implied upper bound	24	16	9.6	6	3.69

Since the highest-level proctoring personnel proctors their own courses and no other, there is some variability. But, the justness constraints (22-23) ensured 0 or very low variability for the remaining levels. The optimal value for α is 24. Evidently, (21) sets proper upper bounds for the hierarchical levels. Still, it is noteworthy that the highest-ranking level benefits from indivisibility the most as they enjoy a gap of 4.5 on average from the implied upper bound.

[1] To access the dataset, and the notebook that contains the codes, please drop a request via email.

$\vec{1} \cdot \vec{\alpha}^{1^*} = 2$. This indicates that there exist 2 instances where the instructor of a 40 or less enrolled course was not the proctor. $\vec{1} \cdot \vec{\alpha}^{2^*} = 15$, which implies there are 15 instances where an instructor of a course with more than 40 enrollment was either a sole proctor or not proctoring at all. Equation 13 is an important family of constraints that improves exam integrity by enabling the instructor to visit and regulate all rooms designated to their course. However, (13) is challenged by (14), which motivates assigning the instructor of a course as a proctor without further criteria. And $\vec{1} \cdot \vec{\alpha}^{3^*} = 37$, meaning there are 37 rooms that the instructor of the course is not a proctor. This does not imply a red flag, particularly as there may be multiple designated rooms and a single proctor cannot be assigned multiple duties at a time, but to minimize $\vec{\alpha}^3$, the instructor may be assigned as a sole proctor competing with $\vec{\alpha}^{2^*}$. Finally, $\vec{1} \cdot \vec{\alpha}^{4^*} = 2$. Therefore, there are only two instances in which a proctor has consecutive assignments. This implies a quite humane working schedule that allows refreshing breaks.

4. Conclusion and Discussion

EPA is not a widely studied problem due to its case-specific nature that restricts generalizability (Çimen et al., 2022). However, this paper provides some catalog-like constraints that serve many possible scenarios an analyst may encounter. The existing work may be referred to for balancing total proctoring time (see Çimen et al, 2022), regulating consecutive assignments, fairness, and distribution of assignments on undesirable date times. This study is a significant addition to the EPA literature for introducing;

- Reflection of a vertical preference structure in terms of geometric series,
- Considering part-time proctors,
- Motivating an availability to patrol multiple designated rooms for course instructors who are also assigned proctoring duties,
- Accounting for pre-determined proctoring assignments,
- A pre-optimization analysis to reallocate student assignments to minimize proctor demands of the exams.

Additionally, executing an operations research cycle and experiencing the evolution of the base EPA model towards its most fitting version to the case is very exciting. The journey of the EPA model had many iterations through the debates with middle managers and early feedback from the faculty.

The proposed model serves as a general framework without delving into individual preferences.

Without having a say in the examination timetabling stage, pre-optimization is very important to reduce possible sub-optimalities before proceeding with EPA. By the maximum 3 proctors rule, it is trivial that assigning rooms with big capacities may affect the number of proctoring duties. On the other hand, allocating students optimally is more efficient as it does not demand any of the shared resources additionally. The pre-optimization stage defined a feasible lower bound to the total proctoring duties. Attaining this target lower bound in the EPA stage, along with the reflection of the hierarchical preferences, justness, humane working schedules, and the provision of necessary conditions for examination integrity, is a significant modeling success. This minimalist assignment approach also resonates with the nurture of research capabilities as the researchers are interrupted as little as possible. Since this claim can only be confirmed in the long run, evidence of better research output is beyond the scope of this research.

In the EPA literature, meta-heuristics is quite common (see Taha, 2013; Hosny & Al-Olayan, 2014; Mansour & Taha, 2015). EPA belongs to the NP-Hard complexity class (Taha, 2013: 4). Therefore, it is plausible to seek good proctoring schedules if the optimal solution is intractable. However, a single department and the examination plans for its two undergraduate-level programs were decided in this case study. Since the problem at hand can be solved exactly within a reasonable timespan, neither heuristics for constructing starting solutions or improving current solutions nor meta-heuristic approaches were considered adequate.

After the deployment, each proctor obtained a distinct perspective on the performance of the schedule. Collecting the feedback, the most common negative feedback is;

- Having too many assignments on a single day,
- Having very distant (in terms of time) assignments on a single day

The deployed model aims to fit the general case and the conflict between the two criticisms. That is, to eliminate distant assignments, densely scheduling some days and freeing others is a plausible path. However, it will directly rival the former criticism. Hence, future versions of the model may include proctor-specific preferences for those favoring dense schedules or for those favoring scattered assignments. During the model updating iterations, the models were run many times. On several occasions, there were multiple optimal schedules for the same objective function value, which can also be referred to as model symmetry (see column generation literature for more details). Future research on multiple objective decision-making approaches to EPA may be on the elicitation of preferences and symmetry eliminations that may improve optimization procedures.

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