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Julian Schulte, Volker Nissen

Holistic Workforce Planning: Integrating Staffing, Shift Design and Scheduling Using Evolutionary Bilevel Optimization

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Technische Universität Ilmenau
Fakultät für Wirtschaftswissenschaften und Medien
Institut für Wirtschaftsinformatik

Autor: Julian Schulte, Volker Nissen

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Technische Universität Ilmenau, Fakultät für Wirtschaftswissenschaften und Medien, Institut für Wirtschaftsinformatik, PF 100565, D-98684 Ilmenau

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Zusammenfassung / Abstract:

Personnel scheduling is an important and challenging task that arises in a variety of application areas. Scheduling quality, however, strongly depends on the results of the preceding activities of staffing and shift design. This paper presents a novel approach that integrates staffing, shift design and scheduling into one optimization problem for the first time, providing a holistic view of the workforce planning process. By applying an evolutionary multi-objective bilevel algorithm, the three objectives staffing costs, number of shifts and scheduling quality are optimized simultaneously. The experimental results show that the presented holistic approach is suitable to support decision making regarding staffing as well as shift design by showing the decision maker tradeoffs between different solution alternatives. Furthermore, applying the holistic approach reveals new promising solution areas and valuable individual solutions, which would not have been found when optimizing sequentially.

Schlüsselwörter: Multicriteria Optimization, Bilevel Optimization, Metaheuristics, Scheduling, Staff Planning

Holistic Workforce Planning: Integrating Staffing, Shift Design and Scheduling using Evolutionary Bilevel Optimization

Julian Schulte • Volker Nissen

Abstract Personnel scheduling is an important and challenging task that arises in a variety of application areas. Scheduling quality, however, strongly depends on the results of the preceding activities of staffing and shift design. This paper presents a novel approach that integrates staffing, shift design and scheduling into one optimization problem for the first time, providing a holistic view of the workforce planning process. By applying an evolutionary multi-objective bilevel algorithm, the three objectives staffing costs, number of shifts and scheduling quality are optimized simultaneously. The experimental results show that the presented holistic approach is suitable to support decision making regarding staffing as well as shift design by showing the decision maker tradeoffs between different solution alternatives. Furthermore, applying the holistic approach reveals new promising solution areas and valuable individual solutions, which would not have been found when optimizing sequentially.

1 Introduction

Getting the right people to the right place at the right time is a challenging task of high practical relevance, arising in a variety of industries such as service, transportation or manufacturing. Therefore, the problem of personnel scheduling has received significant attention in research [10, 24]. However, the activity of scheduling is only the last step in a series of preceding workforce management tasks, especially staffing and shift design [13, 23, 25].

Based on workload forecasting, the purpose of staffing is to determine the size and structure (e.g. skill-mix and contract types) of a company's workforce, i.e. the adequate future number of employees required in different categories. Since this is not an easy task even with just one type of employee, it becomes even more difficult with a heterogeneous workforce due to different qualifications or contracts [3]. Because staffing decisions have direct impact on scheduling quality, integrated planning approaches have been developed (see [16] for an overview on integrated staffing and scheduling problems and solution methods). Considering planning horizons from one day up to one year, these integrated problems are mainly solved by iteratively

Julian Schulte
Technische Universität Ilmenau
E-mail: julian.schulte@tu-ilmenau.de

Volker Nissen
Technische Universität Ilmenau
E-mail: volker.nissen@tu-ilmenau.de

alternating between the staffing part and the scheduling part of the problem as they are creating and evaluating personnel schedules based on certain staffing decisions [1, 12, 16].

Shift design in general aims at finding a suitable set of working shifts, with a shift being defined by its start time and length [13]. The problem that has received most attention in the literature is the minimum shift design problem [8, 9]. Here, the objective is to find a minimal number of shifts and to determine the number of employees needed per shift while minimizing over- and understaffing. The minimization of shifts is argued by the fact that fewer shifts result in schedules that are easier to read and manage (see [9] for an overview on shift design and related problems).

The work on shift design shows that finding a suitable set of shifts is far from trivial and has high impact on the subsequent scheduling task. Within the problem of integrated staffing and scheduling, however, the shift setting is already predefined. This paper aims at closing this gap by proposing a novel approach for integrating all three stages of the workforce management process: staffing, shift design, and scheduling. Using an evolutionary multi-objective bilevel algorithm, the three objectives staffing costs, number of shifts as well as scheduling quality are optimized simultaneously. To the best of our knowledge, there is no such approach in the literature combining all three workforce planning tasks. Furthermore, evolutionary bilevel optimization is applied to shift design (and related problems) for the first time, showing a new possibility of solving this type of problems.

The remainder of the paper is structured as follows: In Section 2 the bilevel problem of simultaneous staffing, shift design and scheduling is presented. The applied algorithms are described in Section 3. To demonstrate the advantages of the proposed holistic approach, in Section 4 the computational results of the considered case study will be discussed. Finally, the conclusions and suggestions for further research are presented in Section 5.

2 Problem Description

The following problem is based on the strategic workforce planning problem in the context of a midsized inbound call center of a German utility presented in [16]. The problem introduced in this section involves staffing, shift design as well as scheduling of the company's workforce.

2.1 Bilevel Problem

Bilevel optimization in general can be considered as a form of hierarchical optimization problem, whose hierarchical relationship is closely related to the problem of Stackelberg [20]. Here, a follower (lower-level optimization problem) optimizes his objective based on the parameters determined by the leader (upper-level optimization problem). The leader, in turn, optimizes his own objective under consideration of the follower's possible reactions [5]. Bilevel optimization problems are proven to be NP-hard [11] and can generally be formulated as follows [5, 19, 22]:

$$\min_{x \in X, y \in Y} F(x, y) \tag{1a}$$

$$\text{s.t.} \quad G(x, y) \leq 0 \tag{1b}$$

$$y \in \underset{y \in Y}{\operatorname{argmin}} \{ f(x, y) : g(x, y) \leq 0 \} \tag{1c}$$

Here, x and y are the vectors of decision variables determined by the upper- and lower-level problem, respectively. Besides, $F(x, y)$ and $f(x, y)$ are the objective functions and $G(x, y)$ and $g(x, y)$ the constraints of the upper- and lower-level problem.

For the considered holistic workforce planning problem, x represents the planning decision regarding staffing and shift design. For each x, the scheduling problem $f(x, y)$ will be optimized yielding personnel schedules for the considered planning horizon (represented by y). Therefore, the planning objective function $F(x, y)$ is dependent on the costs due to the staffing decision, the number of implemented shifts as well as the quality of the created schedules at the lower level, which in turn is influenced by the determined workforce structure and the implemented shifts.

2.2 Staffing and Shift Design Problem

The call center considered in this problem has a need of k different skill types $s \in S$, with $S = \{s_1, s_2, \dots, s_k\}$. The skills are meant to be categorical, i.e. they determine the tasks each employee can perform. However, it is possible to cross-train employees so they can perform more than one type of task [3]. The qualification of an employee can therefore be seen as set of different skill combinations $q \subseteq S$. The contract type $t \in T$ of an employee determines his average weekly working time.

Within its staffing decision, the company has to predefine feasible employee types $\bar{E}$. Each employee type $\bar{e}_{qt} \in \bar{E}$ is defined by its qualification q and contract type t. Moreover, each employee type $\bar{e}_{qt}$ is linked to costs $c_{\bar{e}qt}$ that arise for employing one employee of this type over the considered planning horizon. The number of employees of each type is represented by the decision variable $x_{\bar{e}qt}$. Regarding the shift design decision, the company furthermore has to predefine a set of feasible shifts. Each shift pattern $\bar{m} \in \bar{M}$ is constrained by the operating times of the call center and the minimum and maximum shift length. Whether a shift pattern is implemented or not is represented by the decision variable $x_{\bar{m}}$ (2c). The specific problem setting will be described in Section 4.1.

The objective of the upper-level problem is to minimize the overall staffing costs as well as the number of implemented shifts (2a) subject to constraints (2b) - (2c) and the optimized scheduling decision y at the lower-level problem (2d). The decision vector passed to the lower-level is defined as $x = (x_{\bar{e}qt}, x_{\bar{m}})$.

Parameters

S	set of skills (index s)
q	qualification of an employee ($q \subseteq S$)
T	set of contract types (index t)
$\bar{E}$	set of employee types (index $\bar{e}_{qt}$)
$c_{\bar{e}qt}$	costs for an employee of type $\bar{e}_{qt}$
$\bar{M}$	set of feasible shifts (index $\bar{m}$)

Decision variables

$x_{\bar{e}qt}$	number of employees of type $\bar{e}_{qt}$
$x_{\bar{m}}$	implemented shifts

Upper-level problem

$$\min_{x \in X, y \in Y} F\left(\sum_{\bar{e}_{qt} \in \bar{E}} x_{\bar{e}qt}\, c_{\bar{e}qt}, \sum_{\bar{m} \in \bar{M}} x_{\bar{m}}, y\right) \tag{2a}$$

$$\text{s.t.} \qquad x_{\bar{e}qt} \geq 0 \; and \; integer \quad \forall\, \bar{e}_{qt} \in \bar{E} \tag{2b}$$

$$x_{\bar{m}} \in \{0, 1\} \quad \forall\, \bar{m} \in \bar{M} \tag{2c}$$

$$y \in \underset{y \in Y}{\operatorname{argmin}}\{(3a) - (3j)\} \tag{2d}$$

2.3 Scheduling Problem

The scheduling problem presented in this paper considers the daily staff scheduling of a call center over a planning horizon $W = \{1,2,\dots,w_{max}\}$. Each week of the planning horizon $w \in W$ is partitioned into periods $p \in P = \{1,2,\dots,p_{max}\}$, representing the operating days of the call center. Moreover, each operating day again is segmented into time intervals $i \in I = \{i_1, i_2, \dots, i_{max}\}$. The specific scheduling problem setting will be described in Section 4.1.

The set of shift patterns M and set employees E are determined by the staffing and shift design decision at the upper-level, with a concrete employee for each $x_{\bar{e}qt}$ and with b_{mi} determining whether a shift pattern is covering a specific time interval. In addition, variable n_{es} determines if an employee's qualification contains skill s. The assignment of an employee $e \in E$ to a shift m on day p in week w with skill s is controlled by using the binary decision variable y_{mpw}^{es}. An employee can only be assigned to one shift each day (3e) and only if he is available and has the required skill (3c-3d). While employees may have multiple skills, each employee can only contribute one skill per shift (3e).

For each time interval i on day p in week w and each skill s a certain staffing level d_{ipw}^{s} has to be satisfied. The number of planned employees of each skill at time interval i is determined by variable e_{ipw}^{s} (3f). If a deviation $|e_{ipw}^{s} - d_{ipw}^{s}|$ arises from the staffing target, penalty points are generated by the function P_d (3g). An additional penalty is added if no employees are planned but required or vice versa.

To compensate overtime and minus hours, each employee has a flextime account u_{ew}, which is updated on a weekly basis. Therefore, the deviation of the employee's actual working time l_{ew} (3h) and contractually agreed weekly working time h_e is added to his flextime account (3i). However, to provide an equal workload distribution and to ensure that employees are staffed according to their contract types, the penalty function P_u generates penalty points based on how far employees exceeded or fell below their contractually agreed weekly working time u_{ew}/h_e. The weekly penalty is calculated by multiplying the absolute flextime value times the percentage of deviation (3j).

The objective here is to minimize the overall penalty points over the considered planning horizon (3a) subject to given constraints (3b) – (3j) described above.

Parameters

W	set of weeks in planning horizon (index w)
P	set of periods in planning week w (index p)
I	set of time intervals in planning period p (index i)
E	set of employees (index e) determined by the upper-level decision variable $x_{\bar{e}qt}$
S	set of skills (index s)
M	set of shift patterns (index m)
b_{mi}	1 if shift m covering time interval i, 0 otherwise
n_{es}	1 if employee's qualification contains skill s, 0 otherwise
a_{pw}^{e}	1 if employee e is available on day p in week w, 0 otherwise
d_{ipw}^{s}	demand of skill s at time interval i on day p in week w
e_{ipw}^{s}	number of planned employees with skill s at time interval i on day p in week w
P_d	demand penalty function
u_{ew}	flextime account of employee e in week w
l_{ew}	actual working time of employee e in week w
h_e	contractually agreed weekly working time of employee e
P_u	working time penalty function

Decision variable

y_{mpw}^{es}	1 if employee e is assigned to a shift m on day p in week w with skill s, 0 otherwise

Lower-level problem

$$\min_{y \in Y} f(x, P_d + P_u) \tag{3a}$$

s.t.

$$a_{pw}^{e}, n_{es}, b_{mi}, y_{mpw}^{es} \in \{0,1\} \quad \forall\, e \in E, s \in S, m \in M, p \in P, w \in W \tag{3b}$$

$$y_{mpw}^{es} \leq a_{pw}^{e} \quad \forall\, e \in E, s \in S, m \in M, p \in P, w \in W \tag{3c}$$

$$y_{mpw}^{es} \leq n_{es} \quad \forall\, e \in E, s \in S, m \in M, p \in P, w \in W \tag{3d}$$

$$\sum_{s \in S} \sum_{m \in M} y_{mpw}^{es} \leq 1 \quad \forall\, e \in E, p \in P, w \in W \tag{3e}$$

$$e_{ipw}^{s} = \sum_{m \in M} \sum_{e \in E} y_{mpw}^{es}\, b_{mi} \quad \forall\, s \in S, i \in I, p \in P, w \in W \tag{3f}$$

$$P_d = \sum_{s \in S} \sum_{i \in I} \sum_{p \in P} \sum_{w \in W} \left| d_{ipw}^{s} - e_{ipw}^{s} \right| * \gamma_d, \quad with \quad \gamma_d = \begin{cases} 500, & e_{ipw}^{s} > 0 \text{ and } d_{ipw}^{s} = 0 \\ 500, & d_{ipw}^{s} > 0 \text{ and } e_{ipw}^{s} = 0 \\ 1, & otherwise \end{cases} \tag{3g}$$

$$l_{ew} = \sum_{m \in M} \sum_{s \in S} \sum_{i \in I} \sum_{p \in P} y_{mpw}^{es}\, b_{mi} \quad \forall\, e \in E, w \in W \tag{3h}$$

$$u_{ew} = u_{e(w-1)} + (l_{ew} - h_{ew}), \quad \text{with } u_{e0} = 0 \quad \forall\, e \in E, w \in W \tag{3i}$$

$$P_u = \sum_{e \in E} \sum_{w \in W} \frac{{u_{ew}}^2}{h_e} \tag{3j}$$

3 Evolutionary Bilevel Algorithm

Evolutionary Algorithms (EA) are a common metaheuristic approach to compute good solutions in an acceptable amount of time, especially when working with real world problems that otherwise cannot be solved to optimality within reasonable computation time [14]. This also applies to workforce planning and scheduling problems, with Genetic Algorithms (GA) as the most often used class of metaheuristics in this domain [3, 24]. Due to its widespread usage and successful application to similar problems, GA were chosen in this case, both to solve the upper-level staffing and shift design as well as the lower-level scheduling problem (see [15, 18, 21] for more detailed information on metaheuristic optimization in general and GA in particular).

Evolutionary bilevel optimization has been successfully applied in various areas such as economics, transportation, engineering and management, especially in strategic or long-term contexts (see [19] for a comprehensive review).

3.1 Upper-Level Algorithm

According to the taxonomy given by Talbi [22], the algorithm used to solve the presented problem of holistic workforce planning can be defined as a nested constructing approach with metaheuristics on both levels. In this type of bilevel model, an upper-level metaheuristic calls a lower-level metaheuristic during its fitness assessment. In doing so, the upper-level heuristic determines the decision vector x (here the number of employees of each type and the set of implemented shift patterns) as input for the lower-level algorithm, which in turn determines the decision vector y (optimized schedules). Both decision vectors are subsequently used to solve the bilevel problem at the upper-level. An overview of the applied bilevel algorithm is shown in Algorithm 1.

Algorithm 1 Overview of nested bilevel GA in pseudocode

```
popsize ← desired population size
generations ← number of generations to be evaluated
P ← build initial population of random individuals with size popsize
Best ← { }
for generations times do
    for each individual P_i ∈ P do
        CalculateCosts(P_i)
        SumShifts(P_i)
        call lower-level GA with P_i as input
    end for
    Best ← Fitness(P)
    P ← Reproduction(P, Best)
end for
return Best
```

Within the here discussed problem, the three objectives staffing costs, number of shifts and scheduling penalty have to be minimized. However, both upper-level objectives are in conflict with the lower-level objective, as for example hiring multi-skilled, flexible part-time employees will yield high quality schedules but also increase the staffing costs and on the other hand, reducing the number of employees will reduce labor costs but also the scheduling quality. Furthermore, implementing a large number of shifts may increase flexibility and therefore the quality of the scheduling results.

The resulting multi-objective problem can be solved by using the concept of Pareto efficiency, which will yield a set of Pareto optimal solutions (approximated Pareto front, further referred as Pareto front). The final solution to be selected will therefore be a tradeoff among the three considered objectives staffing costs, shift count and scheduling quality (see [2, 4, 18] for more detailed information on multi-objective optimization).

To solve the upper-level multi-objective problem of minimizing staffing costs, shift count and scheduling penalty, the NSGA-II [6] is used. The chromosomes of the upper-level individuals are composed of two one-dimensional vectors, each corresponding to one subproblem. The integer encoded staffing vector $\boldsymbol{u} = (u_1, u_2, \dots, u_\varrho)$ contains $\varrho = |\bar{E}|$ values corresponding to the number of employee types. Each value u_ζ represents the number of employees to be employed for this type. However, $u_\varrho \in \mathbb{N}$ should be limited in a reasonable manner to reduce the search space. The binary encoded shift vector is denoted by $\boldsymbol{v} = (v_1, v_2, \dots, v_\vartheta)$, with $\vartheta = |\bar{M}|$. Each v_ϑ is linked to one shift pattern $\bar{m} \in \bar{M}$.

As $\boldsymbol{u}$ and $\boldsymbol{v}$ have different search spaces as well as different value ranges, they are handled independently during reproduction. However, for both vectors one-point and uniform crossover are applied, randomly selected for each reproduction process. Furthermore, intermediate crossover and random walk mutation are used for the reproduction of $\boldsymbol{u}$ (both as described in [18]). For mutation of $\boldsymbol{v}$ bit flip mutation is applied.

3.2 Lower-Level Algorithm

At the lower-level, to solve the personnel scheduling problem, an elitist GA with the same elitism principle as NSGA-II is used. Each individual is encoded as $(|E| \times (p_{max} * w_{max}))$-matrix, representing the schedules of the considered planning horizon. Each row corresponds to one concrete employee with each integer value being linked to one of the shift patterns selected at the upper-level. For reproduction, one-point and uniform crossover as well as bit flip mutation are used.

4 Experimental Study and Discussion

In this section, to demonstrate the usefulness of the proposed holistic approach, the tasks of staffing and shift design will be carried out first sequentially and then simultaneously.

4.1 Problem and Algorithm Setting

Within the investigated scenario, the call center is planning its workforce for a 4 week planning horizon $W = \{1,2,\ldots,4\}$. Furthermore, the operating days are Monday till Friday $P = \{1,2,\ldots,5\}$ from 8 a.m. to 6 p.m. $I = \{1,2,\ldots,10\}$ (due to the strategic context, hourly scheduling intervals were chosen). Shifts are allowed in the range between 4 and 8 hours, resulting in 25 possible shift patterns. Regarding its staffing decision, the company has a need of two different skills $S = \{\text{agent}, \text{support}\}$. The forecasted demand of agents is highly volatile both during the day and across the planning horizon. The demand of support employees is calculated based on a staffing ratio of one support for each four agents. Table 1 shows the predetermined employee types with related costs. The costs of each employee type are represented by a relative factor summing up annual wages, payroll taxes, overhead and training costs.

Table 1 Setting of the staffing problem

Contract type	Qualification	Costs
20 h / 40 h	agent	0.6 / 1
20 h / 40 h	support	0.65 / 1.1
20 h / 40 h	agent - support	0.75 / 1.3

For the upper-level GA, a population size of 60, a generation number of 100 and n=10 restarts were chosen, with each restart having a random initial population. Since all results on the upper level are evaluated according to the same algorithm, the goal on the lower level is not to find the best overall solution, but to achieve stable results in order to avoid outliers. Therefore, considering the tradeoff regarding computation time, solution quality and solution noise, the lower-level GA was configured with a population size of 50 and a generation number of 200.

On both levels, the mutation rate was set to 1/v, with v being the number of genes of the encoded individual, and the application of the available crossover operators was uniformly distributed. The fitness at the upper-level was evaluated by Eq. (2a), for the fitness evaluation at the lower-level Eq. (3a) was used.

The optimization software was written in Python/Cython and all experiments were executed on a cluster of 12 Windows 10 machines with Intel Core i7-8700 machines (6 cores, maximum clock rate 3.19 GHz) and 16 GB RAM. The evaluation of the lower-level fitness function was spread among all available cores. One restart took about 1 hour, ten restarts about 8 hours (due to the better exploitation of cores).

4.2 Sequential Workforce Planning

In this subsection, the workforce planning tasks of staffing and shift design are executed one after the other as usual. The sequential problems can be considered as modifications of the problem described in Section 2, taking into account either the staffing or shift design problem and objectives, respectively.

The sequential workforce planning study starts with the staffing task. For this, at first an initial shift setting had to be chosen. Using problem specific insights and considering the volatile demand, four shifts were selected. Two 8 hour shifts covering the base demand starting at 8 a.m. and 10 a.m. and two 4 hour shifts covering peaks in the morning and the afternoon, starting at 10 a.m. and 2 p.m.. Using this setting, the algorithm was executed while ignoring the objective of shift count, resulting in a conventional integrated staffing and scheduling problem (see [16]). As final result, the Pareto fronts of all restarts were combined and a new Pareto front was created (see Fig. 1).

Fig. 1 shows the expected behavior of higher quality schedules with increasing staffing costs, due to more flexible employees. The best possible staffing setting (with the selected shift setting) is marked as solution A. Solution B is selected as an efficient alternative, which reduces staffing costs by 13% with an increase of penalty points by only 3%. The details of both solutions are shown in Table 2. The two staffing decisions, namely the best possible and the more efficient one, will be referred to in the following as scenario A and B. The shifts are encoded as "starting hour"_"duration (h)" (24h clock).

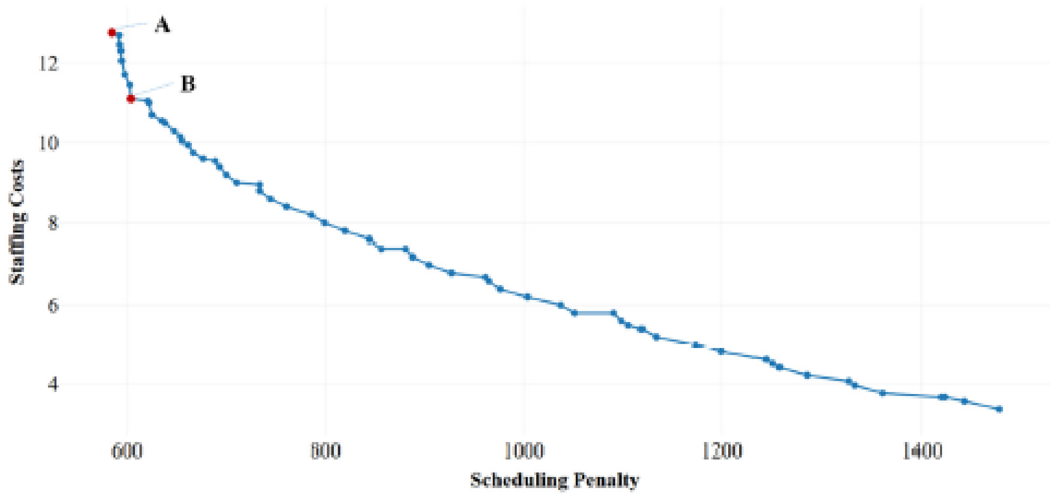

Fig. 1 Possible staffing decisions (Pareto front of n=10 optimization runs)

Table 2 Selected staffing solutions

	Costs	Penalty	#Shifts	Agent		Support		Ag.-Sup.		Shifts
				40	20	40	20	40	20	
A	12.75	585.6	4	5	5	0	3	1	2	8_8, 10_8, 10_4, 14_4
B	11.1	603.6	4	4	6	2	0	1	0	8_8, 10_8, 10_4, 14_4

For the shift design task, the algorithm was executed again with the staffing decisions of solutions A and B. Here, in contrast to the previous experiment, the staffing setting is fixed and only the objective of minimizing the number of shifts is considered. The results of both experiments are shown in Fig. 2 and Fig. 3 as well as in Table 3 and 4, respectively.

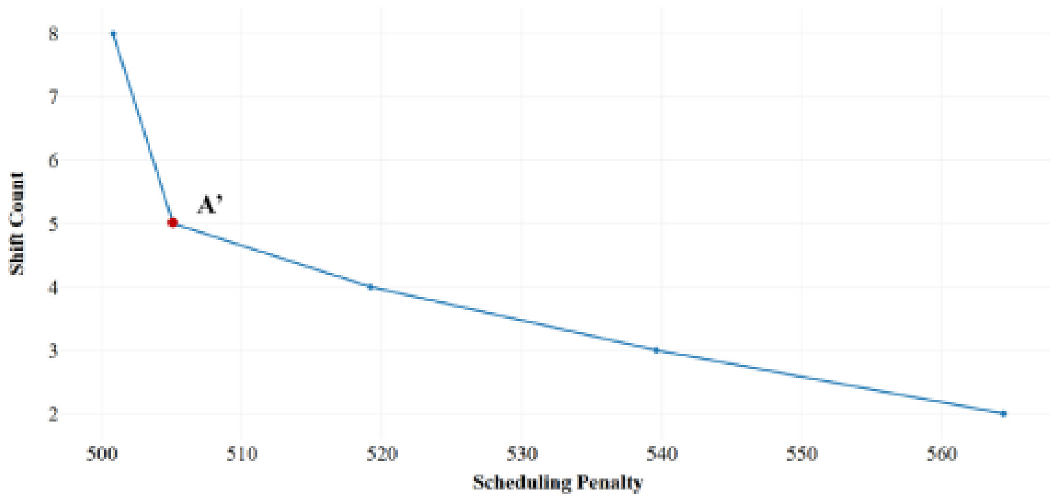

Fig. 2 Possible shift design decisions for scenario A (Pareto front of n=10 optimization runs)

Table 3 Shift design solutions for scenario A

	Costs	Penalty	#Shifts	Agent		Support		Ag.-Sup.		Shifts
				40	20	40	20	40	20	
	12.75	500.5	8	5	5	0	3	1	5	8_4, 8_5, 8_8, 9_6, 9_8, 10_8, 13_5, 14_4
A'	12.75	505.1	5	5	5	0	3	1	5	8_4, 8_7, 9_8, 10_8, 14_4
	12.75	519.2	4	5	5	0	3	1	5	8_4, 9_8, 10_8, 13_5
	12.75	539.6	3	5	5	0	3	1	5	8_4, 10_8, 13_4
	12.75	564.4	2	5	5	0	3	1	5	8_4, 10_8

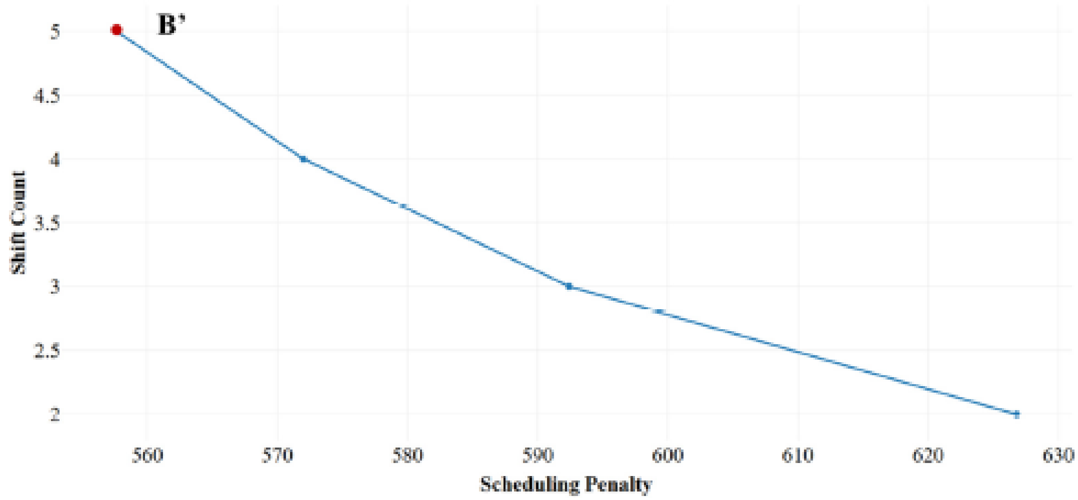

Fig. 3 Possible shift design decisions for scenario B (Pareto front of n=10 optimization runs)

Table 4 Shift design solutions for scenario B

	Costs	Penalty	#Shifts	Agent		Support		Ag.-Sup.		Shifts
				40	20	40	20	40	20	
B'	11.1	557.6	5	4	6	2	0	1	0	8_4, 8_8, 9_6, 10_8, 14_4
	11.1	572	4	4	6	2	0	1	0	8_4, 8_8, 10_8, 14_4
	11.1	592.4	3	4	6	2	0	1	0	8_4, 8_8, 10_8
	11.1	626.8	2	4	6	2	0	1	0	8_8, 10_8

Examining the shift design results of both scenarios, it becomes apparent that the scheduling quality could further be improved by selecting different shift patterns. The second solution of scenario B (see Fig. 3 & Table 4) shows that the initial shift decision (see Table 2) was already quite reasonable. However, this decision was improved by letting the short shift 10_4 (start at 10 a.m., duration 4 hours) start 2 hours earlier (8_4). Looking at the second solution of scenario A (see Fig 2 & Table 3), the scheduling quality as compared to A in Table 2 was improved by about 14% by adding only one more shift. As the 4.6 additional penalty points seem neglectable compared to the three additional shifts (in comparison to the first solution), this solution will be used in the further discussion. In the remainder of this section, the solutions of both scenarios with 5 shifts will be referred as solutions A' and B'.

It may be assumed that, due to the higher flexibility, with an increasing number of shifts the scheduling quality increases as well, which is reflected by the results of both scenarios. Nevertheless, in both scenarios the maximum number of shifts (5 and 8) is way below the maximum amount of 25 possible shifts, which at least relativizes this assumption.

4.3 Holistic Workforce Planning

In this subsection, the entire problem described in Section 2 will be solved and compared to the results of both scenarios described above. Fig. 4 shows the three-dimensional Pareto front for the objectives staffing costs, shift count, and scheduling penalty. As within the previous sequential steps, the pattern of decreasing penalty with increasing staffing costs and number of shifts of the previous sequential steps can be found.

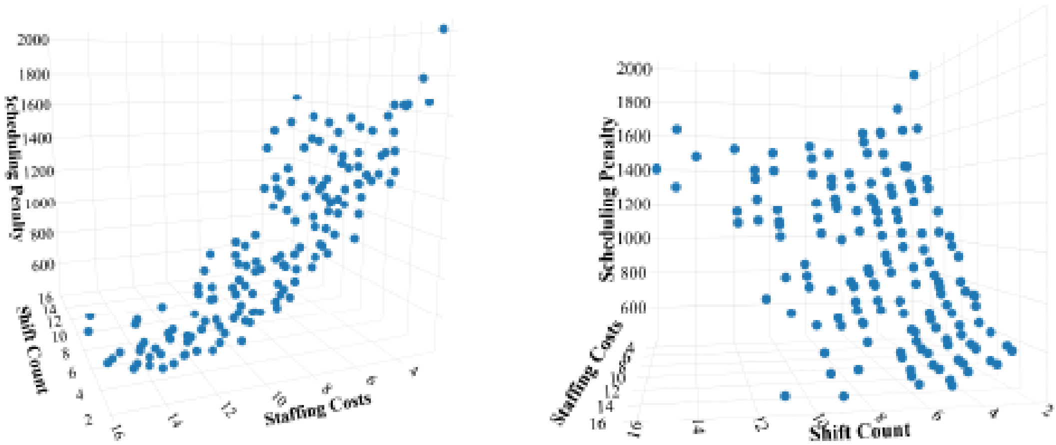

Fig. 4 Possible staffing and shift design decisions (Pareto front of n=10 optimization runs)

The most interesting part, however, is the target area below the penalty of 600 (see Fig. 5 & Table 5). While the smallest penalty found during sequential workforce planning was 500.5 (see Table 3), simultaneously optimizing staffing and shift design was able to further reduce the minimal penalty by about 10% to 452 (see Table 5, Sol. C). In general, applying the holistic workforce planning approach reveals the circled area, which would have remained undiscovered by the sequential approach (see Fig. 5). Providing a broader basis for decision making can therefore be considered as main advantage of integrating all aspects of workforce planning into one optimization problem. For further discussion, solutions C to F are exemplarily selected from this area (see Table 5).

The solutions which are closest to those selected in the previous scenarios are labeled as A'' and B'' (see Fig 5 & Table 5). When comparing these results to those from the sequential steps, it becomes apparent that latter ones are dominating those from the holistic approach. This could be explained by the fact that by combining the staffing and shift design problem the search space increases, which would have required an evaluation of a larger number of solutions to better exploit this more complex search space.

To verify the assumption of a better search space exploitation within the sequential approach, the staffing task is repeated with a shift setting found in the circled area. To keep a reasonable amount of shifts, the shift setting of solutions E and F were chosen. This decision is supported by the fact that most of the shifts can also be found in solutions C and D.

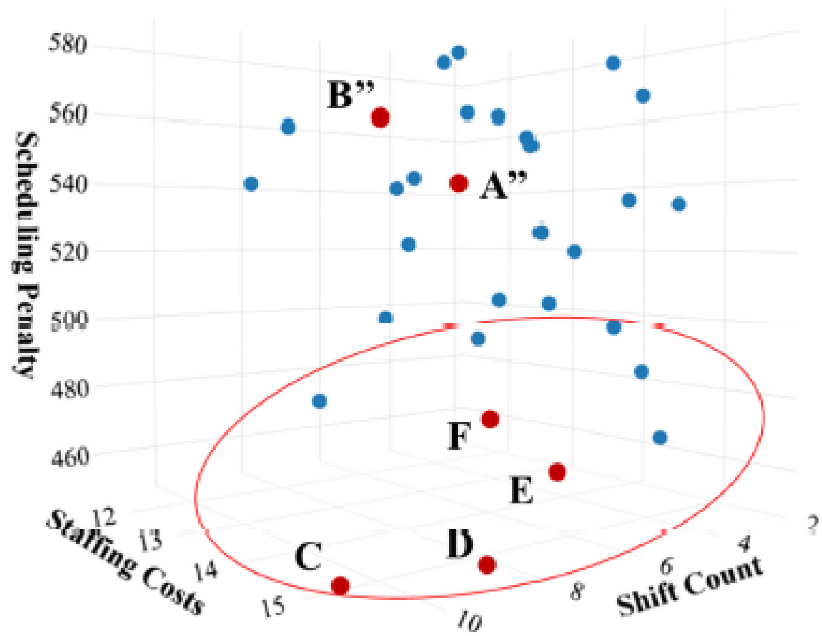

Fig. 5 Target area of holistic workforce planning solutions

Table 5 Selected holistic workforce planning solutions

	Costs	Penalty	#Shifts	Agent		Support		Ag.-Sup.		Shifts
				40	20	40	20	40	20	
A''	13	541.2	5	2	9	0	2	1	4	8_4, 8_5, 10_5, 10_8, 14_4
B''	11.65	564.4	5	4	5	1	2	0	3	8_4, 8_8, 9_8, 10_8, 14_4
C	15.25	452	11	1	10	0	0	0	11	8_4, 8_5, 8_8, 9_5, 10_5, 10_7, 10_8, 11_7, 12_6, 13_5, 14_4
D	15.65	453.8	9	0	6	0	3	2	10	8_4, 8_5, 9_4, 9_6, 9_8, 10_6, 10_8, 13_5, 14_4
E	14.85	463.8	6	0	12	0	2	2	5	8_4, 8_5, 9_6, 10_8, 13_5, 14_4
F	14	473.9	6	0	12	1	1	1	5	8_4, 8_5, 9_6, 10_8, 13_5, 14_4

Fig. 6 shows the results of the integrated staffing and scheduling experiment with the shift setting of solutions E and F. Here, solution A* is dominating solution A' in respect of staffing costs and scheduling penalty. Solutions B* and B' are almost similar, with B* having slightly lower costs and slightly higher penalty. Solution G has the smallest penalty at highest costs across all experiments, with H being seen as an efficient alternative. Solution I dominates all solutions shown in Table 5.

Furthermore, it becomes apparent that due to the selected shift setting with only one full time shift, part time employees are favored. If one might prefer a more full time workforce, this should either be reflected in the staffing costs or a different shift setting of the holistic planning results (Fig. 5) should be chosen.

When looking at the highlighted solutions, the assumption of a better search space exploitation during the sequential experiments can be verified. The advantage of the holistic approach, however, comes to bear again in this last experiment, as without it the selected shift design decision would not have been discovered. Moreover, by adjusting the upper-level algorithm to the increased complexity (e.g. larger population and more generations) the holistic approach very likely would achieve the same search space exploitation.

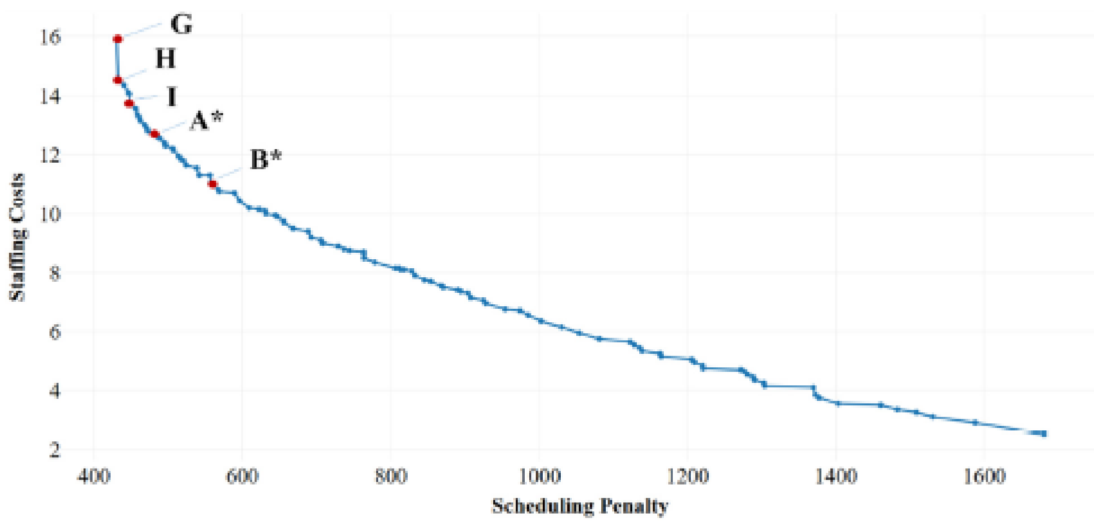

Fig. 6 Possible staffing decisions 2 (Pareto front of n=10 optimization runs)

Table 6 Possible staffing decisions 2

	Costs	Penalty	#Shifts	Agent		Support		Ag.-Sup.		Shifts
				40	20	40	20	40	20	
G	15.9	430.7	6	1	10	0	1	0	11	8_4, 8_5, 9_6, 10_8, 13_5, 14_4
H	14.5	432.4	6	1	8	0	3	0	9	8_4, 8_5, 9_6, 10_8, 13_5, 14_4
I	13.75	448.45	6	1	13	0	3	0	4	8_4, 8_5, 9_6, 10_8, 13_5, 14_4
A*	12.7	481.25	6	1	10	0	3	0	5	8_4, 8_5, 9_6, 10_8, 13_5, 14_4
B*	11.05	557.75	6	1	11	0	3	0	2	8_4, 8_5, 9_6, 10_8, 13_5, 14_4

5 Conclusion

In this paper, a novel approach was proposed for integrating three main stages of the workforce management process: staffing, shift design and scheduling. To demonstrate the advantages of the holistic approach, the tasks of staffing and shift design were first executed sequentially and afterwards simultaneously. The results indicate that when performing staffing and shift design sequentially, the staffing decision is limited by the predefined shifts. The shift design decision, on the other hand, is limited by the selected staffing setting. The proposed holistic workforce planning approach solves this dilemma and shows the decision maker the 'big picture' of the considered problem by revealing tradeoffs regarding staffing and shift design decisions, as well as new promising solution areas and valuable individual solutions, which would not have been found when optimizing sequentially.

For well-founded decision making, however, deeper insights into the problem structure are beneficial [7]. Further research should therefore focus on analyzing the decision variables of the upper-level problem, e.g. for interaction effects, as initially proposed in [17]. Possible questions here could be whether there is a set of dominant shifts, which shifts harmonize with each other or if there are shifts that work better for certain staffing settings. Furthermore, additional parameters could be integrated into the upper-level problem, such as policy making as shown in [12]. In order to achieve best possible results and to avoid an additional optimization step (see Fig. 6), further research should also focus on optimizing the settings of the upper-level algorithm.

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