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Evaluation of Request Order Sequencing Methods in the Selection Process of Substitute Employees

Soichiro Yokoyama[1,*], Tomoya Chisaka[2], Tomohisa Yamashita[1], Hidenori Kawamura[1]

[1] Faculty of Information Science and Technology, Hokkaido University
[2] Graduate School of Information Science and Technology, Hokkaido University
*E-mail (corresponding author): yokoyama@ist.hokudai.ac.jp

ABSTRACT

This paper presents a simulation-based evaluation of various reactive scheduling methods designed to address workforce uncertainty in personnel scheduling, with a focus on substitution requests. We model employee availability and the demand for workers in a call center environment, using a mixed integer programming solver for shift scheduling and a probabilistic model for absenteeism. Our study compares different sequencing methods for substitution requests, assessing their effectiveness across a range of parameters, such as absenteeism probability and employee acceptance rates. The findings highlight the impact of sequencing choices on schedule fulfillment and substitution request efficiency, offering insights for optimizing personnel scheduling in uncertain environments. This research contributes to improving reactive scheduling strategies, essential for efficient workforce management.

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1. Introduction

Personnel scheduling or staff scheduling problems have been widely studied in the last few decades. For many companies, allocating adequate human resources while satisfying employee needs, such as preventing long consecutive working days or ensuring preference for specific off days, is paramount. The uncertainty surrounding daily human resource demands or the availability of assigned employees poses challenges, which are typically dealt with by performing reactive actions to mitigate the effect of the fluctuation and generating robust schedules. Reactive measures typically entail solving supplementary scheduling problems, such as reallocating working days from the original schedule, to accommodate disruptions. To create resilient personnel schedules amidst uncertainty, methods such as introducing surplus personnel for the required number of employees each day or utilizing stochastic programming to account for the potential fluctuations during the optimization process have been proposed (Ernst et al., 2004).

In the real-world workplace, preparing surplus personnel can lead to inefficiency, and tracking the available working hours of each employee for rescheduling or ensuring adherence to the optimized schedule is often impractical. Consequently, when staff shortages occur, company managers negotiate additional working hours with employees to fill the gap while other allocations remain untouched. Since employees can reserve private appointments during their non-working hours at any time, the managers need to confirm the availability of employees and simultaneously request their substitutional work when available. In this situation, the order in which employees are approached plays a significant role in ensuring a stable workforce in the long term and fulfilling the substitution with minimal negotiation overhead. For example, priority should be given to requesting employees who are highly likely to accept the offer, as this can reduce the total number of negotiations. However, it may be advisable to avoid approaching such employees if requesting substitutional work could prevent them from being available for substitution during another time shift. The uncertainty of employees' availability imposes a significant challenge in determining a promising order of substitution requests since the managers have to select an employee to ask based on the previous responses.

This paper presents a simulation-based evaluation of a reactive scheduling method designed to address workforce uncertainty in personnel scheduling, explicitly focusing on substitution requests. We assume a call center environment to model the employee availability and the demand for workers across different hours of operation along with constraints on the working hours of each employee. A work shift schedule is then generated by optimizing the scheduling problem using a mixed integer programming solver. The absenteeism is modeled as an independent probabilistic occurrence on each work shift to introduce the uncertainty of the available workforce, and all the absenteeism on each day is revealed after the end of the last working shift on the previous day. A manager takes reactive actions on absenteeism by ensuring a substitutional worker on each shift with absenteeism. Since employees' availability as substitutional workers is also uncertain, the manager asks each candidate employee whether she or he is willing to perform the additional work shift and participate in an alternative shift arrangement if accepted. Our study aims to assess the effectiveness of the sequencing method of candidate employees for offering the substitutional shift on various parameter sets in the workplace environment, such as the probability of occurrence of absenteeism and available rate as a substitutional worker of each employee.

2. Literature review

Personnel scheduling problems are typically formulated as mixed integer programming problems with decision variables that determine whether a specific employee should be working on a specific shift and constraints such as workforce demands in each work time and preference or legal restriction on the labor hours of each worker. Since the scheduling problem is known to demand a considerable computational burden even without any uncertainty considered, many studies on various application fields with suitable formulations have been conducted (Ernst et al., 2004). Hospital staff allocation is one of the most thoroughly researched areas, often specifically called a nurse scheduling problem. Ikegami and Niwa (2003) proposed a mathematical programming formulation with specific constraints, such as the skill level requirement of a team and the need for balancing workloads among nurses, and a meta-heuristic solver that demonstrated successful solutions on scheduling problems with actual data taken from hospitals. In 2010, a competition on a benchmark problem was held (Haspeslagh et al., 2014). Various algorithms were compared on problems with different timespans, and a two-phase approach that decomposed the problem into smaller-sized sub-problems that can be practically solved using integer programming (Valouxis et al., 2012) showed a promising result.

Two-stage stochastic programming is typically utilized to handle uncertainty, where probabilistic factors like the required daily workforce are represented as random variables with some distribution assumed. While some decision variables, like employee allocation for each day, need to be determined prior to the revelation of random variables in the first stage, others, such as the discrepancy between the workforce requirement and the actual provision, are determined subsequently in the second stage. Stochastic programming approaches are utilized to deal with uncertainty by generating scenarios, each represented by a specific set of realized values for the involved random variables. In this methodology, decision variables determined in the first stage are shared across all scenarios, while those in the second stage are tailored to each individual scenario. The objective is to optimize a statistical index, for instance, minimizing the average discrepancy between the required and provided workforce across scenarios. In hospitals, emergency departments require careful consideration of uncertainty since the arrival of emergency patients is highly unpredictable, and strict temporal constraints hold. EL-Rifai et al. (2015) modeled physicians who perform initial assessments and nurses who provide afterward treatments to optimize their personnel schedules. Retail shop staff allocation also suffers from uncertain customer demands on each shift. Parisio and Neil Jones (2015) estimated the requirement by fitting a hidden Markov model from historical data and obtained effective solutions with stochastic programming on real outlet retail data. In call centers, staff allocation has to conform to Service Level Agreements, guaranteeing the long-term performance of customers' waiting time within a specific range. Whitt (2006) proposed a method that determines near-optimal staffing levels with uncertainty of both customer arrival rates and staff absenteeism. Atlason et al. (2008) utilized stochastic programming to obtain staff allocations that keep SLAs in situations where customers' arrival rate dynamically changes over time. Later, their method was expanded to workplaces where multiple tasks are available and different skills are needed to assign employees to them (Robbins & Harrison., 2010). The second stage of stochastic programming can also include managers' reactive procedures. One such example is airline crew allocation (Yen & Birge, 2006), where the effect of flight delay is mitigated by rearranging subsequent crew allocation, and robust original allocation to delays is searched, assuming such resolution.

Another approach to deal with the uncertainty by reactive actions after a lack of human resources becomes apparent is rescheduling, which revises the original shift schedule so that the lack is replenished with minimum changes in personnel allocation. Pato and Moz (2008) formulated rescheduling as a bi-objective problem, focusing on both the efficiency of the revised schedule and the similarity of schedules between revisions. They proposed a utopic Pareto genetic algorithm to find Pareto optima. Similarly, Bard and Purnomo (2005) developed a feasibility heuristic to find an upper-bound solution for integer programming to achieve hospital-wide reactive scheduling. These approaches assume managers know in advance which days employees can go to work. Furthermore, the revised shift schedule is supposed to be announced to all involved employees every time a schedule is revised, which can incur significant costs for the management. Hatamoto et al. (2019) developed a simulation model of substitute attendance requests using a messaging app for such situations. In contrast to the current request method of telephone calls, the messaging app can automatically distribute requesting messages to multiple employees simultaneously. Experiments are conducted to predict the performance of such a method in a real-world call center. Based on our research, this paper examines the effectiveness of request sequencing methods in various phone-based environments. The simulation is performed on various scenarios by verifying multiple parameters, such as the acceptance probability of employees, offering insights into the relationship between the number of requests in different environments and the insufficient number of employees.

3. Simulation model

The proposed simulation model comprises shift generation and absenteeism handling modules. In both modules, the number of employees, the length of the target period for simulation, and constraints on personnel allocation are shared and given explicitly before the simulation. First, the shift generation model generates a shift for the whole period to meet all the constraints. Then, in the absenteeism handling module, unexpected absences of employees are stochastically obtained and reactively resolved by requesting a substitutional shift to employees. Absenteeism and reactive actions are simulated daily for the entire period. This section presents the formulation of personnel allocation in the simulation, followed by a detailed description of the two modules.

3.1. Formulation of personnel allocation

In this study, we examine the allocation of $E = \{e_1, e_2, \ldots, e_m\}$ employees across $D = \{d_0, d_1, \ldots, d_n\}$ consecutive days, divided into three shifts per day: w_0 for day work, w_1 for half-day work, and w_2 for night work. Employees work on at most one shift on the same day and cannot work more than r consecutive days with any shift and no more than s days on the night shift consecutively. It is also prohibited for an employee to be assigned to day shift (w_0) if the employee worked night shifts (w_2) on the previous day. Furthermore, each employee may be scheduled for a maximum of q shifts and a minimum of zero shifts during the period. For each shift, strictly a employees are required to ensure adequate staffing for all days. Each employee also submits a set of days when they request vacations explicitly. Each request for vacations is represented by a pair of an employee and a day, and the collection is represented by $A = \{(e_i, d_j) | e_i \in E, d_j \in D\}$. Whether the employee e_i works on the day d_j in shift w_k is denoted by the decision variable x_{e_i,d_j,w_k}.

Table 1. Constants for the formulation of personnel allocation used in the proposed simulation.

Explanation	Symbol
The employees available on the allocation period	$E = \{e_1, e_2, \dots, e_m\}$
The days that consist of the allocation period	$D = \{d_1, d_2, \dots, d_n\}$
The shifts considered in the allocation	$W = \{w_0, w_1, w_2\}$
The pairs of an employee and a day representing vacation request	$A = \{(e_i, d_j) \| e_i \in E, d_j \in D\}$
The number of required working employees on each shift	a
The maximum number of shift each employee can work on period	q
The number of max consecutive work of each employee	r
The number of max consecutive night work of each employee	s
The number of max substitutional work of each employee	b
Decision variables of if employee e_i works on day d_j in shift w_k	x_{e_i,d_j,w_k}

Table 1 summarizes the parameters and corresponding symbols. With these symbols, the constraints on allocations are represented as follows.

$$\sum_{w_k \in W} x_{e_i,d_j,w_k} \leq 1 \qquad \forall e_i \in E, \forall d_j \in D \tag{1}$$

$$\sum_{e_i \in E} x_{e_i,d_j,w_k} = a \qquad \forall e_i \in E, \forall d_j \in D \tag{2}$$

$$\sum_{d_j \in D} \sum_{w_k \in W} x_{e_i,d_j,w_k} \leq q \qquad \forall e_i \in E \tag{3}$$

$$\sum_{l=0}^{r} \sum_{w_k \in W} x_{e_i,d_{j+l},w_k} \leq r \qquad \forall e_i \in E, \forall j \in \{1, 2, \dots, n-r\} \tag{4}$$

$$\sum_{l=0}^{s} x_{e_i,d_{j+l},w_k} \leq s \qquad \forall e_i \in E, \forall d_j \in D, \forall j \in \{1, 2, \dots, n-s\} \tag{5}$$

$$x_{e_i,d_j,w_2} + x_{e_i,d_{j+1},w_0} \leq 1 \qquad \forall e_i \in E, \forall j \in \{1, 2, \dots, n-1\} \tag{6}$$

$$x_{e_i,d_j,w_k} = 0 \qquad \forall (e_i, d_j) \in A, \forall w_k \in W \tag{7}$$

Equation (2) states the total number of workers required each day while Eqs. (1) and (3)-(7) restricts each employee's working shifts.

Note that while some constraints, such as the number of required workers on a shift, are kept constant across the days in this formulation for simplification, extending the formulation with additional hard constraints or soft constraints as objective functions with a penalty is straightforward. The shift generation and absenteeism handling modules need to be modified to fit with the extension, and their details are discussed along with the modules' explanation.

3.2. Shift generation module

The shift generation module prepares the initial shift schedule before any absences occur. This process involves acquiring a personnel allocation that adheres to all the predefined constraints within the formulation. The formulation is based on the constraint optimization problem, which allows for the use of general solvers like CPLEX. In instances where additional soft constraints are introduced as the minimization of the objective function with penalties to address practical scheduling considerations, such as balancing workload across employees, the formulation can be represented as mixed integer programming. In such cases, general mixed integer programming solvers or heuristic solvers for scheduling problems can be applied.

While the problem of generating an optimal shift schedule that meets all constraints can be inherently complex, this study primarily focuses on the subsequent absenteeism resolution methods. Therefore, for the purpose of our research, we will handle a more straightforward setup were obtaining a near-optimal schedule before absences occur is practical, yet ensuring the substitutional workers in response to absences needs careful consideration. This approach allows us to concentrate on examining the effectiveness and efficiency of different methods for managing unexpected absences rather than delving into the complexities of shift generation itself.

3.3. Absenteeism handling module

The absenteeism handling module generates employee absences and simulates identifying employees' availability for substitution, followed by the reservation of substitute workers if available. Its fundamental principle lies in the uncertainty among workplace managers regarding which employees are willing to substitute. Furthermore, we assume that employee absences become apparent only after completion of work on the previous day. Hence, the occurrences of absences and requests for substitution are simulated on a daily basis.

The occurrence of absence and the requests to ensure substitutional workers are iteratively simulated for each day of the period. On each day, absences are stochastically generated first. If any absences occur, candidate employees for substitutional work are listed. The manager determines the sequencing of the candidates and requests to each employee in that order. Each employee stochastically responds to the request, and substitute attendance is assigned if the employee is available. Since it is assumed that the manager calls employees by telephone, the requests are conducted sequentially, and a response always follows the call to the next candidate. Additionally, being declined can be considered to include employees not answering the phone. The detailed discussions and proposals on the sequencing are described in the following subsection. When the absences are fulfilled during the requests, the requests are not performed on the subsequent candidates. Otherwise, if the absences are not fulfilled after the requests for all the candidates, the number of unsatisfied absences on the day is recorded, and the simulation proceeds. This process is sequentially performed for each day in the period. Since absences can occur across different shifts on the same day, candidate lists of employees are separately generated for each shift, and the same employees can exist on multiple lists for different shifts. This means an employee can be asked for a shift, and after denying the offer, the same employee can also be requested for another shift later on the same day, leading to the need for sequencing shifts of absences on which requests are made. For the sake of simplicity, however, absences are sorted by employee ID, and corresponding shifts are requested in that order. The investigation of sequencing requesting shift types is a further challenge.

The occurrence of employee absenteeism at date d_j is represented by replacing $x_{i,j,k}$ with 0 with absence probability p for all pairs i, k that satisfy $x_{i,j,k} = 1$. Employees who already have working shifts on d_j obviously cannot substitute the absence, and thus, any candidate e_i must satisfy Eq. (8).

$$\sum_{w_k \in W} x_{e_i,d_j,w_k} = 0 \tag{8}$$

Additionally, the constraints of Eq. (1) and (3)-(7) in Section 3.1 must not be violated by accepting the substitute attendance request. Since accepting substitutional work burdens employees considerably, constraints on the total number of substitutions are imposed. The total number of accepted substitutions of e_i before d_j is denoted by s_{e_i,d_j}, and e_i is excluded from the candidates if $s_{e_i,d_j} = b$. Managers confirm employees' availability and request substitutional attendance continuously if available. The manager contacts one of the employees who meets these constraints to confirm their availability and immediately reserves substitutional attendance if available. This continuity between confirmation and reservation is forced because confirming only they are available to work and putting off the request until later complicates management. It is even unpractical as the employees can always make private appointments before the request.

The overall process performed in the absenteeism module is summarized as follows.

1. Let t denote the date of interest and initialize t with one.

2. For each $x_{d_t,e_j,w_k} = 1\ \forall e_j \subset E, \forall w_k \subset W$, the variable is independently replaced with zero with probability p to generate absences stochastically. A set of absent employees are denoted by $A_{d_t} \subset E$.
3. Let $C_{d_t,w_k} \subset E\ \ \forall w_k \in W$ denote the candidate lists for shift w_t, whose elements are employees that satisfy Eqs. (1) and (3)-(8) even when the variable x_{d_t,e_j,w_k} is replaced with one. Note that the employees who were absent in Step 2 are excluded.
4. Pick e_u from A_{d_t} with the minor ID, remove it from A_{d_t}, and denote $w_v \in W$ by the shift where e_u is absent. If A_{d_t} is empty, proceed to Step 7.
5. Pick $e_{v'}$ from C_{d_t,w_v} following a sequencing method, remove it from C_{d_t,w_v}, and request substitution work to $e_{v'}$ on w_v. If C_{d_t,w_v} is empty, return to Step 4.
6. e_v answers the request with yes or no based on the acceptance probability. If the answer is yes, replace $x_{d_t,e_{v'},w_v}$ with one; otherwise, go back to Step 5.
7. Increment t and go back to Step 2. If $t = n$, finish the process.

3.4. Substitution Sequencing Methods

We propose online sequencing methods that prioritize requests based on specific criteria for each employee, such as the total number of prior substitutions accepted. Because of the uncertainty about responses to substitution requests, traditional planning methods become impractical, especially with the increasing number of scenarios.

In the proposed simulation model, sequencing of employees for the confirmation and the request is crucial for the efficient allocation of substitutional workers because an employee who accepts the substitutional work first will be assigned for the substitution. For allocating substitutions for only one day, the order does not affect the probability of obtaining sufficient substitutional workers. Therefore, to reduce the number of total substitution confirmations, asking for employees in descending order of likeliness of acceptance is always appropriate. However, in allocations spanning more than two days, the order of requests can significantly impact the likelihood of securing the necessary workforce for the entire duration.

Suppose an instance of two days for which one substitutional worker is needed each day. There is one worker with a high probability of acceptance and ten workers with a low probability, with a constraint that each worker can perform substitutional work at most on one day. Furthermore, one worker with a high probability can work on both days, while the remaining workers can only work on one day each; specifically, seven out of the ten workers are available for the first day, leaving the other three available for the second day. In this situation, prioritizing the worker with a high probability at first among all candidates on the first day leads to a high chance of a shortage of workers on the second day. This order increases the chance of allocation where the worker who can work on both days is assigned on the first day, decreasing the expected number of candidate workers on the second day. Note that the total number of requests tends to decrease in such order since the first employee is likely to accept the substitution work on the first day, and the other seven workers are not requested in that case.

In this paper, the following four methods are proposed. Note that all the methods assume that constraints of Eq. (1) to (8) are given (For example, when each employee has submitted available workdays to create the initial work shift). The first two methods also assume that each employee's acceptance probability is somehow known. Examples of ways to achieve this include asking how they are willing to accept substitute work or accurately estimating it through an extensive history of substitute requests.

3.4.1. Ascending order of employee's acceptance probability

The employee who is the least likely to accept the substitution on the day is asked for the request first. This method assumes that employees with a high probability can easily reach the maximum number of substitutions if they are requested on all available days. In such cases, prioritizing employees with a lower probability can lead to a high utilization of candidate workers in exchange for more requests.

3.4.2. Descending order of employee's acceptance probability

Contrary to the previous method, employees with a high probability are prioritized. This method is expected to decrease the total number of requests by greedily avoiding declines. The increase in unsatisfied shifts can be negligible if sufficient employees are available.

3.4.3. Ascending order of the number of previous substitutional work

In order to balance the number of substitutional works of each employee, the one with the least number of previous substitutions is requested first. This method can also be considered an alternative to 3.4.1 when employees' probability of accepting substitution is unknown.

3.4.4. Ascending order of the number of days of possible substitutional work in the future

This method focuses on the fact that employees cannot be one of the candidates for substitution when constraints in Eq. (3)-(8) are not met. If an employee is in such a condition for most of the subsequent days of the day of the order determination, preserving the employee for later substitution is not adequate, and thus, prioritizing them can lead to better allocation.

4. Experiments

We conducted numerical experiments using the proposed simulation model to assess the efficiency of each request sequencing method on a wide range of parameters, such as the possibility of absenteeism to require a substitutional shift and the probability of each employee's acceptance of substitutional work.

Table 2. Constants for formulation of personnel allocation used in the proposed simulation.

Explanation	Symbol	Value
The employees available on the allocation period	m	50
The days that consist of the allocation period	n	28
The number of required working employees on each shift	a	8
The maximum number of shift each employee can work on period	q	20
The number of max consecutive work of each employee	r	3
The number of max consecutive night work of each employee	s	3

Table 3. Range of the parameters in which all combinations are performed in the experiment.

Explanation	Sym.	Min.	Max.	Step
The probability of absenteeism on each employee on each shift	q	0.05	0.15	0.05
The number of max substitutional work of each employee	b	2	10	2
The number of employees with a high acceptance probability	n_{high}	5	15	5
Acceptance probability for high-acceptance employee group	p_{low}	0.05	0.20	0.05
Acceptance probability for low-acceptance employee group	p_{high}	0.50	0.90	0.20

4.1. Experiment Settings

We performed simulations with the proposed model for each sequencing method and evaluated the results. Since the simulation involves probabilistic events, simulations are conducted in 300 trials for each condition to approximate the expected outcome. Experiment parameters are determined based on a comparative study of human resources in call centers (Nitta, 2007). The number of employees, the days for the simulation, the required number of employees, the maximum number of shifts per employee, and consecutive work for day/night shifts are shown in Table 2. Each employee's vacation request in equation (2) is assigned rotating every seven days, with equal distribution among employees with different starting dates. The probability of absenteeism, acceptance of substitution of each employee, and number of maximum substitutions per employee are examined exhaustively within the ranges shown in Table 3 for all combinations, each corresponding to a specific workplace environment, leading to a total of $3 \times 5 \times 3 \times 4 \times 3 = 540$ parameter sets and 300 trials for each.

The employees are divided into two groups with a low and a high probability of substitution acceptance. This grouping reflects that call centers have full-time and part-time workers with different absenteeism rates, as reported in the comparative study. The number of employees with a high probability is determined by n_{high}, and a low acceptance probability is assigned to the rest of the employees $n - n_{high}$.

The overall range of parameters in Table 3 is determined to be consistent with actual call centers and to ensure that the sequencing order plays a crucial role in efficient allocation. The expected number of occurrences of absences should be the same as or lower than the expected total number of employees who accept substitution when all the employees are asked for it. They should also have the same relation with the total number of maximum allowed substitutions among all employees. These relationships ensure that absences in the simulation can typically be accommodated with substitution requests, at least when constraints are disregarded.

The evaluation compares the number of unfilled shifts and requests throughout the simulation period for each sequencing method in the same workplace environment. We primarily focus on the number of fulfillment failures since actual call centers often need a specific number of shift workers to meet the Service Level Agreement (SLA). If the average fulfillment number is similar among the methods, the number of requests is considered to reduce the management burden. In the proposed simulation model, absenteeism independently occurs on each shift, and each vacant shift is tried to be fulfilled with substitution requests to available employees. We count the number of shifts where absenteeism occurs and is not fulfilled with another employee after the simulation process and call it *the number of unfulfillments*. The total number of offering substitutional work for all absent shifts for each candidate employee and receiving responses is referred to as *the number of requests*. The smaller number of unfulfillments and requests indicates a preferable allocation.

4.1.1. Baselines

The results of each sequencing method are compared with two baselines. One is the result of randomized sequencing, and the other is the solution of a combinatorial optimization problem in which the uncertainties of absenteeism occurrence and substitution acceptance are relaxed. Hereafter, they are referred to as *Random sequencing* and *Solutions of relaxed instances*. The former suggests a situation where managers have no clue about determining the order other than the constraints of employees' working shifts, while the latter estimates the results of the best possible sequencing method.

Since acquiring results that can be achieved by the best possible sequencing method for comparison is challenging, we relax uncertainty about the occurrence of absences and the acceptance of substitution and obtain the optimal allocation. Unfortunately, calculating all possible combinations of absences and substitution acceptances and acquiring the optimal allocation with relaxed uncertainty requires enormous computational resources. Therefore, we estimate the expected result by sampling some absence and acceptance patterns. Additionally, we approximate the optimal allocation by stopping the mixed integer programming solver before guaranteeing the optimality of a tentative solution. A detailed procedure is as follows.

1. In each output of the shift generation module, replace $x_{e_i,d_j,w_k} = 1\ \forall e_i \in E, d_j \in D, w_k \in W$ with zero with probability of absence. Let $v_{e_i,d_j,w_k} \in \{0,1\}\ \forall e_i \in E, d_j \in D, w_k \in W$ be one if absence occurs in the corresponding shift and otherwise zero.

2. For each $v_{e_i,d_j,w_k} = 1\ \forall e_i \in E, d_j \in D, w_k \in W$ of an output of the shift generation module, randomly replace x_{e_i,d_j,w_k} with zero with a probability of absence.
3. Solve a combinatorial problem that maximizes the number of fulfilled shifts $\sum_{e_i \in E} \sum_{d_j \in D} \sum_{w_k \in W} x_{e_i,d_j,w_k}$, subject to constraints from Eqs. (1)-(7), as well as additional constraints $x_{e_i,d_j,w_k} + c_{e_i,d_j,w_k} < 1$ and $x_{e_i,d_j,w_k} \le v_{e_i,d_j,w_k}$ ensuring that absent or denied employees do not substitute. To solve this problem, we utilize CPLEX and adopt the best tentative solution after 10 seconds of computation.
4. Repeat the above procedures 15 times for each parameter set to acquire the average number of unfilled absent shifts.

4.2. Results

We analyze the experiment results from three perspectives: comparison between sequencing methods on different parameter sets, differences caused by uncertainties available for allocation, and trade-offs between the unfulfilled absences and the number of requests.

Table 4. The number of parameters sets where each method yields the average number of unfilled absenteeism per day of specified ranges.

Method	The avg. number of unfilled absenteeism per day							
	[0.0, 0.5)		[0.5, 1.0)		[1.0, 1.5)		[1.5, inf)	
Ascending of acceptance prob.	386	(71.5%)	94	(17.4%)	36	(6.7%)	24	(4.4%)
Descending of acceptance prob.	336	(62.2%)	112	(20.7%)	62	(11.5%)	30	(5.6%)
Ascending of past substitution	374	(69.3%)	100	(18.5%)	41	(7.6%)	25	(4.6%)
Ascending of future substitution	369	(68.3%)	98	(18.1%)	48	(8.9%)	25	(4.6%)
Random sequencing	365	(67.6%)	98	(18.1%)	52	(9.6%)	25	(4.6%)
Solution of relaxed instances	486	(90.0%)	33	(6.1%)	15	(2.8%)	6	(1.1%)

Table 5. The number of parameters sets where each method yields the average number of requests for substitution per day of specified ranges.

Method	The avg. number of substitution requests per day							
	[0.0, 7.5)		[7.5, 15.0)		[15.0, 22.5)		[22.5, inf)	
Ascending of acceptance prob.	91	(16.9%)	218	(40.4%)	194	(35.9%)	37	(6.9%)
Descending of acceptance prob.	233	(43.1%)	235	(43.5%)	72	(13.3%)	0	(0.0%)
Ascending of past substitution	130	(24.1%)	244	(45.2%)	144	(26.7%)	22	(4.1%)
Ascending of future substitution	162	(30.0%)	256	(47.4%)	108	(20.0%)	14	(2.6%)
Random sequencing	159	(29.4%)	249	(46.1%)	119	(22.0%)	13	(2.4%)

4.2.1. Overview of results on different parameter sets

Table 4 shows the number of parameter sets where each method yielded an average number of unfulfilled absenteeism per day within a specific range. Within the sequencing methods that assume uncertainty of acceptance of substitution, the descending order of acceptance probability yields the highest fulfillment in broad parameter sets, followed by ascending order of future possible and past substitution. The descending order of the acceptance probability performed the worst regarding average fulfillment. There is also a large gap between the solutions of relaxed instances and the best-performing sequencing method.

The number of parameters sets with each method regarding the number of average requests for substitution per day is shown in Table 5. Note that solving relaxed instances does not assume the need for substitution requests; thus, the corresponding values are unavailable. For the ascending and descending order of acceptance probability, the average number of requests shows the opposite trend against that of unfulfillment numbers. The ascending order decreases the number of unfulfillments while increasing the number of requests and vice versa.

Table 6. The number of parameters sets where the difference of the number of average unfulfillments for 28 days between two methods are within the specified ranges.

Compared methods	Difference of the avg. number of unfulfillment for 28 days				
	[-1.0, 0.0)	**[0.0, 1.0)**	**[1.0, 2.0)**	**[2.0, 3.0)**	**[3.0, inf)**
The best in proposed methods vs. random sequencing method	5	274	122	80	59
	(0.9%)	(50.7%)	(22.6%)	(14.8%)	(10.9%)
The best in not utilizing acceptance prob. vs. random sequencing	55	337	108	35	5
	(10.2%)	(62.4%)	(20.0%)	(6.5%)	(0.9%)
The best in utilizing acceptance prob. vs. other sequencing methods	64	355	78	31	12
	(11.9%)	(65.7%)	(14.4%)	(5.7%)	(2.2%)
Solutions of relaxed instances vs. the best of all sequencing methods	0	73	69	61	337
	(0.0%)	(13.5%)	(12.8%)	(11.3%)	(62.4%)

4.2.2. Differences caused by assumptions of uncertainty for allocation

To analyze the efficiency of the proposed sequencing methods in reducing unfulfillments in environments with the uncertainty of substitution acceptance, the number of parameter sets where the proposed methods decrease the unfulfillment is counted. Table 6. shows the number of parameter sets where the difference in the average unfulfillment for 28 days between the two methods. For example, the first row indicates that out of 540 parameter sets, random sequencing resulted in only five instances with fewer unfulfillments compared to the proposed sequencing method that achieves the least unfulfillment. In these cases, the difference is less than one unfulfillment for 28 days.

The first row of Table 6 shows that the proposed methods can decrease more than one unfulfillment on average in almost half of the investigated parameter sets by choosing the best-performing method for each parameter set. The second row shows the result when the proposed methods are chosen among those that do not require employees' acceptance probability of substitution, namely the ascending order of the number of past substitutions or future possible substitutions. In this case, the proposed methods decrease unfulfillment by more than one in 27.4% of parameter sets. The third row compares the best-performing proposed methods between those utilizing acceptance probability and others, showing that the former decreases unfulfillment by 22.4%. Finally, the fourth row shows the difference between the solutions of relaxed instances and the best results among the proposed methods, resulting in more differences in unfulfillment.

Table 7. List of investigated parameter sets.

	Index and explanation of a parameter set	q	b	n_{high}	p_{low}	p_{high}
I	Most restrictive about substituting absenteeism	0.15	2	5	0.05	0.5
II	Most permissive about substituting absenteeism	0.05	10	15	0.20	0.9
III	Most differences in avg. unfulfillment between the solution of relaxed instances and the best-performing proposed method	0.15	4	5	0.10	0.5
IV	Most differences in avg. unfulfillment between the best-performing proposed method and random sequencing	0.15	4	15	0.10	0.9
V	Most differences in avg. unfulfillment between the best-performing proposed method utilizing and not-utilizing acceptance probability of employees	0.15	2	15	0.10	0.7

Table 8. The average numbers of unfulfillment of absenteeism and request for substitution per day yielded with each method for parameter sets of I and II.

Index	Methods	# of avg. unfulfillment per day	# of avg. requests per day
I	Ascending of acceptance prob.	2.17	23.48
	Descending of acceptance prob.	2.24	21.90
	Ascending of past substitution	2.17	22.95
	Ascending of future substitution	2.20	22.85
	Random	2.25	22.78
	Solution of relaxed instances	1.77	-
II	Ascending of acceptance prob.	0.00	5.43
	Descending of acceptance prob.	0.01	1.72
	Ascending of past substitution	0.00	3.80
	Ascending of future substitution	0.00	3.26
	Random	0.01	3.41
	Solution of relaxed instances	0.00	-

Table 9. The average numbers of unfulfillment of absenteeism and request for substitution per day yielded with each method for parameter sets from III to V.

Index	Methods	# of avg. unfulfillment per day	# of avg. requests per day
III	Ascending of acceptance prob.	1.18	21.60
	Descending of acceptance prob.	1.34	19.02
	Ascending of past substitution	1.22	20.76
	Ascending of future substitution	1.25	20.11
	Random	1.27	20.30
	Solution of relaxed instances	0.50	-
IV	Ascending of acceptance prob.	0.37	19.04
	Descending of acceptance prob.	0.85	11.76
	Ascending of past substitution	0.50	16.32
	Ascending of future substitution	0.58	14.29
	Random	0.62	15.17
	Solution of relaxed instances	0.06	-
V	Ascending of acceptance prob.	1.15	16.35
	Descending of acceptance prob.	1.48	13.57
	Ascending of past substitution	1.29	15.38
	Ascending of future substitution	1.35	14.82
	Random	1.35	14.69
	Solution of relaxed instances	0.71	-

4.2.3. Differences caused by assumptions of uncertainty for allocation

To focus on parameter sets where the average number of absenteeism unfulfillments significantly differs from the baselines, Table 7 shows the parameter sets where the average number of unfulfillments is most different between the best-performing method among the proposed methods and baselines. For comparison, the most restrictive and permissive parameters about the fulfillment of absenteeism are also shown. The differences are evident when absenteeism frequently occurs and the number of maximum substitutions per employee is comparatively low. When the number and acceptance probability of employees with a high acceptance probability are high, there is a significant difference between the solution of relaxed instances and the proposed method. On the other hand, when the opposite is held, the difference between the proposed methods and random sequencing is maximized.

Tables 8 and 9 show the average number of unfulfilled absences and requests issued for substitution per day yielded with each compared method. Daily unfulfilled absenteeism exceeds two regardless of the sequencing methods in the restrictive parameter set. In the permissive parameter set, daily unfulfilled absenteeism is almost nonexistent on any of the methods, and the number of requests considerably differs. Other parameter sets show clear trade-offs between the number of unfulfillments and requests among the proposed methods.

4.3. Discussions

The overview of the results in Tables 4 and 5 show that the proposed sequencing methods generally perform as expected in terms of the number of unfulfilled absenteeism and requests. The ascending order of substitution acceptance probability leads to a smaller number of unfulfilled absenteeism and a larger number of requests in broad parameter sets. In contrast, the descending order exhibits the opposite. The large gap between the results of solutions of relaxed instances and the proposed methods suggests significant room for improvement in sequencing algorithms or an essential challenge of considering the uncertainty of substitution acceptance.

Comparisons between the allocation methods on the same parameter set in Table 6 reveal that the sequencing method of substitution requests plays a significant role in promoting worker fulfillment in the non-negligible proportion of situations. The first row in Table 6 indicates that the proposed method successfully decreases the number of absenteeism unfulfillments by more than one in 28 days in nearly half of the investigated parameter sets, indicating the effectiveness of the proposed methods in employee fulfillment. The proposed methods can still be effective in some situations where each employee's acceptance probability is unavailable, as shown in the second and third rows.

The results of each method on distinct parameter sets shown in Tables 7, 8, and 9 suggest that the proposed methods' improvement is most evident when absenteeism is frequent and the number of substitutions per employee is limited. In the permissive parameter set where the frequency of absenteeism is low, and employees are likely to accept the substitution, all considered methods, including random baseline, yield sufficiently small unfulfillment. Since employees with a high acceptance probability consist of a small portion of the entire employees and fulfilling absenteeism with only such a group is impossible, the ascending order that gives priority to other employees when available leads to better utilization of employees regarding shift assignment constraints. Otherwise, the ascending order of the acceptance probability of substitution achieves the smallest unfulfillments in exchange for the largest number of requests. In the ascending order, employees with a high acceptance probability tend to be allocated on greedy allocated on shifts whenever absenteeism occurs, leading to inefficient allocation. If decreasing the number of requests is more significant, the descending order of the acceptance probability is the most suitable, albeit its larger unfulfillments.

Last but not least, the ascending order of the number of possible substitutions in the future performs better in terms of both the number of unfulfillments and requests in parameter sets III and IV without the need to estimate the acceptance probability, although by a smaller margin. This result implies the possibility of further development of more intelligent sequencing methods with better trade-offs. Such a future challenge can be accomplished with knowledge of online scheduling algorithms where deep reinforcement learning techniques are currently being focused.

5. Conclusion

This paper presents a reactive scheduling model for personnel scheduling, focusing on substitution requests amidst uncertain employee availability. Through simulation-based evaluation within a call center environment, we investigated the impact of various sequencing methods for substitution requests on the efficiency of schedule fulfillment. The key findings from our study highlight the possibility of improvements in substitution requests of random order and the trade-offs between the fulfillments and the number of requests.

Our experiments, conducted across a wide range of parameters reflecting different workplace environments, demonstrate that the choice of sequencing method significantly affects both the number of unfulfilled absenteeism and the number of substitution requests. Among the methods evaluated, ascending order of acceptance probability often resulted in the lowest number of unfulfilled shifts, albeit with the potential cost of increased requests for substitution. Conversely, the descending order of acceptance probability showed promise in reducing the total number of requests but at the risk of higher unfulfillment rates.

We found that the effectiveness of sequencing methods varies with the parameter sets, such as the frequency of absenteeism, the number of maximum substitutions per employee, and the distribution of employees' acceptance probabilities. The difference between sequencing methods becomes evident when absenteeism is frequent, and substitutions per employee are limited.

Future research may explore further integrating advanced optimization techniques and machine learning algorithms to enhance substitution sequencing methods' efficiency, improving trade-offs between substitution fulfillments and requesting burden.

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