Operations Research for Health Care 38 (2023) 100389

Contents lists available at ScienceDirect

Operations Research for Health Care

journal homepage: www.elsevier.com/locate/orhc

A preventive–reactive approach for nurse scheduling considering absenteeism and nurses' preferences

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ARTICLE INFO

Article history:
Received 19 January 2021
Received in revised form 26 April 2023
Accepted 10 May 2023
Available online 19 May 2023

Keywords:
Nurse scheduling problem
Nurse absenteeism
Preventive and reactive scheduling
Genetic algorithm

ABSTRACT

The nurse scheduling problem (NSP) has become significant in recent years due to its direct impact on patient healthcare. This problem involves assigning nurses' shifts while fulfilling a set of hard constraints associated with labor regulations and soft constraints related to personal preferences, workload balance, among others. Most studies have focused on providing solutions for deterministic scenarios without considering unexpected disruptions, such as an unscheduled nurse absence. This study integrates two of the most common approaches to address absenteeism: preventive and reactive. First, we propose a multiobjective linear model for staff scheduling that preventively assigns backup nurses for each day. The NSP is known to be an NP-hard problem. Therefore, we used a genetic algorithm to obtain solutions in a reasonable amount of time. To mitigate the effect of unscheduled nurse absences, we propose two reactive rescheduling policies, one that seeks to maintain the baseline schedule and another that prioritizes the exclusive use of backup nurses. We used Montecarlo simulation under different problem settings to compare the proposed policies with a policy that does not use the preventive approach. The probability that a nurse will accept an additional shift to cover an absence was also considered. Simulation results suggest that both of our preventive–reactive policies outperform the non-preventive policy, especially in the presence of a small probability that a nurse will accept an additional shift. Finally, we used the proposed policies to create the monthly nursing schedule in a reference hospital in Bogotá-Colombia.

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1. Introduction and problem description

Healthcare effectiveness depends heavily on the excellent management of its resources. In such a manner, the human workforce is crucial because it determines the possible number of patients a hospital can serve. Particularly, nurses represent most of the human labor in a hospital, influencing all processes related to patient care. Health work units must plan the nurse scheduling, keeping in mind that a lack of nurses for a specific shift may cause a decrease in the quality of the health services provided [1].

Nurses are among the most complex resources to manage due to several factors, such as workload balance, demand fulfillment, timetable preferences, among others that need to be considered when planning their schedule. Hence, a good schedule policy is compulsory to improve hospital staff and patient satisfaction, resource efficiency and administrative workload [2,3].

Generally speaking, health care units have a predefined policy for scheduling nurses that seek to fulfill the demand, nurses' preferences and labor regulations associated with working time and rest periods. Shift assignment also addresses hospital requirements, such as nurse classification based on skills, experience or type of contract. Similarly, hospitals establish requirements to manage demand and preferences, for example, prohibiting the assignment of consecutive shifts or a maximum number of each type of shift in a nursing schedule. Legal regulations and hospital requirements are treated as hard constraints and nurse preferences as soft constraints [4]. In most cases, soft constraints are considered a low priority in the hospital scheduling process. Unfortunately, this might increase nurses' dissatisfaction due to inequity in workload and shifts conflicting with nurses' preferences.

Nurses' preferences have been one of the main factors studied in recent years. These preferences include rest days, preferred shifts, vacation periods, among others [5,6]. Research has shown that by meeting these requests, staff satisfaction increases, and as a result, the quality of service provided improves [7]. Although the schedule may not meet all nurses' preferences, researchers propose to maximize nurse satisfaction [8]. Schedules must also consider equity in the preferences met to each nurse since it could also affect the overall nurse satisfaction [9,10].

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https://doi.org/10.1016/j.orhc.2023.100389
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According to Maenhout & Vanhoucke [5], one of the problems in shift assignment is the increased workload generated by the absenteeism of nurses. If the workload in a nurse's schedule is not equally distributed, the physical and mental wellbeing of a nurse will decay [6]. Typically, unscheduled nurse absences require a modification of the original schedule. Schedule planners have to find a nurse to cover the absence *reactively*. This process involves contacting several nurses to negotiate and agree on the new shift they will now work. These last-minute changes often lower the satisfaction of the nurse who performs the replacement, degenerating the original schedule. As presented in the next section, a less explored way to deal with absenteeism is to *preventively* create a schedule that considers absences that could occur in the future. This approach requires more complex policies to build nurses' schedules since it relies heavily on the data collected to characterize absenteeism, but allows nurses to know in advance what additional shifts they might cover. Therefore, staff requests, fairness in shift assignment and unscheduled nurse absences will be considered in this work.

An unscheduled absence occurs when a nurse informs that they will not attend to a previously scheduled shift. These absences are often related to personal leave, medical or sick leave, school activities, jury duties, and others. When a head nurse is informed about an unscheduled absence, they must contact other nurses to inquire about their availability and willingness to cover the shift. Once a nurse accepts the shift, the head nurse must update the schedule. In this case, the head nurse might choose a suboptimal nurse to cover the shift since nurses have different shift preferences and not all nurses are necessarily consulted. When a nurse agrees, the search stops. Moreover, nurses are consulted only after the head nurse is informed about the absence, so it may not be possible for nurses to rearrange their personal schedules to cover the shift even if they would want to accept it.

The Nurse Scheduling Problem (NPS) is a well-known problem in the operations research community. It involves assigning nurses shifts while fulfilling a set of hard constraints associated with labor legislation, demand and a set of soft constraints related to personal preferences and workload balance. Approaches like mathematical programming, heuristics, simulation and others have been implemented to address several variations of the NSP [6]. The NSP is known to be an NP-hard problem [3,5], so heuristic approaches are popular for solving the NSP when dealing with an extensive set of shifts or nurses. In this paper, to create a schedule that preventively deals with future absences, we proposed a mixed-integer programming model that pre-assigns nurses as a backup for each shift. The model satisfies all the constraints for regular nurses and backup nurses. Due to its computational complexity, we addressed the model using a genetic algorithm (GA). If an unscheduled absence arises, one of the previously assigned backup nurses will cover the shift. However, since absences are not known at the moment the model assigns the backup nurses, it is not straightforward to decide how to react to all future absences that could materialize during the planning horizon. For example, if a nurse had to previously cover an absence, using that particular nurse again to cover additional absences may violate some labor constraints. Therefore, to deal with unscheduled absences, we propose two policies to update the original schedule, one that prioritizes maintaining the original schedule and another that prioritizes using only backup nurses. As a base approach, we also implemented a policy that does not predetermine backup nurses. We compare the policies through numerical experiments varying the probability that an scheduled nurse will be absent from work. Additionally, to mimic reality, for the last policy with no backup nurses, we also varied the probability that a nurse will refuse to accept to cover a shift.

As a case study, we implemented our approach in the surgical department of a Colombian reference hospital. Currently, the head nurse manually defines the monthly schedule. In addition, for each unscheduled absence of a nurse, the head nurse must contact other nurses who may or may not agree to cover the shift, and modify the original schedule accordingly, leading to a higher management burden and a frequent decrease in general nurse satisfaction.

This paper is organized as follows. Section 2 reviews the most recent and relevant studies based on the nurse scheduling problem. Section 3 describes the methodology implemented to address our particular NSP and presents the mixed-integer model, the genetic algorithm, and the proposed reactive policies. Section 4 describes the computational experiments. Section 5 presents the case study and explains the current process used to elaborate the monthly schedule by the hospital. Finally, Sections 6 and 7 state the most relevant results and the management implications for practitioners.

2. Literature review and contributions

The NSP has been an attractive research area in recent years due to the complexity of satisfying the hospitals' requirements and nurses' preferences. The United States stands out over the other countries trying to address this issue, followed by Japan and the United Kingdom [4].

NSP studies have been adapted for each internal hospital policy, the legislation of each country, and the objectives that the researchers seek to achieve. For example, some studies incorporate nurses' skills to develop staff assignments [11,12]. To address the NSP, it is appropriate to classify the related constraints into hard and soft constraints. Usually, hard constraints are related to labor law impositions and the prohibition of consecutive assignment of shifts, and soft constraints are associated with the number of working days and the number of assignments of each type of shift. Consequently, there are different approaches to evaluate the fulfillment of these constraints. One way to do this is to first focus on obtaining an initial schedule that fulfills hard constraints, and then improve this schedule by trying to maximize the compliance of the soft constraints [13]. Constantino, De Melo, Landa-Silva, & Romao [14] considered a different approach by penalizing the violation of hard and soft constraints on the objective function to obtain a solution. Another course of action is to generate a solution by relaxing the soft constraints. For example, Zanda, Zuddas, & Seatzu [15] relaxed the soft constraints according to the importance of each one, giving more weight to the more relevant constraints.

Health care institutions usually seek to optimize specific types of objective functions when solving the NSP. For instance, objective functions related to staff satisfaction and balanced workload have received major attention in recent years. The most common staff satisfaction objective functions are typically related to the maximization of nurses' preferences [16,17], where each preference of a single nurse can be related to desirable working shifts and days off during the planning horizon. On the other hand, balanced workload objective functions usually seek to control the gap between the working hours of all the assigned nurses [3]. Furthermore, other common objective functions aim to minimize overtime costs and hiring costs, to maximize coverage, to minimize the number of nurses and to minimize wasted time, among others [18]. For our particular problem, we included as hard constraints all labor related specifications and nurses preferences were used in the objective function.

Studies associated with the NSP have used different optimization techniques. Mixed-integer programming provides an optimal schedule subject to predetermined constraints and objective functions [19–21]. Nonetheless, for the problem at hand, the MIP model could only reach to an optimal solution for small

instances. This is expected since Hamid et al. [22] showed how the computational time ascends exponentially as the size of the NSP increases when solving it with an integer linear optimization solver. Nevertheless, integer linear programming can be very efficient in small instances. For example, Widyastiti et al. [11] implemented an integer mathematical model to define the number of nurses on each shift, looking for a schedule that maximizes their days off, considering their performance and qualification level. Other researchers provided a solution through the application of several mixed-integer linear programming models to control the nurses' shift assignment [2,8,23].

Heuristic algorithms are another approach used to generate efficient schedules when the NSP is too large to be tackled with a MIP model. Wong et al. [13] proposed a solution procedure that decomposes the problem into two stages. In the first stage, a shift assignment heuristic is used to obtain an initial schedule that satisfies hard constraints. Subsequently, in the second stage, a local search algorithm tries to improve the initial solution by maximizing the fulfillment of the soft constraints. Moreover, different solution procedures have been applied that include heuristics to solve the NSP with the nurses' preferences. Burke et al. [24] developed a hybrid ordering heuristic and a variable neighborhood search for the NSP. Constantino et al. [14] implemented the multi-bottleneck-assignment-problem-based algorithm (MBAP). This latter solution approach ensures that nurses' preferences are met as uniformly as possible, minimizing the maximum individual cost.

Our approach uses a metaheuristic for obtaining good solutions in a reasonable amount of time. Metaheuristics are another well-explored optimization technique to solve the NSP, which can generate a satisfactory solution in terms of running time, as shown by Hamid et al. [22]. Furthermore, tabu search and genetic algorithms (GA) are the most common metaheuristics that have been used to solve the NSP [25–27]. For example, Lin et al. [16] proposed a genetic algorithm considering the overall nurse satisfaction. In addition, Hamid et al. [22] proposed a non-dominated sorting genetic algorithm (NSGAII), tabu search, and Keshtel algorithm to minimize cost and incompatibility among nurses assigned to the same shift and maximize nurse satisfaction based on shift preferences. This study evidences the strength of the mentioned metaheuristics to solve the NSP with less run time than the integer linear programming model solved with the optimization solver GAMS. Nonetheless, other solution procedures, such as the electromagnetism metaheuristic have also been implemented for solving NSP with nurses' preferences [28]. As was already mentioned, GA is one of the most used solution methods for the NSP, which enhances the encoding of feasible schedules considering the variants of the problem at hand. Therefore, our paper proposes the implementation of a NSGAII, which allows the generation of feasible schedules to handle multiple objective functions.

Multiobjective approaches are an excellent alternative to satisfy the nurses' preferences considering other aspects, such as overtime costs and balance in the schedule. The problem addressed in this paper deals with two types of objective functions related to nurses preferences satisfaction including also certain constraints related to balanced workload and remuneration. Despite the fact that these mentioned features have not been considered altogether in a single investigation, various solution strategies have been developed to tackle similar multiobjective NSP problems. For instance, Mutingi & Mbohwa [29] presented a simulated fuzzy metamorphosis algorithm that can be a practical approach to optimizing multiobjective problems with conflicting fuzzy goals. Another common approach to address multi-criteria decision problems is integer linear programming. Wright & Mahar [17] used CPLEX solver to reach a solution by establishing a hierarchy level for each objective. Nasiri & Rahvar [30] proposed a multiobjective mathematical model and used the augmented epsilon constraint method to generate efficient solutions on the Pareto set. They worked with three objectives. The first two seek to meet the preferences of nurses and the last to minimize the workload. The analytical hierarchical process (AHP) is another method used to handle the multiobjective feature in the NSP. For example, Jafari & Salmasi [31] implemented the AHP method to define weights for each of the objectives related to nurses' preferences for weekends off and working shifts. Afterward, the problem was solved using a metaheuristic based on simulated annealing. Certain studies related to the NSP use this method to minimize soft constraint violations. More specifically, Jlassi et al. [4] used goal programming to minimize the deviations from successive shifts limit. Mohammadian, Babaei, Jarrahi, & Anjomrouz [32] used this technique to minimize violations of seven constraints related to nurses' preferences, such as days off, the number of requests satisfied, and preferred workdays. This previous literature review related to multiobjective NSP problems gives us mainly a notion of approaches based on exact and metaheuristic solution methods. One particular approach that is also used in the proposed solution strategy is the epsilon constraint method, which allows the generation of pareto efficient solutions that can be compared with the ones obtained using the proposed NSGAII.

Solving the NSP gives the hospital a baseline schedule, but unexpected disruptions such as nurse absences will undoubtedly occur. Although absenteeism has not received major attention in the available NSP literature, preventive and reactive approaches are the most commonly used to address this issue. Preventive approaches focus mainly on assigning nurses to predefined backup shifts to cover possible absences or on increasing the number of required nurses in determining shifts. In the case of assigning workers to backup shifts, a nurse may know in advance if she or he should be available to cover an absence that may occur on a particular shift. The main methods used to create the schedule are stochastic programming, robust optimization and buffering [33–35]. For instance, Ingels & Maenhout [36] improved the robustness of the schedule by assigning reserve duties to staff on a particular day and shift. In another study, Ingels & Maenhout [33] proposed a model that maximizes individual and group substitutability of staff to address the problem of unscheduled absences. Individual substitutability is defined as the possibility of an employee taking over a shift assigned to another employee. Group substitutability is established by increasing the number of employees to be on duty in determining shifts. Nonetheless, the previous approaches do not give a detailed method on how to update the schedule when absences are realized. Regarding reactive approaches, the baseline schedule is updated according to an unscheduled disruption caused by a nurse absence [37]. To cover an absence, it is plausible to choose a nurse at random [38], use optimization techniques to update the schedule based on mixed-integer models that minimize changes from the baseline schedule [39] or use heuristics to select a suitable nurse according to planners needs [40]. As in the latter, we developed specific heuristics that respond to hospital's needs in the case study.

The quality of both preventive and reactive approaches is usually evaluated through event-driven simulation for generating nurse absences [33,38]. In these studies, whenever a nurse absence occurs, the selected replacement nurse should be available to cover it. Nevertheless, this assumption ignores the possibility that the replacement nurse does not accept to cover an absence. Therefore, it is important to outline the relevance of exploring the effect of preventive and reactive approaches in more realistic scenarios where a nurse may be unable or unwilling to cover an absence. Furthermore, besides the limited available research that

addresses the absenteeism feature, there is room for new solution methods that explore the interaction between preventive and reactive approaches. This literature gap suggests the importance of proposing new rescheduling policies that exploit the advantages of considering backup personnel when building the baseline schedule with a preventive approach and particular policies used to deal with absences.

Based on the literature review presented, the main contributions of this article are listed below:

1. This study proposes a solution approach to generate feasible schedules that consider nurses' preferences, balanced workload, remuneration and absenteeism. These features have not been considered altogether in a single investigation to the best of our knowledge.
2. The proposed solution includes preventive and reactive approaches to manage absenteeism among nurses.
3. Specific rescheduling policies are proposed to reassign nurses to cover unscheduled absences. According to the related literature review, rescheduling policies are purely reactive since there is usually no interaction with a baseline schedule that provides preventive methods to handle absences.
4. This study evaluates a scenario where a nurse is unable or unwilling to cover an absence. This situation may be more realistic to validate the impact of the rescheduling policies. The few studies that consider the characteristic of absenteeism usually assume that selected nurses can cover an absence when it occurs.

3. Methodology

The methodology used to address the proposed problem is summarized in Fig. 1. First, in a reference hospital in Bogota-Colombia, we interviewed the head nurse and regular nurses to identify features and constraints related to the monthly nurse schedule. Based on the information collected, we create a baseline schedule using a mixed-integer model that preventively schedules backup nurses for each shift. The model guarantees that if a nurse is required to cover an absence, all hard constraints will be satisfied and violations of soft constraints will be minimized. To confirm the feasibility and accurate representation of the NSP in the reference hospital, we, together with the head nurse verified the optimal solutions for a variety of problem configurations using small instances (small set of nurses and a short planning horizon). It was necessary to iterate between additional interviews and additional testing until the model was finished. For small instances, we solved the mixed-integer model using an epsilon constrained representation of the two objective functions. For larger instances, we used a Non-Sorting Genetic Algorithm (NSGA II), explained in detail in the next section. Using the baseline schedule generated using the NSGA II, we proposed two policies to update the schedule when an unscheduled absence occurs. We tested our approach to create schedules based on synthetic data and in the study case in the reference hospital.

3.1. Mixed-integer linear model for the non-preventive approach

The following proposed model is inspired by the actual configuration of the hospital in the case study. This is a base model used to assign nurses to shifts in a particular service on a particular day but does not consider absenteeism. At the hospital, surgical services are divided into categories according to the type of assistance that a nurse has to attend. While surgical services may require different skills, all nurses at the reference hospital can work in any service. In fact, they usually work on several services if the schedule requires it. Due to contract differences, we consider two types of nurses, day working and night working. Shifts represent the working hours while slots refers to morning, afternoon and night. We decided to include both, shifts and slots, since the hospital estimates nurse demand in slots but nurses are scheduled to shifts.

This particular NSP seeks to schedule all nurses in a planning horizon according to labor regulations and hospital business rules while optimizing nurse staff satisfaction by assigning nurses in accordance with their preferences and requests. The preference of any nurse to be scheduled in a given service in a particular time slot is modeled on a Likert scale from 1 to 5, with being 5 the most preferable and 1 being the least. Additionally, on a given day, a nurse can request not to be scheduled in a specific slot or to be scheduled as a day off or as a full shift.

The sets, parameters, variables, objective functions and constraints of the proposed model are presented below.

Sets	
I	Nurses
S	Services
W	Types of nurses
T	Shifts
J	Slots (morning, afternoon, evening)
D	Days on the planning horizon
K	Weeks in the planning horizon
Subsets	
I_w	Nurses in I of type $w \epsilon W$
D_k	Days in week $k \epsilon K$ (According to each particular month)
T_j	Shifts within slot $j \epsilon J$
$N \subset T$	Night shifts
$C \subset T$	Full shifts
$F \subset D$	Weekdays
$G \subset D$	Saturdays on the planning horizon
$L \subset D$	Sundays and holidays on the planning horizon
Parameters	
$PREF_{its}$	Preference of the nurse $i \epsilon I$ in the shift $t \epsilon T$ in the service $s \epsilon S$ (1–5 Likert scale)
$PREFS_{is}$	Preference of the nurse $i \epsilon I$ in the service $s \epsilon S$ (1–5 Likert scale)
$PREFR_{ij}$	Preference of the nurse $i \epsilon I$ in the slot $j \epsilon J$ (1–5 Likert scale)
COEF1	Coefficient that penalizes each unfulfilled slot request
COEF2	Coefficient that penalizes each unfulfilled day off request
COEF3	Coefficient that penalizes each unfulfilled full shift request
REM_{td}	Remuneration of the shift $t \epsilon T$ in the day $d \epsilon D$
DEM_{djws}	Number of nurses required in day $d \epsilon D$ of type $w \epsilon W$ in slot $j \epsilon J$ in service $s \epsilon S$
DT_t	Duration of the shift $t \epsilon T$ in hours
HM	Maximum working hours allowed per month
HS_k	Maximum working hours allowed per week $k \epsilon K$
$VACI_i$	The start date of nurse $i \epsilon I$ vacations
$VACF_i$	The end date of nurse $i \epsilon I$ vacations
MAXF	Maximum consecutive full shifts allowed
MAXN	Maximum consecutive night shifts allowed
$MINWD$	Minimum number of days off on weekends per month
$MAXDO$	Maximum of consecutive days off
PET_{itd}	1 if nurse $i \epsilon I$ does not prefer to work in the shift $t \epsilon T$ on day $d \epsilon D$,0 otherwise
$PETD_{id}$	1 if nurse $i \epsilon I$ prefers a day off on the day $d \epsilon D$,0 otherwise

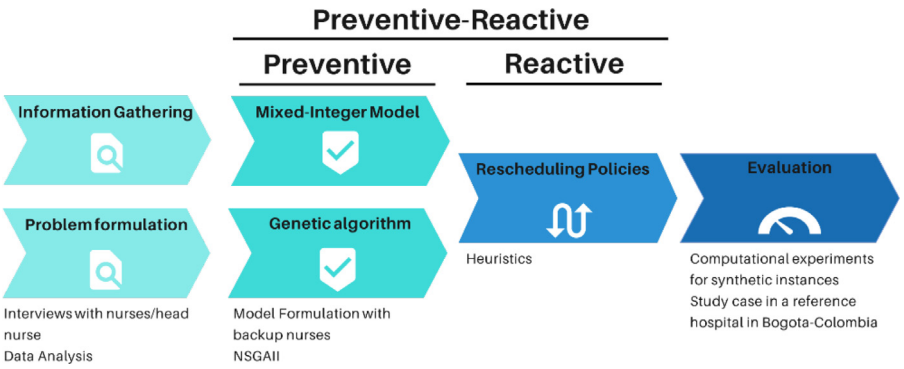


Fig. 1. Methodology of the presented study.

$PETC_{id}$	1 if nurse $i \epsilon I$ prefers a full shift on the day $d \epsilon D$,0 otherwise
$HMAX_w$	Maximum difference of worked hours allowed between nurses of type $w \epsilon W$
$REMAX_w$	Maximum difference of remuneration allowed between nurses of type $w \epsilon W$
$Trans_{tl}$	1 if the ending time of shift $l \epsilon T$ matches the start time of shift $t \epsilon T$,0 otherwise
Decision variables	
X_{itsd}	1 if the nurse $i \epsilon I$ is assigned to the shift $t \epsilon T$ in the service $s \epsilon S$ in the day $d \epsilon D$,0 otherwise
Y_{id}	1 if the nurse $i \epsilon I$ has a day off on day $d \epsilon D$,0 otherwise
SAT_i	Total satisfaction of a nurse $i \epsilon I$
$MINSAT_w$	Minimum satisfaction among the nurses of type $w \epsilon W$
$PETS^+_{itd}$	Positive deviation of slots requested by nurse $i \epsilon I$ in shift tϵT in the day $d \epsilon D$
$PETD^+_{id}$	Positive deviation of days off requested by nurse $i \epsilon I$ in the day $d \epsilon D$
$PETC^+_{id}$	Positive deviation of full shifts requested by nurse $i \epsilon I$ in the day $d \epsilon D$
$PETS^-_{itd}$	Negative deviation of slots requested by nurse $i \epsilon I$ in shift tϵT in the day $d \epsilon D$
$PETD^-_{id}$	Negative deviation of days off requested by nurse $i \epsilon I$ in the day $d \epsilon D$
$PETC^-_{id}$	Negative deviation of full shifts requested by nurse $i \epsilon I$ in the day $d \epsilon D$
RE_i	Total remuneration of nurse $i \epsilon I$
$MAXREM_w$	Maximum remuneration among the nurses of type $w \epsilon W$
$MINREM_w$	Minimum remuneration among the nurses of type $w \epsilon W$
$HOURST_i$	Total number of worked hours by the nurse $i \epsilon I$
$MAXH_w$	Maximum number of hours worked among the nurses of type $w \epsilon W$
$MINH_w$	Minimum number of hours worked among the nurses of type $w \epsilon W$
Objective functions	

$$\textbf{Max Z1}: \sum_{i \epsilon I} SAT_i \quad (1)$$

$$\textbf{Max Z2}: \sum_{w \epsilon W} MINSAT_w \quad (2)$$

Constraints

$$SAT_i = \sum_{t \epsilon T} \sum_{s \epsilon S} \sum_{d \epsilon D} X_{itsd} * PREFS_{is} + \sum_{t \epsilon T} \sum_{s \epsilon S} \sum_{d \epsilon D} X_{itsd} * PREF_{itd} - COEF1 * \sum_{t \epsilon T} \sum_{d \epsilon D} PETS^-_{itd} - COEF2 \sum_{d \epsilon D} PETD^-_{id} - COEF3 \sum_{d \epsilon D} PETC^+_{id} \; i \in I \quad (3)$$

$$MINSAT_w \leq SAT_i \; i \in I_w, w \in W \quad (4)$$

$$\sum_{t \epsilon T} \sum_{s \epsilon S} X_{itsd} + Y_{id} = 1 \; i \in I, d \in D \quad (5)$$

$$\sum_{s \epsilon S} X_{itsd} \leq 1 \; i \in I, d \in D, t \in T \quad (6)$$

$$\sum_{t \epsilon T} \sum_{s \epsilon S} \sum_{d \epsilon D} X_{itsd} * DT_t \leq HM \; i \in I \quad (7)$$

$$\sum_{t \epsilon T} \sum_{s \epsilon S} \sum_{d \epsilon D_k} X_{itsd} * DT_t \leq HS_k \; k \in K, i \in I \quad (8)$$

$$\sum_{i \epsilon I_w} \sum_{t \epsilon T_j} X_{itsd} = DEM_{djws} \; s \in S, d \in D, j \in J, w \in W \quad (9)$$

$$\sum_{t \epsilon T} \sum_{s \epsilon S} X_{itsd} = 0 \; i \in I, d \in D, VACI_i < d \leq VACF_i \quad (10)$$

$$\sum_{t \epsilon C} \sum_{s \epsilon S} \sum_{d \epsilon D} X_{itsd} \leq \sum_{d \epsilon D} Y_{id} \; i \in I \quad (11)$$

$$\sum_{t \epsilon C} \sum_{s \epsilon S} \sum_{z=0}^{MAXF} X_{its(d+z)} \leq MAXF \; i \in I, \; d \in D, d < |D| - MAXF \quad (12)$$

$$\sum_{t \epsilon C} \sum_{s \epsilon S} \sum_{z=0}^{MAXN} X_{its(d+z)} \leq MAXN \; i \in I, \; d \in D, d < |D| - MAXN \quad (13)$$

$$\sum_{d \epsilon G} Y_{id} + \sum_{d \epsilon L} Y_{id} \geq MINWD \; i \in I \quad (14)$$

$$\sum_{z=0}^{MAXDO} y_{i(d+z)} \leq MAXDO \; i \in I, \; d \in D, d < |D| - MAXDO \quad (15)$$

$$HOURST_i = \sum_{t \epsilon T} \sum_{s \epsilon S} \sum_{d \epsilon D} X_{itsd} * DT_t \; i \in I \quad (16)$$

$$MAXH_w \geq HOURST_i \; \forall \; i \in I_w \; w \in W \quad (17)$$

$$MINH_w \leq HOURST_i \; \forall \; i \in I_w \; w \in W \quad (18)$$

$$MAXH_w - MINH_w \leq HMAX_w \; w \in W \quad (19)$$

$$RE_i = \sum_{t \epsilon T} \sum_{s \epsilon S} \sum_{d \epsilon D} X_{itsd} * REM_{td} \; i \in I \quad (20)$$

$$MAXREM_w \geq RE_i \; i \in I_w, w \in W \quad (21)$$

$$MINREM_w \leq RE_i \; i \in I_w, w \in W \quad (22)$$

$$MAXREM_w - MINREM_w \leq REMAX_w \; w \in W \quad (23)$$

$$\sum_{i\in I_w} X_{itsd} = \sum_{i\in I_w}\sum_{l\in T} X_{ilsd} * Trans_{tl} \quad s\in S, d\in D, t\in T, w\in W \tag{24}$$

$$\sum_{s\in S} X_{itsd} + PET_{itd} + PETS^{+}{}_{itd} - PETS^{-}{}_{itd} = 1 \; i\in I, d\in D, t\in T \tag{25}$$

$$\sum_{s\in S}\sum_{t\in T} X_{itsd} + PETD_{id} + PETD^{+}{}_{id} - PETD^{-}{}_{id} = 1 \; i\in I, d\in D \tag{26}$$

$$\sum_{s\in S}\sum_{t\in C} X_{itsd} - PETC_{id} + PETC^{+}{}_{id} - PETC^{-}{}_{id} = 0 \; i\in I, d\in D \tag{27}$$

$$X_{itsd}\in\{0,1\}\; i\in I, t\in T, s\in S, d\in D \tag{28}$$

$$Y_{id}\in\{0,1\}\; i\in I, d\in D$$

$$SAT_i, RE_i, HOURST_i \geq 0, i\in I$$

$$MINSAT_w, MAXREM_w, MINREM_w \geq 0, w\in W$$

$$PETD^{+}{}_{id}, PETC^{+}{}_{id}, PETD^{-}{}_{id}, PETC^{-}{}_{id} \geq 0, i\in I, d\in D$$

$$PETS^{+}{}_{itd}, PETS^{-}{}_{itd} \geq 0, i\in I, t\in T, d\in D$$

We propose a biobjective model that uses Eq. (1) to maximize the overall nurse satisfaction and Eq. (2) to maximize the total minimum satisfaction among all types of nurses. The last objective ensures fairness among the satisfaction fulfilled for each type of nurse. Eq. (3) calculates the total satisfaction by adding the preferences and subtracting the penalty incurred for not meeting a previously requested rest day, a specific shift, or a full shift on a particular day. Eq. (4) obtains the minimum satisfaction of any nurse of each type. Hard constraints related to the standard NSP are presented in (5)–(10). Eq. (5) ensures that for any given day, the nurse is scheduled or in a day off. Eq. (6) confirms the assignment of a nurse to a maximum of one type of service during a given day. Constraints (7)–(8) prevent scheduling nurses for more hours than are allowed per week and planning horizon, respectively. Eq. (9) guarantees to schedule the number of nurses needed of each type for a specific time slot. Constraint (10) ensures the compliance of nurses' vacation by not assigning shifts during this period. Hard constraints related to the hospital business rules are presented in (11)–(24). Eq. (11) guarantees that nurses are assigned fewer full shifts than days off. Eqs. (12)–(13) prevent the model from assigning nurses more than an upper limit of consecutive full and night shifts, respectively. Constraint (14) gives nurses a certain amount of days off on weekends. Eq. (15) guarantees that nurses do not exceed the maximum number of consecutive days off. Eqs. (16)–(19) balance the workload by not allowing the maximum difference in hours worked between nurses of the same type to exceed a predefined limit. Likewise, Eqs. (20)–(23) balance the total remuneration by not allowing the maximum difference in remuneration between nurses of the same type to exceed a predefined limit. Eq. (24) ensures that the start time of each shift corresponds to the end time of the preceding shift. The temporal overlap is fundamental for efficient patient care coordination and the transfer of critical patient information among the nursing team. Soft constraints related to improve the fulfillment of the requests made by nurses to schedule particular days off, night shifts and full shifts are presented in Eqs. (25)–(27). Eq. (25) uses the variable $PETS^{-}{}_{itd}$ to store the number of times a nurse is requested not to work a shift on a particular day but the model could not satisfy the request. Eqs. (26)–(27) are similar to (25) but deal with requested days off and requested full shifts. Finally, (28) represents domain constraints.

The value of the parameters must be selected according to the particular features of the NSP at each hospital. Parameters such as *REM*, *DEM*, *DT*, *HM*, *HS*, *VACI*, *VACF*, *MAXF*, *MAXN*, *MINWD*, *MAXDO*, depend on specific legislation or mandatory business rules. To estimate parameters *PREF*, *PREFS*, *PREFR*, *PET*, *PETD*, *PETC*, it is necessary to implement surveys or interviews among nurses to collect the relevant data. Parameters *HMAX*, $REMAX_w$ must be proposed by the head of nurses according to their experience and the requirements of the healthcare department. Meanwhile, penalty coefficients are often more difficult to estimate. The experience in this study suggests that the head nurse must first get used to the schedules proposed by the model and then, together with the researchers, explore the best alternative for the penalty coefficients for the particular elements of the NSP at hand. Due to confidentiality, we cannot share the value of the parameters implemented in the model since they were estimated using the input of the nurses and the head nurse.

3.2. Mixed-integer linear model for the preventive approach

To deal with unscheduled absences of nurses, we propose to use backup nurses as buffers (similar to a safety stock in inventory management). Some nurses will be assigned to additional slots during the planning horizon, so they might have to cover an absence happening on any shift on any service in that particular slot. Nurses scheduled as buffers will be informed of the backup slots at the time of developing the nurse schedule and notified again when an unscheduled absence occurs to confirm if they must cover a shift.

The previous model does not include any preventive approach to dealing with absences, so the objective function $Z1$ needs to be updated and additional variables, parameters and constraints must be added.

Parameters	
$MAXB_w$	Maximum number of nurses type wϵW assigned as backup
$MINB_w$	Minimum number of nurses type wϵW assigned as backup
$MAXHP_k$	Maximum working hours allowed in week $k\epsilon K$
$MAXS_{wk}$	Maximum number of backup shifts assigned to nurse of type wϵW in week $k\epsilon K$
OTDO	Number of hours a nurse must work when she/he is covering an absence in a day previously scheduled as a day off
OTAS	Number of hours a nurse must work if she/he is assigned to cover an absence on a previously scheduled working day
$PENI_i$	Penalty for selecting a nurse $i\epsilon I$ as backup according to the number of absences covered in the previous month
Decision variables	
W_{idj}	1 if nurse $i\epsilon I$ is assigned as backup to day $d\epsilon D$ in the slot jϵJ,0 otherwise
$W2_{id}$	1 if nurse $i\epsilon I$ is assigned as backup to a day $d\epsilon D$ where she/he is already scheduled as a day off, 0 otherwise
$W3_{id}$	1 if nurse $i\epsilon I$ is assigned as backup to a day $d\epsilon D$ where she/he is already scheduled in a different slot, 0 otherwise

$SATR_i$	Total satisfaction of nurse $i \epsilon I$ considering the backup shifts
HRS_{ik}	Total hours worked by nurse $i \epsilon I$ in the week $k \epsilon K$ considering the backup shifts

Objective functions

$$\textbf{Max } Z1 = \sum_{i \in I} SAT_i + \sum_{i \in I} SATR_i, (2) \quad (29)$$

Modelconstraints

(3)–(28)

$$SATR_i = \sum_{d \in D} \sum_{j \in J} W_{idj} * (PREF_{ij} - PENI_i)\, i \in I \quad (30)$$

$$\sum_{s \epsilon S} X_{itsd} + PET_{itd} + W_{idj} \leq 1\, i \in I,\ d \in D, j \in J, t \in T_j \quad (31)$$

$$\sum_{j \in J} W_{idj} \leq 1 \forall\, i \in I, d \in D \quad (32)$$

$$\sum_{j \in J} W_{idj} + Y_{id} \leq 1 + W2_{id}\ i \in I, d \in D \quad (33)$$

$$\sum_{j \in J} W_{idj} + Y_{id} \geq 2 * W2_{id}\ i \in I, d \in D \quad (34)$$

$$\sum_{j \in J} W_{idj} = W3_{id} + W2_{id}\ i \in I, d \in D \quad (35)$$

$$\sum_{i \in I_w} W_{idj} \leq MAXB_w\ d \in D, j \in J, w \in W \quad (36)$$

$$\sum_{i \in I_w} W_{idj} \geq MINB_w\ d \in D, j \in J, w \in W \quad (37)$$

$$\sum_{j \in J} W_{idj} + \sum_{j \in J} W_{i(d-1)j} \leq 1\, i \in I, d \in D, d > 1 \quad (38)$$

$$\sum_{t \epsilon T} \sum_{s \epsilon S} \sum_{d \epsilon D_k} X_{itsd} * DT_t = HRS_{ik}\, i \in I, k \in K \quad (39)$$

$$HRS_{ik} + OTDO{*}W2_{id} + OTAS{*}W3_{id} \leq MAXHP_k\, i \in I,\ d \in D_k, k \in K \quad (40)$$

$$\sum_{d \in D_k} \sum_{j \in J} W_{idj} \leq MAXS_{wk}\, i \in I_w, w \in W, k \in K \quad (41)$$

$$W_{idj} \in \{0, 1\}\ i \in I, d \in D, j \in J \quad (42)$$

$W2_{id}, W3_{id} \in \{0, 1\}\ i \in I, d \in D$

$SATR_i \in \{0, 1\}\ i \in I$

$HRS_{ik} \in \{0, 1\}\ i \in I, k \in K$

Objective function Z1 shown in (29) now includes the satisfaction related to backup shifts. Eq. (30) computes, for each nurse, the satisfaction gained in the backup shifts. Constraints (31)–(32) ensure that if a nurse is previously assigned to that specific time slot or requested not to work on that particular day, they will not be designated as a backup. Eqs. (33)–(34) compute variable $W2$. Constraint (35) links variable W_{idj} with variables $W2_{id}$ and $W3_{id}$. Constraints (36)–(37) limit the number of nurses assigned as a backup for the same time slot. Eq. (38) ensures that no backup nurses will be assigned for two consecutive days. Constraints (39)–(40) limit the number of working hours if nurses are required to cover backup shifts. Finally, restriction (41) limits the number of backup assignments in a week and (42) represents the domain constraints for the additional variables.

3.3. Model solution

Because of the NP-hard nature of the NSP, we used a non-sorted genetic algorithm NSGAII to solve it. A basic GA is a metaheuristic inspired by natural biological selection. It starts with an initial population of candidate solutions and then implements operators such as selection, crossover and mutation to improve the population of each generation [41]. Selection and crossover improve solutions over time, while mutation helps the algorithm escape from local optima. On the other hand, NSGAII is a multiobjective metaheuristic used to obtain a good approximation of a set of effective solutions. Contrary to the basic GA, the selection operator orders the solutions based on a non-dominated strategy to compare candidates. A candidate is a non-dominated solution if none of the other candidates outperform it on any objective function. To foster diversity, it uses the crowding distance to select candidates that are not in a crowded space of the Pareto solutions [42]. Solutions with a greater crowding distance are selected because these points may require further exploration around them [43]. Particular operators of the NSGAII used in this study are mentioned below.

Encoding: We used a matrix whose rows represent nurses (I) and columns represent days in the planning horizon (D). The matrix stores integer numbers ranging from 0 to $|T|\,|S|$, that represent all possible combinations between shifts and services, where a value of zero indicates a day off. **Fitness evaluation:** First, we applied a greedy heuristic, described below, to assign backup nurses to initial schedules represented by a candidate solution. Then, we use Eqs. (28) and (2). **Selection:** we used the NSGAII selection strategy previously mentioned. **Crossover:** We used a one-point crossover, selecting a day at random. Two offspring are created from two parents. For instance, child one will have the same schedule as parent one until the randomly chosen day, and from that day forward, the schedule will be the same as parent two. **Mutation:** We defined a candidate mutation probability threshold and a day probability threshold. If a randomly generated number is below the mutation probability threshold, the selected candidate could mutate according to $|D|$ independent and randomly generated numbers used to decide wheatear the elements of a particular day schedule must change. The mutation consists of scrambling all the elements in the column vector of the matrix. **Reparation:** We had to implement a repair procedure to deal with offspring or mutated candidates that represented infeasible solutions. It consists of a swapping-based heuristic. First, we list all nurses who do not meet a particular constraint and rank them in descending order according to the related attribute. (e.g., worked hours). We then store the remaining nurses in ascending order of the same attribute in a list. We then try to swap the first nurses on the former list with the last ones on the latter list until the constraint is satisfied for all nurses. Finally, we repeat the procedure with all constraints until the solution becomes feasible. **Choosing a candidate:** from the set of candidate solutions in the last generation, if any, we chose the non-dominated candidate; otherwise, we chose the candidate with the highest value of Z1. **Tuning parameters:** We implemented a grid search to define the appropriate values for population size and mutation probabilities.

We implemented a greedy heuristic to add backup nurses for each schedule represented by a candidate solution. In a greedy manner, the heuristic selects the nurse with the best preference for each shift and day combination ensuring that the schedule satisfies all the hard constraints if a nurse must cover an absence. The fitness evaluation will penalize the candidate solution if the heuristic does not find a feasible schedule. The pseudocode is presented below.

Preventive approach heuristic

```
Begin
Sort nurses in descending order according to the total preferences for each shift of each day
For each week in the planning horizon (s):
    For each nurse (i):
        Sort days in ascending order according to the number of already backup nurses assigned
            For each shift (j) and day (d) in the current week:
                If feasible, assign nurse (i) to shift (j) on day (d)
Return the solution with the backups assignment
End
```

The solution obtained with the NSGAII is denoted as *baseline schedule* in the next sections.

3.4. Rescheduling heuristics

The baseline schedule must be updated each time an unscheduled absence is reported. Hence, selecting a suitable nurse to cover the absence is necessary. To do this, the following proposed heuristics are based on swaps between nurses. The immediate alternative could be to swap the absented nurse with any backup nurses assigned in the baseline schedule. However, this might work only for absences that arise at the beginning of the planning horizon. Nonetheless, if there have been many absences in the past, it is plausible that the previously assigned backup nurses are no longer a feasible solution. This is due to the constraints on the maximum limit of absences, hours or shifts that a nurse can have.

We define *policies* as preventive–reactive strategies that create a baseline schedule and update it according to the unscheduled absences that might occur using swap-based heuristics. Additionally, the policies minimize the number of backup shifts a nurse must cover to improve nurse wellbeing.

3.4.1. Policy 1

This policy uses the NSGAII solution as the baseline schedule so all backup nurses can cover one of the shifts they were preassigned without violating any hard constraint. When an unscheduled absence is informed, all swaps between the absent nurse and the backup nurses in the baseline schedule are evaluated. The policy will select the nurse with the higher total satisfaction (e.g., their individual contribution for that particular shift, day and service in Eq. (3)). Still, if all backup nurses have already been selected to cover previous shifts or if all backup nurses are ineligible due to a violation of any hard constraint, the policy will consider a swap between the absent nurse and non-backup nurses, i.e., the nurses that were not scheduled as a backup for that shift in the baseline schedule. As before, the policy will select the non-backup nurse with higher total satisfaction. It may not often happen in practice, but if it is not possible to make the schedule feasible with one swap using the backup or non-backup nurses, the policy will change the schedule of the days after the absence until it is possible to update the schedule (more details in Section 3.4.4). This policy prioritizes maintaining the baseline schedule because it will consider backup nurses before making any changes to the future schedule. Nevertheless, this policy may use non-backup nurses unaware of the shift to be covered. A general pseudocode is presented below.

Policy 1

```
Input: NSGAII solution as the baseline schedule
Begin
Evaluate all swaps between the absent nurse and the backup nurses
If all backup nurses have already been selected to cover previous shifts or all backup nurses are ineligible due to a
violation of a hard constraint:
    Evaluate all swaps between the absent nurse and the non-backup nurses
        If it is not possible to make the schedule feasible with a swap using the backup or non-backup nurses:
            Change the schedule of the days after the absence for all nurses and select
            the best swap (more details in section 3.3.4)
        Else:
            Choose the feasible non-backup nurse with the highest total satisfaction for the shift that needs to be covered
        End if
Else:
    Choose the feasible backup nurse with the highest total satisfaction for the shift that needs to be covered
End if
End
```

3.4.2. Policy 2

As in the previous policy, policy 2 uses the NSGAII solution as the baseline schedule. Then, when an unscheduled absence is informed, all swaps between the absent nurse and the backup nurses in the baseline schedule are evaluated. The policy will select the nurse with the higher total satisfaction, including backup nurses who have already been selected to cover an absence before. If no backup nurses are eligible to cover the absence because it will violate a hard constraint, this policy will change the schedule for the days following the absence until it is possible to update the schedule to cover the absence using only backup nurses. This policy prioritizes the use of backup nurses only but changes the baseline schedule more frequently than policy 1. Moreover, this policy may require a nurse to cover more than one absence during the planning horizon. If it is not possible to update the schedule using only backup nurses, this policy will change the schedule of the days following the absence until it is possible to update the schedule to cover the absence using any type of nurse. A general pseudocode is presented below.

Policy 2

```
Input: NSGAII solution as the baseline schedule
Begin
Evaluate all swaps between the absent nurse and the backup nurses
If all backup nurses are ineligible due to a violation of a hard constraint:
    Change the schedule of the days after the absence for the backup nurses and select
    the best swap (more details in section 3.3.4)
    If it was not possible to find a feasible solution:
    Change the schedule of the days after the absence for the non-backup nurses and select
    the best swap (more details in section 3.3.4)
Else:
    Choose the feasible backup nurse with the highest total satisfaction for the shift that needs to be covered
End if
End
```

3.4.3. Policy 3

To compare the two policies with a non-preventive approach, we proposed a third policy that uses the solution of the NSGAII of the model with no preventive strategy as a baseline schedule. When an unscheduled absence is informed, all swaps between the absent nurse and the other nurses are evaluated. As in the two previous policies, if the assignment of any of the nurses is not feasible, this policy will change the schedule of the days following the absence until it is possible to find a feasible solution. A general pseudocode is presented below.

Policy 3

```
Input: NSGAII Solution as the baseline schedule
Begin
Evaluate all swaps between the absent nurse and all the nurses
If all the nurses are ineligible due to a violation of a hard constraint:
    Change the schedule of the days after the absence for all nurses and select
    the best swap (more details in section 3.3.4)
Else
    Choose the feasible nurse with the highest total satisfaction for the shift that needs to be covered
End if
End
```

3.4.4. Changes in the future schedule

In all three policies, if there is a high number of previous absences, it might be that none of the backup or non-backup nurses can cover an absence since all alternatives would end up violating one or more hard constraints. If that happens (although it was not likely in our numerical experiments or case study), as stated in the pseudocodes, we must modify the future schedule (after the absence) for a particular nurse that will be selected to cover the absence. For example, in a specific week, a backup nurse was assigned to cover an absence on Monday. Due to a high number of absences, the same nurse has to cover a new absence on Wednesday. However, that nurse is also scheduled for additional shifts during the weekend, making it not possible to cover the absences on Wednesday since it would exceed the maximum number of working hours in a week. To allow the nurse to cover the absence, we could swap one of their weekend shifts

Table 1
Characteristics of each one of the proposed policies.

	Policy 1	Policy 2	Policy 3
Preventive approach?	Yes	Yes	No
First attempt	Swap with backup nurses	Swaps with backup nurses	Swaps with any nurse
If the first attempt is not possible	Swap with non-backup nurses	Changes the schedule of the days following the absence	
If there is not any feasible swap	Change the schedule of the days following the absence accordingly	Change the schedule of the days following the absence accordingly	Change the schedule of the days following the absence accordingly
Pros[a]	Do not change the baseline schedule	Do not use non-backup nurses	Do not require to build a preventive schedule
Cons	Use non-backup nurses to cover the absences	Change the baseline more often than policy 1	Both disadvantages of policies 1 and 2

[a]If there is not a feasible swap, any of the policies could select a non-backup nurse.

with another nurse. To keep the quality of the original schedule, we evaluated all possible feasible schedule modifications and selected the best according to the total nurse satisfaction. A general pseudocode is presented below.

Change the schedule of the days after the absence

Set I: Group of nurses considered according to the specific policy.
Begin
For *all the nurses (i)* ***in*** *I:*
  For *d starting in the day after the absence* ***to*** *the end of the planning horizon:*
    Evaluate all feasible swaps (e.g., respect the maximum number of hours, consecutive days, vacation, etc.) in day d between the nurse (i) and all the other nurses in I
    Save the best possible swap between the nurse (i) and the other nurses on this ***specific day*** *d according to the total change in the satisfaction of both nurses*
  Next *d*
Save the best possible swap for the nurse (i) according to the total change in the satisfaction of both nurses
Next *i*
End

The Table 1 summarizes the features of the proposed policies.

It is important to note that any change in the baseline schedule could affect the overall nurse satisfaction in the schedule. If a nurse must cover an absence, they might work on a day off or in a non-desired shift. Thereby, we propose three indicators to compare the proposed policies. (1) The percentage decrease in overall nurse satisfaction ($\sum_{i \epsilon I} SAT_i$ in the model) at the end of the planning horizon compared to the baseline schedule. This was used to measure how effective the rescheduling heuristics are in maintaining the quality of the baseline schedule. Values closer to one are desired. (2) The average number of overtime hours worked by nurses. A common practice in some hospitals is to cover an absence with a nurse even if it surpasses their maximum number of working hours a week. (3) Since the head nurse must contact the nurses to ask to cover the absence, we included that administrative burden measuring the number of times a nurse declined to cover an absence.

4. Computational experiments

All computational results were obtained on an HP laptop Intel Core i5 - 9300H PC with 4.8 GHz and 8 Gb RAM.

4.1. Preventive scheduling

Using small synthetic instances, we compared the performance of NSGAII solutions with optimal solutions obtained using the epsilon constrain method [44]. From the set of solutions obtained using epsilon constrain, we applied the same selection strategy as the NSGII mentioned in Section 3.3. Table 2 presents the GAP of each objective function from the optimal values achieved with single objective models. The optimal solutions of the model were obtained using CPLEX solver.

The results suggest that the NSGA II is competitive in small instances compared to the epsilon constrain method. Moreover, NSGA II was faster in all cases. For larger instances with more than 25 nurses and 21 days, the epsilon constrained method failed to find a feasible solution under 1 h. For the rest of this document, all the reported solutions were obtained using the NSGA II.

4.2. Instance generation

We tested all three policies using a problem setting similar to the reference hospital in the case study. That is 61 nurses and 30 days. We used a random variable following a binomial distribution to represent unexpected absences on each day. The number of trials is represented by the number of nurses scheduled in a day, and we tested the following probabilities, 0.001, 0.007, 0.013, 0.019, for a nurse absence. The absence probabilities were selected according to the absence behavior of the reference hospital in the case study. The duration of the absences was represented using a discrete uniform random variable between 1 and 3 days. The maximum number of backup nurses per shift was tested with values from 2 to 5.

To incorporate the benefits of a nurse being informed in advance about their backup shifts in the baseline schedule, we defined a probability that a nurse will decline to cover the absence. This happens quite often in hospitals. The head nurse must contact several nurses to find the one willing to cover an absence. Due to personal agendas, not all nurses will be available to cover an unscheduled shift. We tested the following probabilities 0.00, 0.05, 0.10, 0.15, 0.20. A probability of zero was assigned for all backup nurses as they were informed of the shifts they might have to cover from the beginning of the planning horizon. In each replication, the probability was the same for all nurses and declines were considered independent.

Combining all the alternatives for the policy used, the probability of an absence, the number of backups nurses and the probability that a nurse declines to cover an absence, there are $4 \times 4 \times 4 \times 3 = 192$ scenarios. For each scenario, we ran 1000 replications. In each of them, a month baseline schedule was built, and for each day, the schedule was updated according to the upcoming absences.

4.3. Policy comparison

For each scenario, the NSGAII created the baseline schedule that was updated according to the implemented policy. Each one of the indicators is presented on a different chart. Fig. 2 compares the change in overall nurse satisfaction at the end of the planning horizon where each boxplot represents a scenario. Fig. 3 and Fig. 4 compare the average number of overtime hours used in the planning horizon and the number of times that a nurse declined to cover an absence, respectively.

In scenarios with a lower probability of an absence, all three policies report a similar decrease in overall nurse satisfaction.

Table 2
Comparison between NSGA II and epsilon constraint method.

Instance	No. Nurses	Planning horizon in days	NSGA II			Epsilon Constraint		
			Z1	Z2	Time (s)	Z1	Z2	Time (s)
1	11	7	2%	8%	25	0%	31%	162
2	19	7	5%	0%	40	5%	0%	100
3	26	7	6%	1%	35	0%	13%	1310
4	61	7	9%	6%	47	10%	3%	1440
5	11	14	4%	2%	49	4%	0%	128
6	19	14	4%	4%	62	5%	0%	842
7	26	14	11%	0%	58	10%	0%	1635
8	11	21	6%	5%	46	0%	14%	115
9	19	21	8%	6%	149	10%	0%	306
Average			6%	4%	79	5%	7%	649

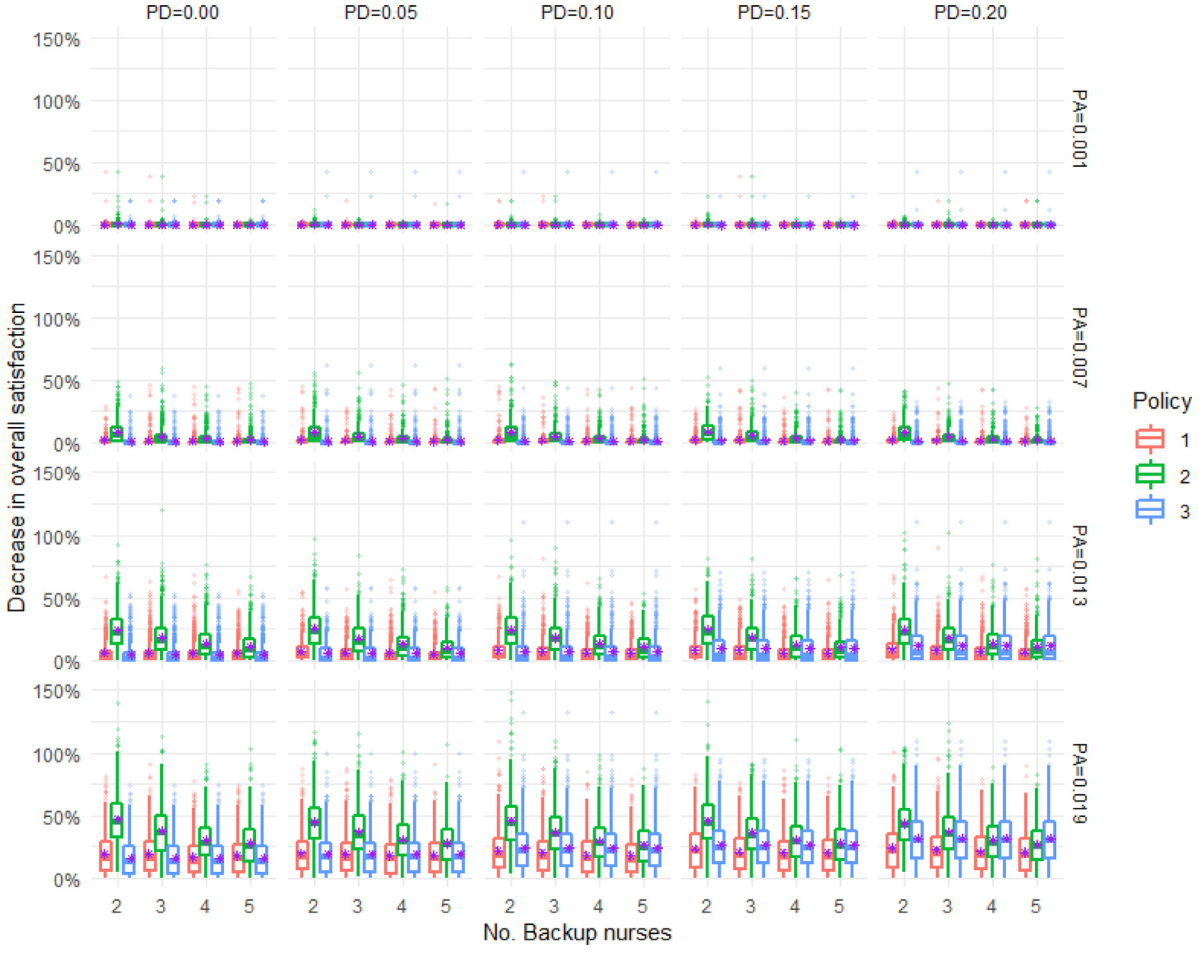


Fig. 2. Boxplots representing the decrease in overall satisfaction. PA = Probability of an absence, PD = Probability of a nurse declining to cover an absence. Asterisk represents the mean.

If the absence probability increases, overall satisfaction worsens in all policies. However, policies 1 and 3 obtained a smaller decrease in satisfaction, although policy 1 performs better than policy 3 as the absence and decline probabilities increase. Policy 2 performance is the one that may be more susceptible to the number of backup nurses. As can be deducted from the behavior shown in Fig. 2, this policy could lead to a smaller decrease in satisfaction than policy 3 and closer to the one that can be obtained with policy 1, as the number of backup nurses increases, especially when considering high decline and absence probabilities. Furthermore, additional backup nurses do not seem to significantly prevent the decrease of the overall satisfaction with policies 1 and 3. The average number of overtime hours did not change in the scenarios with a small probability of an absence. Although policies 1 and 3 achieved a lower average of overtime working hours in all tested scenarios, policy 2 can reach a similar performance as the number of backup nurses increases. The non-preventive policy encountered more declines compared to the preventive policies. Policy 2 outperforms other policies in the number of declines since it only uses backup nurses in most cases. Overall, it can be outlined the viability of using policy 1, which benefits from prioritizing the utilization of backup nurses, combined with the possibility of considering non-backup nurses to cover absences. The advantages of using this policy

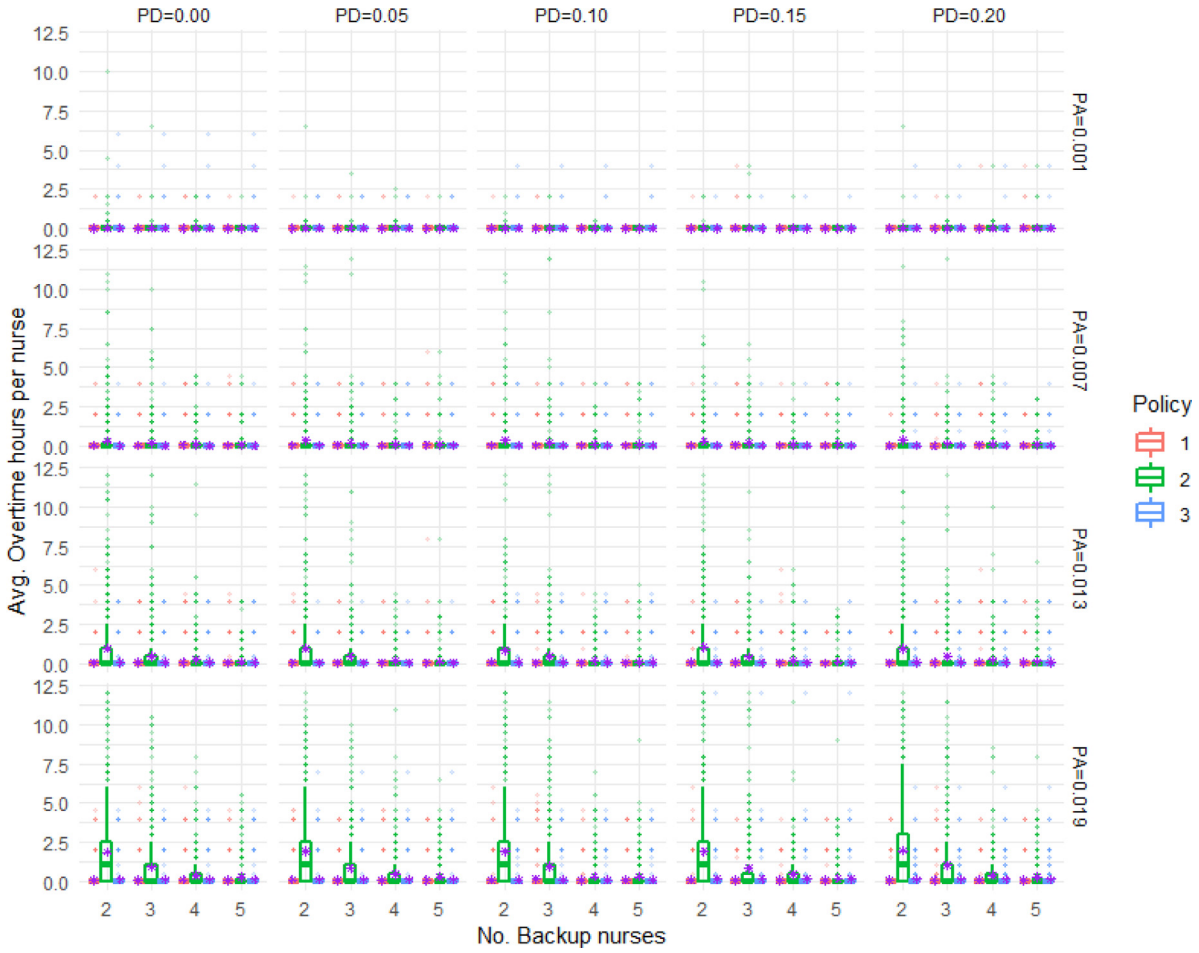


Fig. 3. Boxplots of the average number of overtime hours for all scenarios. PA = Probability of an absence, PD = Probability of a nurse declining to cover an absence. Asterisk represents the mean.

are more noticeable in scenarios with high absence and decline probabilities. Policy 2, which only prioritizes the utilization of backup nurses to cover absences, may also be a viable alternative, mainly when fixing a higher number of backup nurses and under scenarios with high absence and decline probabilities.

5. Case study

We tested the three policies in the surgical department of a reference hospital in Bogota-Colombia. This section briefly describes the current scheduling process at the reference hospital and how we selected the parameters for the preventive model. Then, we compare the results of the preventive scheduling against a real month schedule. Finally, we compare the previous three policies with the policy used by the hospital to handle unscheduled absences.

5.1. Current scheduling at the hospital

The surgical department consists of three services, surgery, recovery and ambulatory. The number of nurses assigned to each service depends on the number of surgeries scheduled for that particular day. Schedules are done every month. At the time of this research, there were 61 nurses available. There are two types of nurses, those who work in the morning and those who work at night. All nurses are able to work in any service, so no skills constraints were considered. Also, there are seven types of shifts distributed throughout the day.

The head nurse in charge of planning the schedule gathers all the data related to the preferences and requests of the nurses. All this information is stored in a spreadsheet. Then the head nurse decides who will work at each service. All nurses can work in any service, but they might prefer one of them. After that, the head nurse selects the nurses who will work night shifts. Later, the head nurse allocates vacation periods and, if possible, all requests. Finally, the head nurse distributes shifts according to the preferences of the nurses, labor regulations and internal policies of the hospital. This whole process can take between 8 to 16 h. The step-by-step process is summarized in Fig. 5.

The rescheduling process used to manage unscheduled absences consists of contacting any nurse and asking if they are willing to cover the absence. If the nurse is not available or not interested in covering the absence, the head nurse contacts another nurse, and so forth. If feasible, the head nurse will only select nurses who have not previously covered any absences. According to data provided by the head nurse, on average, 1 of 10 nurses declines the request to cover an absence.

5.2. Parameter configuration for the preventive scheduling

Based on labor regulations, the maximum of monthly working hours was established as 192 and the weekly maximum as 48. According to the previous experience of the head nurse, the maximum difference in working hours between nurses must be eight. The head nurse requested three backup nurses for each shift. Nurses' preferences and requests were obtained using an

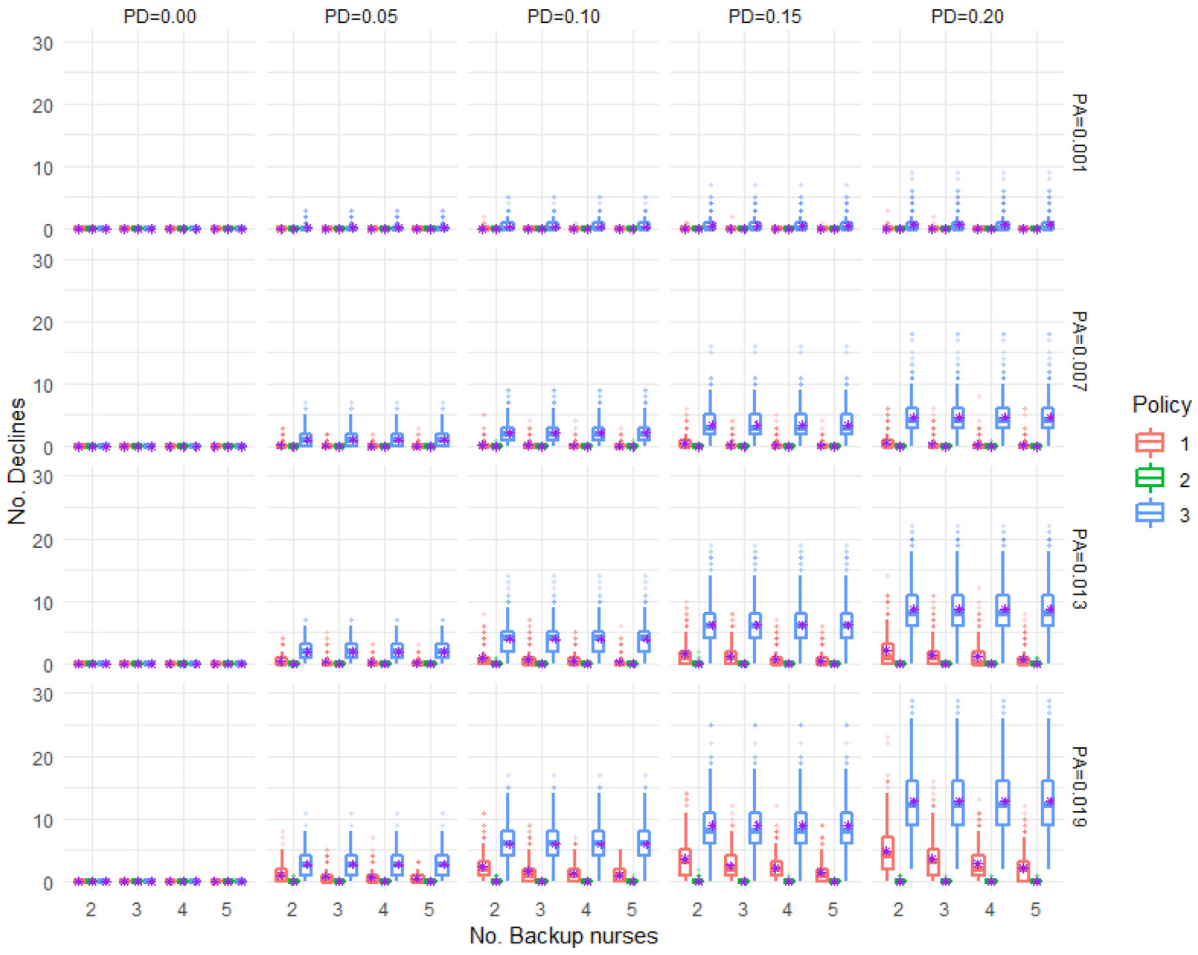


Fig. 4. Boxplots of the total number of declines to cover an absence. PA = Probability of an absence, PD = Probability of a nurse declining to cover an absence. Asterisk represents the mean.

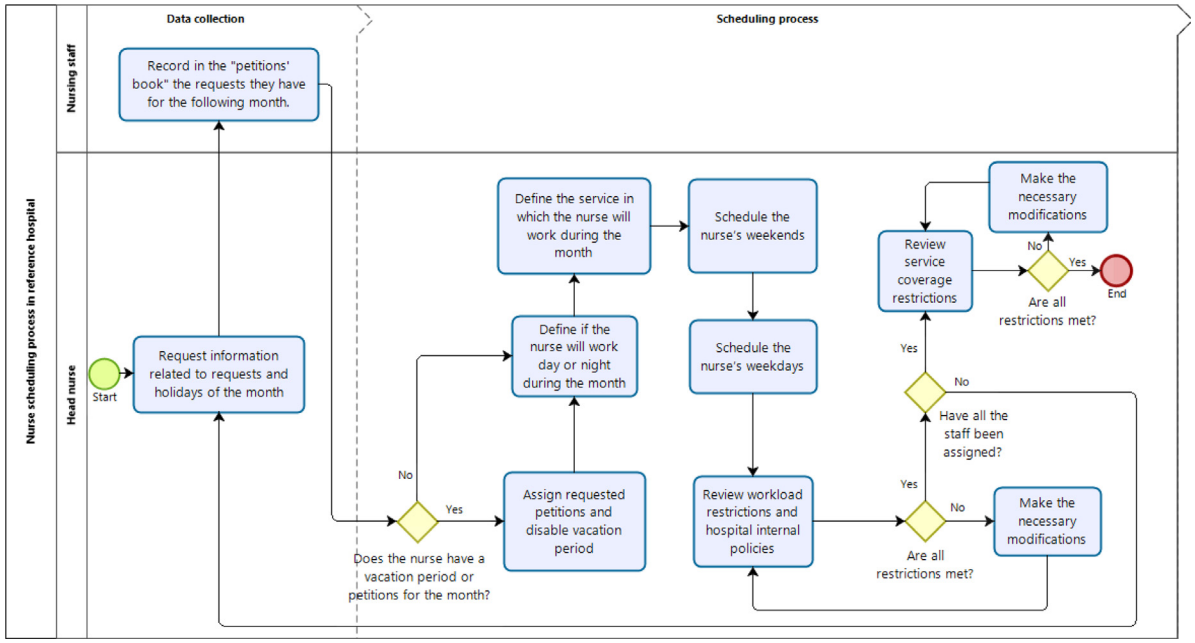


Fig. 5. Current nurse scheduling process at the reference hospital.

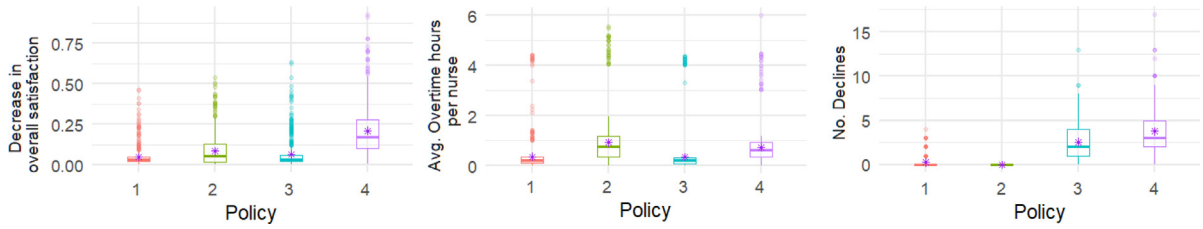


Fig. 6. Boxplots for policies comparison.

Table 3
Estimated absences probabilities based on data provided by the hospital.

Day	Slot	Probability
Tuesday	Night	0.0010[a]
Wednesday	Night	0.0010[a]
Thursday–Monday	Night	0.0028
Tuesday	Morning–afternoon	0.0132
Wednesday	Morning–afternoon	0.0064
Thursday-Monday	Morning-afternoon	0.0091

[a]Hospital records did not have any absences in those time slots.

electronic survey. After becoming familiar with our proposed policies, the penalty coefficients were decided together with the head nurse (more details in Section 5.4).

5.3. Parameter estimation for policies comparison

To compare our proposed policies with the current situation at the hospital, we coded the current hospital policy used to deal with unscheduled absences. Table 3 shows the estimated probability of an absence from the data provided by the hospital. We stipulated a probability of 0.001 for the time slots in which no absences were reported. Furthermore, data showed that approximately 50% of absences last one day, 30% between two and three days, and 20% of absences are equally likely to last between 4 and 7 days.

5.4. Results

All computational results were obtained on an HP laptop Intel Core i5 - 9300H PC with 4.8 GHz and 8 Gb RAM.

5.4.1. Preventive scheduling

We select the last monthly schedule done by the head nurse. Based on the same information we created the schedule using our proposed preventive approach. Table 3 compares the results of both schedules. The running time was 813 s (see Table 4).

Our proposed approach achieves considerably better solutions than the hospitals' current schedule for that particular month. The baseline schedule has an overall satisfaction of 11% higher than the hospital's schedule. Since the head nurse does not contemplate the balance of worked hours between nurses, the baseline schedule achieves a 76% improvement over the maximum difference in hours worked between nurses.

5.4.2. Policies comparison

We used the above estimated probabilities and absence durations to run 1000 replicas for each scenario, varying the policy used. The hospital's current policy corresponds to policy 4. Fig. 6 compares the change in all the indicators at the end of the planning horizon.

The results show that in all policies, even the non-preventive policy 3, outperformed the current policy used by the head nurse in all indicators.

5.5. Proof of concept of a desktop application

We developed a user-oriented desktop application to build the nurses' schedules at the reference hospital. Using the application, the head nurse can create monthly schedules, record absences and update the schedule using policies 1 or 2. Fig. 7 represents the user-diagram related to the application.

To build a schedule, the head nurse selects the month and uploads the preferences and requests data. If needed, the head nurse can add or remove nurses. The schedule presents the nurses assigned to each day slot. The application updates the schedule each time the user registers a new absence. The changes are shown in the red cells. Finally, the application shows nurses-related information such as worked hours, total preferences, number of requests fulfilled and others. The application helped the head nurse get familiar with our automated proposed schedule process.

6. Discussion

We proposed two preventive–reactive policies to deal with nurse absenteeism in nurses' schedules. The most important feature of our approach is two optimization-based policies that integrate a preventive schedule with backup nurses along with reactive heuristics used to select the most suitable nurse to cover the absence. Both policies select an eligible nurse looking to maximize overall satisfaction. Policy 1 seeks not to change the baseline schedule and avoids assigning a nurse who has previously covered an absence; meanwhile, policy 2 prioritizes the use of backup nurses. The results demonstrate that our approach effectively creates a baseline nurse schedule and deals with absences better than a non-preventive policy.

The welfare of nurses is one of the main concerns for the head nurse. Lower satisfaction could potentially affect nurses' performance. Computational experiments show that our policies reach better overall satisfaction in almost all scenarios. The probability of an absence directly affects overall nurses' satisfaction. A higher probability of absence requires many baseline schedule updates, making it difficult to maintain nurses' preferences. In theory, a higher decline probability may affect overall satisfaction since the most suitable nurse might decline to cover an absence. Nonetheless, overall satisfaction was not significantly affected. The fact that policy 2 prioritizes the use of backup nurses leads to nurses covering more than one absence or being required to work on an undesired shift, which reduces overall satisfaction. In contrast, policy 1 achieves better overall satisfaction because it uses non-backup nurses to avoid selecting nurses who have already covered an absence. Accordingly, policy 2 is more likely to require higher overtime hours since a nurse can cover more than absence. However, it rarely encounters a decline.

The most appropriate policy for a hospital will depend on how important it is to maintain the baseline schedule compared to using backup nurses. Assigning only backup nurses is needed in hospitals where it is troublesome to find last-minute absences. On the other hand, keeping the baseline schedule will improve overall nurses' satisfaction. In any case, if the absence probability

Table 4
Hospital schedule vs. proposed preventive schedule.

Criteria	Hospital schedule	Proposed preventive schedule	Improvement (%)
Overall nurses' satisfaction	10131	11284	11%
Maximum difference of working hours among nurses	34	8	76%

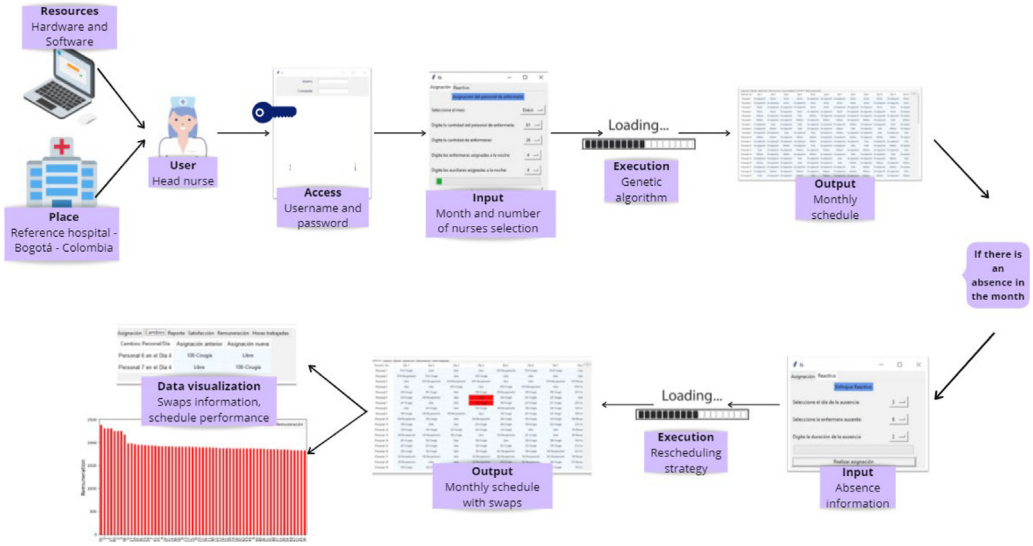


Fig. 7. User-application interaction diagram.

is small, policy 1 will be able to handle most absences using only backup nurses.

Other studies have demonstrated the benefits of using optimization strategies to deal with disruptions in the nurses' schedules [33,38,39]. The results in the case study also demonstrate the advantages of using this kind of strategy compared to real hospital practices. All policies outperformed the policy used by the hospital in all indicators. As expressed by the head nurse in the case study, these automated and optimization-oriented strategies help hospital administration deliver better healthcare by assigning nurses properly. Additionally, the implementation of our proposed policies to schedule nurses in a real-world setting at a reference hospital demonstrated that to effectively integrate optimization tools into daily operations, head nurses must be actively involved in the problem definition, constraints identification, parameter configuration and application design.

In future research, our policies could be tested to deal with the uncertainty of nurse demand. Additionally, our model and heuristics could be extended to more complex operating environments with additional constraints related to nurse skills. Finally, our policies could be combined with operation room scheduling to create nurses' schedules according to the planned surgeries.

7. Conclusions

We proposed two preventive–reactive policies to plan nurse scheduling and deal with nurse absenteeism. Our methodology starts with a baseline schedule that preventively assigns backup nurses while maximizing nurses' preferences. This approach guarantees that nurses are aware of the shifts they might cover since the beginning of each month, making it easier for the head nurse to find an eligible nurse to cover an absence. Moreover, to cover an absence, both policies assign nurses according to their preferences and request, which prevents the deterioration of the baseline schedule. Computational experiments using syntactic data confirmed the benefits of incorporating a preventive baseline schedule. The benefits were more significant in scenarios with a higher absence probability and a higher probability of a nurse declining to cover an absence.

This study fosters other hospitals to apply these policies as decision support tools on nurse schedules since they are faster and outperform manually built schedules in indicators related to no nurse wellness. Generally speaking, our proposed policies are applicable to any other hospital configuration with similar operation settings. Close collaboration with head nurses and nurses is essential to estimate the preferences needed to implement our approach.

CRediT authorship contribution statement

Ricardo Otero-Caicedo: Conceptualization, Methodology, Validation, Formal analysis, Writing – review & editing, Visualization, Supervision. **Carlos Eduardo Montoya Casas:** Conceptualization, Writing – review & editing, Supervision. **Carolina Barajas Jaimes:** Software, Investigation, writing – original draft. **Cristian Felipe Guzmán Garzón:** Software, Investigation, Writing – original draft. **Edwin Andrés Yáñez Vergel:** Software, Investigation, Writing – original draft. **Julián Camilo Zabala Valdés:** Software, Investigation, writing – original draft.

Data availability

The authors do not have permission to share data.

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