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Nurse Schedule Evaluation through Simulation with integrated Rescheduling

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Research-in-Progress

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Abstract

Nurse scheduling is a complex planning task in which many constraints, e.g. meeting the required demand or considering employees' satisfaction, are considered. However, employee absences due to uncertain events require rescheduling of former planned optimal schedules, which is often impossible without exceeding some of previous assumed limitations. Within this paper, we evaluate the ability of planned schedules to react to changes during the planning horizon. We present a discrete event-driven simulation system to emulate shifts and assignment of nurses and include real-world data schedules as well as different rescheduling strategies, which address staff shortage. To gain insights in the schedules' practicability, their effects regarding employee satisfaction, extra hours and additional costs are evaluated. First numerical experiments show that it is hard to find any substitution in case of an unforeseen absence. Thus, rescheduling with constraint relaxation generates significantly better results regarding the use of temporary staff and costs.

Keywords: Discrete event simulation, rescheduling, nurse scheduling, uncertainty, real-world data

Introduction

Nurse schedules are commonly generated by deterministic models generating good or even optimal schedules under the known requirements. Due to different characteristics and hospital policies, various descriptions and optimization models for the Nurse Scheduling Problem (NSP) exist (Constantino et al. 2014). Besides different workplace conditions, specific limitations regarding the scheduling period may require disparate problem handling. Therefore, diverse objective functions become relevant. In addition to coverage constraints, a feasible schedule has to meet many legal, tariff, care and staff requirements, which are typically considered hard constraints. Usually, schedule quality is determined by the compliance with soft constraints. However, previous assumed requirements may change during the ongoing period and staff shortage due to uncertain events can occur. Thus, the optimal schedule can be inoperative and substitutions have to be scheduled. This task is known as rescheduling. Bard & Purnomo (2005) define the aim of rescheduling as minimization of changes between the original schedule and the new one. The smaller the number of changes, the more reliable is the original schedule. In recent years, this uncertainty of nurses and staff demand has become a growing field in the academic literature (Wright and Mahar 2013).

Rescheduling has a great impact on the employees' perceived satisfaction (Ingels and Maenhout 2015): Short-term shift changes do affect leisure times of nurses and hence should be avoided as much as possible. Considering employees' satisfaction has received huge interest in recent years since demographic changes leads to an increased demand of nurses and staff shortage concurrently (Van den Bergh et al. 2013). Accordingly, care facilities and hospitals struggle to acquire and keep good employees in the long term and try to take counteractions by considering employees' demands. However, it is hard to quantify schedule satisfaction as it is mainly based on individual perception. We look at a satisfaction score, that incorporates the matches and mismatches in between the schedule and expressed individual preferences such as requests for or against specific shifts or days. Besides minimizing the scores' variance, the extra hours – both over- and undertime – should be spread evenly across all nurses.

Rescheduling is often done manually by a manager or head nurse. This is also the case in the care facility of our case study. However, a variety of approaches to support decision-making can be found in literature. Moz and Pato (2007) present constructive heuristics and various versions of genetic algorithms for rescheduling. Hospital data with randomly generated absences are used for their tests with good results. Gross et al. (2017) handle the trade-off between schedule quality and schedule stability using a mixed-integer linear programming model and generate an exact optimal schedule in the event of rescheduling. During this procedure, changes to the initial schedule are penalized in the objective function. They suppose the probability of an employee absence on any day to be 2.5% (Gross et al. 2017, p. 18).

In this paper, we are looking at unexpected events of employee absence due to illness. The considered schedules are generated with an optimization model based on real-world data. The schedules differ in their weighting of the objective criteria and thus in the allocation of nurses to shifts. In doing so, we focus on objective criteria such as a satisfaction score which can be increased by fulfilling individual preferences, balancing extra hours between nurses, and the deployment of temporary staff.

The first aim of this study is the development of different rescheduling strategies. Thus, we look at the vacant shift and seek for a substitution by a regular nurse. In case of necessity, a temporary worker can be hired. The second aim is to evaluate different schedules for one scheduling period in terms of practical usability. In addition, the generated rescheduling strategies are evaluated with regard to practical realization. In practice, it is not possible to test different schedules in one period. Therefore, we use a discrete-event simulation framework with integrated rescheduling strategies. The simulation is driven by the results of an illness statistic analysis, which determined the number and frequency of nurses' absences due to illness. To analyze the results, performance indicators such as objective criteria are compared. In addition, we also examine the timing of rescheduling, because a change at short notice is much more inconvenient for nurses.

The next section contains a discussion of the necessity of considering uncertainty during schedule construction in order to increase schedule robustness. The rescheduling strategies and the simulation framework are described subsequently, followed by first computational results. In the end, we conclude our findings and give a brief outlook into future research.

Uncertainty in Scheduling

According to Ingels and Maenhout (2015), various assumptions are made during scheduling that relate to the nurses' availability, care needs and other aspects. One of those assumptions expects all nurses to be available for work, if not assigned to a special task, on a long-term sick-leave or on vacation. However, during the execution of the schedule, nurses may not be able to fulfill their assigned shifts, e.g. due to illness. Thus, the schedule may have become infeasible, as the events may have changed constraints, which have been considered during optimization. Yet, most of the academic literature and solution approaches for the NSP are deterministic and "hardly ever take into account the unpredictable presence of workers due to illness" (Van den Bergh et al. 2013, p. 378). When looking at NSPs, uncertainty is regularly neglected and a stochastic component is often omitted.

In care facilities and hospitals, a service level corresponding to care needs has to be maintained independently of the number of available nurses. Therefore, the scheduler needs to be capable of handling the staff shortage or additional care demands. In practice, substitutions are typically selected by choosing any available nurse or looking for temporary staff. This procedure does not incorporate regulations such as balancing extra hours or the number of short-term substitutions and thus is not perceived as sufficiently justified and fair.

Van den Bergh et al. (2013) indicate, that as an alternative to integrating uncertainty aspects in the optimization approach, the schedule robustness can be examined by a simulation study. In doing so, we do not adjust the optimization model concerning uncertainty, but test the schedules regarding their ability to react to uncertain events. To be able to deal with such events, we present rescheduling strategies in the next section, which can easily be implemented in a decision support system in practice.

Rescheduling Strategies

Rescheduling is the task of altering a schedule in such a way that it remains feasible. Online rescheduling refers to in-period modifications (Caprara et al. 2010). A schedule needs to be adapted to unexpected events influencing the realization of the original schedule. Commonly, unexpected events such as unpredictable absences or changing staff demand cause rescheduling. It is a difficult task, because the original schedule plus the large number of constraints can make rescheduling quite impossible. In such cases, hard constraints may have to be softened and thus, formerly infeasible solutions become feasible. Constraint relaxation of hard constraints is commonly used in practice to avoid additional costs or major schedule changes.

Cacchiani et al. (2014) point out some differences between scheduling and rescheduling: During rescheduling, there is less time available and thus a solution has to be found fast. As time passes, the problem is becoming more complex by less flexibility restricting the solution space even more. In addition, the following practical requirements regarding rescheduling have to be taken into account. First, the covering and scheduling constraints have to be met. Second, it is desirable to generate a modified schedule with a minimum of assignment changes which take into account nurses, according to their extra hours and satisfaction. Especially, time-related constraints regarding the assignments of a single nurse restrict the rescheduling options, i.e. minimum and maximum consecutive working days. Third, to limit extra personnel costs, the use of temporary staff should be an exception.

Two rescheduling strategies have been implemented in order to react to short term cancellations: a *random* and a *ratio approach*. Both can be modified by either relying on *hard constraints* for generating a solution or by using *soft constraints* allowing for a greater solution space. Therefore, the *soft constraints* (constraint relaxation) allow for a violation of specific constraints such as the maximum number of Sundays a nurse can be assigned to. Initially for both approaches, a set of nurses, which would be able to fill the vacant shift, considering the chosen constraint variant is generated. The *random approach* then chooses a substitute purely by rolling the dice for each nurse. In contrast, the *ratio approach* aims to increase the rescheduling fairness by picking a substitute through minimizing the variance of extra hours and satisfaction between the nurses. If no alternative nurse can be found for a shift, a temporary worker is assigned to it. Hence, these strategies use schedule changes to match shifts' supply and demand, but do not consider swaps of nurses or the like since only the affected shift is examined. Integrated in a simulation framework as described in the following section, an evaluation of the strategies is possible.

Discrete-event Simulation Framework

A discrete-event simulation is used to evaluate the optimization model and to examine which objective criteria weights will generate good schedules for practical operations. Simulation is an appropriate instrument to validate schedules and the underlying optimization approach (Van den Bergh et al. 2013). In addition, testing different objective functions in practice is not possible since only one schedule can be used per period. Therefore, a practicable and good schedule should be identified prior to the period. Caprara et al. (2010) use a simulation framework for analysis of robust planning and rescheduling strategies in the context of train routing. We use simulation for validation of schedules generated by our optimization approach as Qi & Bard (2006).

The optimization model was tested for several months in the care facility. For a typical scheduling period, the large-scale optimization model contains more than 1,000 variables and 3,000 constraints. The optimization model has been implemented in Java. Accepting a 1% optimality gap, it takes up to ten minutes to solve the model with Gurobi 7.0.1 on a Unix machine with an i5 dual core (2.6 GHz) and 8 GB of RAM.

The simulation process is designed as follows: The model uses a dynamic approach to simulate the monthly schedule for one period over a set time course. Uncertain events such as illness are generated stochastically. All events can occur time-discrete, in this case every 30 minutes. The state of the simulation system is determined by multiple system variables. Our system is described by the nurses' states (*Work*, *Vacation*, *Sick*, *None*). While *Work* and *Vacation* are self-explanatory, *None* describes the state of currently not being assigned to any shift. Nurses with state *None* can be rescheduled for shifts at the same time if no constraints are violated. The state *Sick* labels a nurse in case of an absence due to illness. In contrast to the other states, *Sick* can only be reached by a stochastic event. During an illness, all assigned shifts have to be rescheduled to other nurses (except a nurse becomes sick during a shift that lasts only two more hours).

We consider six events in our simulation framework. Each event triggers a change of a nurse's state. A nurse starts to work a shift with *ShiftBegin* (state changes from *None* to *Work*) and ends with *ShiftEnd* (state changes from *Work* to *None*). The specific event times depend on the corresponding times in the given schedule. The events *VacationBegin* and *VacationEnd* work in the same manner, but are always scheduled at 12 AM. The two stochastic events are *IllnessBeginn* (state changes to *Sick*) and *IllnessEnd* (state changes from *Sick* to *None*). Sick-leave ends at 0:30 AM. Thus, *IllnessBeginn* is the only one event type that can be scheduled at any time.

Our simulation framework addresses two issues. The first issue concerns the occurrence of nurse absences because of illness. Therefore, we analyzed illness statistics collected in 2016 and 2017 by the care facility with respect to frequency and duration of sick-leave and vacation days. The analysis results show the possibility of assigning each month to one of four equivalence classes according to the overall number of absence days during each month. We also look at vacation days because a nurse will then be absent and cannot be considered during rescheduling.

Table 1. Classification of months based on absence days

Equivalence class	Number of sick days	Number of vacation days	Months
1	≤ 20	≥ 40	July, August, September, December
2	30-40	30-40	January, February, April
3	≥ 40	≤ 20	March, October, November
4	20-30	20-30	May, June

Table 1 summarizes the analysis results of one care unit with nine to ten nurses. The numbers refer to the overall amount of absence days and allow a classification of each month. Equivalence class 1 contains months with the highest number of vacation days and a low number of sick days (July, August, September, December). Months with many sick and vacation days are January, February and April which are grouped in equivalence class 2. The highest number of sick days in combination with few vacation days can be found in equivalence class 3 (March, October, November). Months with a lower number of absence days are May and June which belong to equivalence class 4. We expect rescheduling to identify regular nurses as substitution possibilities far more frequently for equivalence class 4 because there are more possibilities provided. The results of this analysis are incorporated in the probabilities of the stochastic events. We apply the simulation to only one month per equivalence class (August, April, October and May) to get first insights.

The second issue addressed by the simulation framework is rescheduling. Whenever an event leads to staff shortage due to absences of formerly assigned nurses, rescheduling is necessary. We tested different rescheduling strategies such as *random* and *ratio approach* with using *hard* or *soft constraints*.

The components and the procedure of the developed simulation framework are shown in Figure 1. A planned schedule works as input as well as the results from the analyzed illness statistics. According to this, stochastic events occur. In case of a cancellation due to illness, a rescheduling strategy searches for a substitution and generates an adjusted schedule. After simulating the planning period, the frameworks output is an actual schedule, which serves as a basis for evaluating the planned respectively actual schedule and the rescheduling strategies. We present first evaluation results of this framework in the next section.

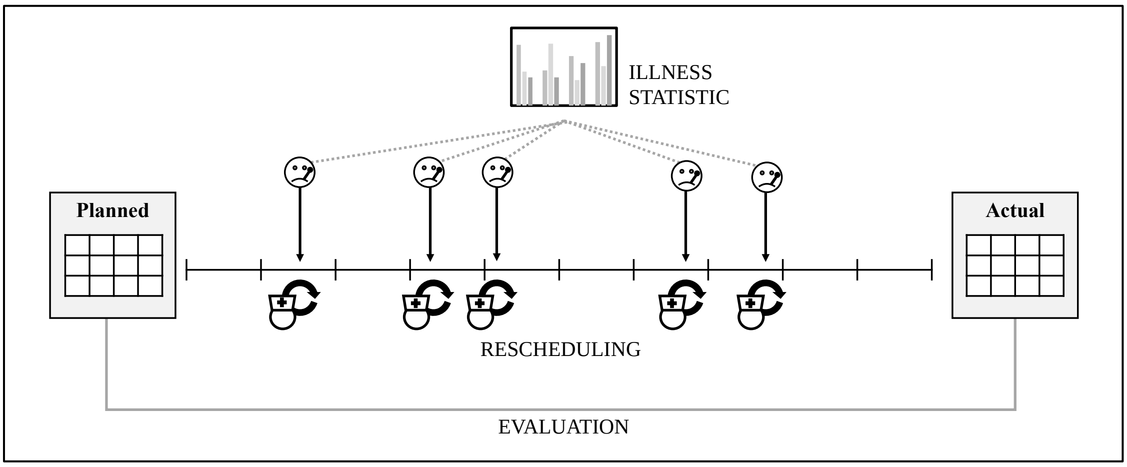

Figure 1: Simulation Framework

Computational Results

Following the case study, we assume that constraints regarding coverage and care needs are known and have to be considered for each schedule generation. Our schedules consist of nine to ten nurses. Past illness occurrences within the care unit serve as data for modeling and incorporating stochastic events in our simulation study. The schedules are optimized regarding the following objective function:

$$min\ \alpha \cdot (sat_{max} - sat_{min}) + (1-\alpha) \cdot (eh_{max} - eh_{min}) + 2h_{temp}$$

with α: emphasis of satisfaction score/extra hours
$sat_{min/max}$: minimum/maximum satisfaction score of all nurses
$eh_{min/max}$: minimum/maximum extra hours of all nurses
h_{temp}: working hours that are performed by temporary workers

The objective function minimizes the gap between the maximum and minimum nurses' satisfaction score as well as their extra hours, both being considered according to a given weight α and (1-α), respectively. Additionally, a penalty for working hours performed by temporary workers is considered. We solve each instance systematically with different levels for α: 0, 0.25, 0.5, 0.75 and 1. Combining the four rescheduling strategies with the four selected months and the different values of α results in 80 scenarios. To allow for representative results, we simulate each scenario multiple times and present results based on the average of 100 independent simulation runs.

Figure 2 shows the obtained results for the objective function values split into the satisfaction score, the extra hours as well as temporary staff hours for each level of α. For example, for α = 0.0 (in the leftmost position), the nurses' satisfaction score is not considered within the objective function which results in an extra hour value of 130 as displayed by the light blue bar. A higher value of α leads to a stronger impact of the satisfaction score on the overall score represented by the increasing green colored bar. We can also see that there is a disproportionate influence of the two goals within the objective. A small increase of α leads to a strong decrease in the overall extra hour, while the satisfaction score shows only a slight increase. A reason for this particular observation might be found in the underlying real-world data. This data does not contain a high quantity of individual shift or day preferences influencing the satisfaction score.

However, different levels of α seem to have almost no impact on the temporary staff hours as can be seen by the relatively constant level of the dark blue line in Figure 2. Accordingly, temporary staff work 144 to 158 hours on average. This large number of hours can be traced back to the limited instance size because finding a regular nurse as substitute obviously is easier when many nurses are accessible.

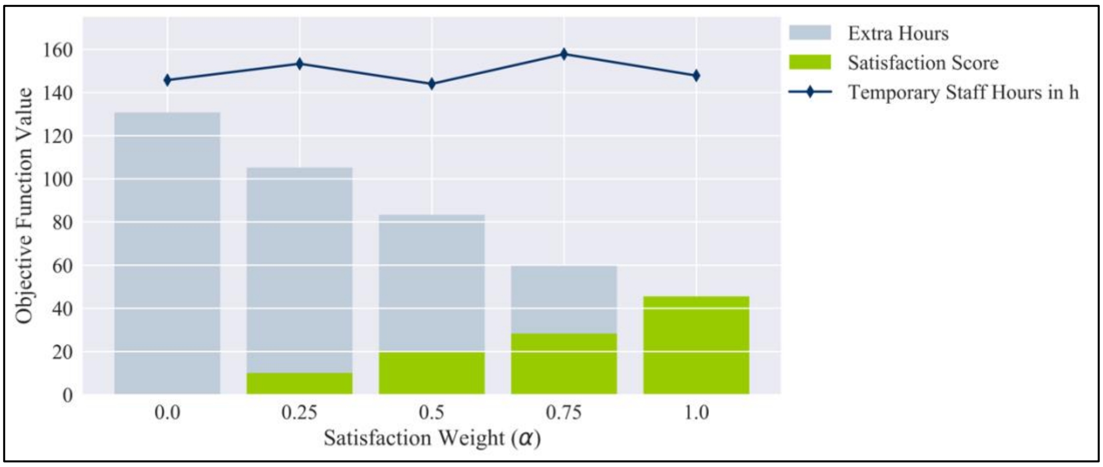

Figure 2: Average Objective Function Values according to α

Comparing the four months' instances, we identify two categories: those instances with few possibilities for substitution with regular nurses and those with more frequent substitutions. Due to few available nurses in the equivalence classes 1, 2 and 3, for only about 7% of the rescheduled working hours the rescheduling strategies identify substitution possibilities with regular nurses. Consequently, the objective value does not change significantly between different scenarios. There are less absence days in equivalence class 4, hence to find a substitution solution without relying on temporary staff is easier. The results of the study confirm this assumption, because on average 29% of the working hours are rescheduled to regular nurses in May. Due to this fact, the results for May are primarily taken into account when examining the rescheduling strategies.

To figure out, whether or not constraint relaxation offers advantages, we compare the corresponding effects in the following. Figure 3 shows the satisfaction score (in green) and extra hours (in light blue) of the individual nurses depending on the constraint relaxation displayed as a boxplot. The strategy *soft constraints* corresponds to True and *hard constraints* to False with regard to constraint relaxation. While the medians only differ slightly for the extra hours, the range of the boxplot whisker has a larger span considering constraint relaxation and the outliers are distributed more evenly. The satisfaction score also shows a wider span of the whisker and more outstanding outliers for the relaxed constraints. At first glance, it seems that there are more data points of employees with negative extra hours if the constraints are relaxed. However, a closer examination shows, that without constraint relaxation a total of 202 data points have negative extra hours of less than -75. With constraint relaxation, this number is reduced to 113 data points. With the 89 other data points, their negative extra hours have been reduced accordingly, thus creating a visually higher number of outliers. To sum up, 332 data points have negative extra hours of less than -25 with constraint relaxation, whereas 401 points have negative extra hours without.

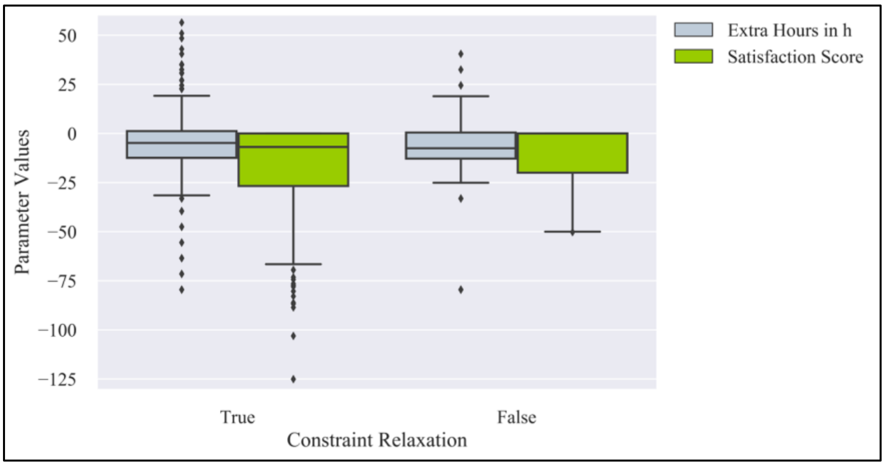

Figure 3: Extra Hours and Satisfaction Score according to Constraint Relaxation

By allowing constraint violations of some specific constraints such as minimum and maximum consecutive working days, regular nurses are more often chosen as substitutions. Their satisfaction decreases accordingly while their extra hours increase. Both alterations were verified through statistical tests. Based on their distribution and variance, an F-test was chosen for the employee satisfaction, while a Welch test was selected for the overtime. The resulting p-values were both smaller than $8x10^{-6}$, showing significance at all significance levels. This decrease in satisfaction and increase in extra hours results in less used temporary staff and therefore lower additional costs.

A comparison between *random* and *ratio approach* has shown no significant difference on employee satisfaction and extra hours. This has been verified by another Welch- and F-Test, whereas the extra hours and employee satisfaction resulted in p-values of 0.21 and 0.47 respectively, showing no significant distribution differences between both approaches. That can be traced back to the limited number of alternative employees in the used instances. The higher we emphasize the influence of the employees' satisfaction, the lower the value of the objective function is. This finding is essential for improving the optimization model.

Conclusion and Future Research

Various optimization models exist for the NSP. However, due to unforeseen events rescheduling of previous optimal schedules is needed. Especially short term changes are relevant within rescheduling as those have a huge impact on employee satisfaction. Within this paper, we evaluated schedules and rescheduling strategies to test their ability to reschedule shift assignments, which becomes necessary due to illness absences of nurses. The introduced rescheduling strategies take nurses' satisfaction and extra hours into account. In addition, we presented a simulation framework which allows for rescheduling of schedules based on a given objective function. To test our rescheduling strategies, we incorporated real-world data.

To obtain realistic results and provide methods for practical use, some constraints have to be relaxed (*soft constraints* rescheduling strategy). The disproportionate influence of extra hours on the objective function caused by rare regular nurse substitutions can be controlled by adjusting the optimization model. Additional restrictions and a different weighting of the objective function can solve this issue.

The approach described serves as a first step in using simulation for schedule validation in order to acquire a better understanding of the practicability of optimized schedules. To revise our findings, additional computational studies with larger instances have to be conducted. In addition, the use of other advanced rescheduling strategies guided by practical knowledge are desirable. Moreover, the whole approach could be extended by predicting illness trends and epidemics through usage of data science tools. In this way, an optimized schedule is created by proactively dealing with uncertainty.

References

Bard, J. F., & Purnomo, H. W. 2005. "Short-term nurse scheduling in response to daily fluctuations in supply and demand," *Health Care Management Science* (8:4), pp. 315-324. doi:10.1007/s10729-005-4141-9

Burke, E. K., De Causmaecker, P., Vanden Berghe, G., and Van Landeghem, H. 2004. "The state of the art of nurse rostering," *Journal of Scheduling* (7:6), pp. 441-499. doi:10.1023/B:JOSH.0000046076.75950.0b

Cacchiani, V., Huisman, D., Kidd, M., Kroon, L., Toth, P., Veelenturf, L., and Wagenaar, J. 2014. "An overview of recovery models and algorithms for real-time railway rescheduling," *Transportation Research Part B: Methodological* (63), pp. 15-37. doi:10.1016/j.trb.2014.01.009

Caprara, A., Galli, L., Kroon, L., Maróti, G., and Toth, P. 2010. "Robust train routing and online re-scheduling," *OASIcs-OpenAccess Series in Informatics* (14). doi:10.4230/OASIcs.ATMOS.2010.24

Constantino, A. A., Landa-Silva, D., de Melo, E. L., de Mendonça, C. F. X., Rizzato, D. B., and Romão, W. 2014. "A heuristic algorithm based on multi-assignment procedures for nurse scheduling," *Annals of Operations Research* (218:1), 165-183. doi:10.1007/s10479-013-1357-9

Gross, C. N., Fügener, A., & Brunner, J. O. (2017). Online rescheduling of physicians in hospitals. *Flexible Services and Manufacturing Journal*, 1-33. doi:10.1007/s10696-016-9274-2

Ingels, J., & Maenhout, B. 2015. "The impact of reserve duties on the robustness of a personnel shift roster: An empirical investigation," *Computers & Operations Research* (61), pp. 153-169. doi:10.1016/j.cor.2015.03.010

Moz, M., & Pato, M. V. (2007). A genetic algorithm approach to a nurse rerostering problem. *Computers & Operations Research*, 34(3), 667-691. doi:10.1016/j.cor.2005.03.019

Qi, X. T., & Bard, J. F. 2006. "Generating labor requirements and rosters for mail handlers using simulation and optimization," *Computers & Operations Research* (33:9), pp. 2645-2666. doi:10.1016/j.cor.2005.02.022

Van den Bergh, J., Beliën, J., De Bruecker, P., Demeulemeester, E., & De Boeck, L. 2013. "Personnel scheduling: A literature review," *European Journal of Operational Research* (226:3), pp. 367-385. doi:10.1016/j.ejor.2012.11.029

Wright, P. D., & Mahar, S. 2013. "Centralized nurse scheduling to simultaneously improve schedule cost and nurse satisfaction," *Omega* (41:6), pp. 1042-1052. doi:10.1016/j.omega.2012.08.004