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# Incorporating nurse preferences in the Nurse Scheduling Problem

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**Abstract**

A recent study in The Netherlands, reports an expected shortage of 140,000 healthcare employees by 2031. Two main reasons for this shortage are an increased demand for healthcare and a shortage on the healthcare labour market. The irregular shifts and unconventional working hours make nurses quit their profession or refrain others from applying. This thesis explores the effect of scheduling decisions on job satisfaction of nurses in Dutch hospitals. Applying mathematical optimization, we examine if nurse satisfaction can be improved and at what cost.

Incorporating results from interviews and a survey, this thesis presents a formulation of the nurse scheduling problem including both capacity coverage and nurse satisfaction in the problem's objective. The problem is solved using an exact (mixed integer programming) approach and a heuristic based on a Variable Neighbourhood Search approach. Using benchmark instances for the nurse scheduling problem, results show that nurse satisfaction can be improved at no cost of capacity coverage. Since these results are based on only simulated preferences, the thesis ends with some suggestions for further research.

*Keywords:* nurse scheduling problem; schedule satisfaction; nurse job satisfaction; mathematical programming; variable neighbourhood search

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# Chapter 1

# Introduction

A recent study in The Netherlands, reports an expected shortage of 140,000 healthcare employees by 2031. Two main reasons for this shortage are an increased demand for healthcare by a growing elderly population and a shortage in the healthcare labor market. Based on this study, the Dutch ministry of Long term Healthcare assigns high priority to the development of policy to increase the attractiveness of healthcare work (Algemene Zaken, 2022). Nursing schedules are one aspect of such healthcare work attractiveness.

Nurses are often required to work irregular shifts such as night shifts and working on weekends. However, the conventional approaches to scheduling often neglect the impact on nurses' well-being and job satisfaction, potentially leading to burnout, reduced productivity, and increased turnover rates. Nurses play a critical role in delivering high-quality care and ensuring patient well-being. The creation of balanced and healthy nursing schedules is therefore important to maintain a well-functioning healthcare system.

## 1.1 Crew satisfaction in scheduling problems

The Nurse Scheduling Problem (NSP) is a well-known problem in operations research regarding the scheduling of nurses. The problem recurs every planning cycle and requires decisions on the trade-off between minimizing total costs, maximizing crew satisfaction and ensuring a fair distribution of the workload (Legrain et.al, 2015). Planners ideally take all these objectives into account. However, besides the total costs of a schedule, its fairness and satisfaction are more difficult to measure. The attractiveness of a schedule is based on an employee's personal preferences.

For example, someone might enjoy working all of their shifts back-to-back whereas another person might prefer to split them evenly throughout the month. With this thesis, we explore the trade-offs planners make between nurse schedule satisfaction and capacity coverage. We aim to reformulate the nurse scheduling problem such that we maximise satisfaction of nurses (fairly) while still minimising the number of unassigned shifts.

The incorporation of employee input has been used in the scheduling of railway employees as a solution to a massive strike in The Netherlands (Abbink et al., 2005). Research was done through focus groups and interviews into the requirements of the employees. At the same time, using a parallel approach, operations research methods were applied to add these new requirements to the existing crew scheduling solution approach.

The aim of this research is to provide insights into the effects of including crew satisfaction in the nurse scheduling problem. First, indicators of this satisfaction are explored through a survey. Second, given the results of the survey, nurse schedule satisfaction is formulated mathematically. Finally, using this formulation of nurse satisfaction, experiments are done to gain insight into the effect of including crew satisfaction on crew satisfaction levels and a trade-off between crew satisfaction and capacity coverage on the workfloor.

## 1.2 Research questions

The main research question used in this thesis is:

**What is the effect of incorporating nurses' personal scheduling preferences into the Nurse Scheduling Problem?**

To answer this question, the following sub-questions are considered throughout this thesis:

RQ1. What scheduling preferences can be used to measure (indicate) nurse schedule satisfaction?

RQ2. How can these preferences be translated using the decision variables in the nurse scheduling problem's mathematical formulation?

RQ3. What is the effect of including crew satisfaction in the objective function compared to only optimizing for capacity requirements?

RQ4. What is the trade-off between coverage and crew satisfaction in optimal schedules?

## 1.3 Contributions

Improving the satisfaction of nurses is important for society as retention is a large problem in the healthcare sector. By improving nurses' schedule satisfaction, we aim to improve their overall job satisfaction and keep them happily employed in the healthcare sector.

Also, since we are confronted with a growing number of applications of optimisation software in our daily (professional) lives, these systems should be adapted to our users' needs. When designing such systems, it is important to discuss the design of the system and what it actually optimises for. Originally, we might only care about minimising costs or maximising efficiency but social factors such as the well-being of employees and the environmental effect of business processes should be measured too. With this thesis, we aim to present a framework for incorporating such "soft" factors into a mathematical optimisation model.

Additionally, previous research on the optimisation of crew satisfaction has mainly taken a (personalised) satisfaction function as given (Bard and Purnomo, 2005; Dowsland, 1998). Here, satisfaction is taken as a sum of penalties assigned per nurse per schedule to get satisfaction scores for all possible schedules. However, the definition of the penalties or calculation of the actual score is not part of the research. Therefore, this thesis connects survey results on nurse scheduling preferences with the formulation of a satisfaction function in terms of the decision variables used in the mathematical (IP) formulation.

## 1.4 Overview

The remainder of this thesis is structured as follows. Chapter 2 presents an overview of related research on the incorporation of nurse schedule satisfaction in the nurse scheduling problem. Chapter 3 describes the scheduling problem in more detail and introduces benchmark problem instances. Chapter 4 aims to answer the first research questions using a survey on nurse scheduling preferences. Chapter 5 presents the mathematical formulation of the problem and explains the formula used for schedule satisfaction. Chapter 6 describes an exact solution method and heuristic to solve the formulated problem. Chapter 7 presents computational results of both of these solution approaches used to solve the benchmark problem instances. The thesis is concluded in Chapter 8.

# Chapter 2

# Related literature

This chapter reviews literature on the nurse scheduling problem and the optimisation of crew satisfaction. First, it describes different approaches to including and measuring crew satisfaction (fairly) in the mathematical formulation of the optimisation's objective. Second, approaches to solving the nurse scheduling problem are described.

## 2.1 Formulations of crew satisfaction

Social sciences research on nurse job satisfaction focuses more on factors such as salary rather than scheduling. However, scheduling has a large effect on nurses' personal lives and work-life balance. It determines the amount of rest nurses get between work and affects their perceived workload. In order to keep nurses healthy, not burned-out, their personal scheduling preferences should be incorporated in the scheduling process (Bergh et al., 2013; Al Maqbali, 2015).

### 2.1.1 Measuring crew satisfaction

Related literature on the incorporation of nurse schedule satisfaction into a mathematical formulation of the Nurse Scheduling Problem (NSP) started with studies by Warner (1976) and Miller et al. (1976). Warner (1976) presents a set of questions to gather input from nurses on their personal scheduling preferences. For example, nurses are asked to divide penalty points over a set of unpreferable components of a schedule (such as having only one day off in between blocks). Other research also uses penalty points per violation to incorporate nurse preference in the NSP formulation (Burke et al., 2001b; Randhawa and Sitompul, 1993).

Most recent OR research on nurse satisfaction, however, seems to assume a certain variable can be used to measure individual schedule satisfaction but does not cover the actual calculation of this variable (Bard and Purnomo, 2005; Dowsland, 1998). Also, most other studies generalise the scheduling preferences on a group or department level. This ignores the presence of personal preferences and differences among nurses. Previous research showed that nurses can differ substantially in their preferences (Rooijen, 2023). In practice, not only the preferences differ among nurses but also the priorities. For example, nurses might have a preference for two aspects of the schedule: workload division and requests for incidental day offs. Nurse A finds the workload division relative to incidental requests off much more important than nurse B. Therefore, we should not only focus on generalised scheduling preferences but make the formulation of a satisfaction score flexible such that it allows for differences among nurses.

Incorporating the (individual) preferences of workers is also relevant for scheduling problems in other sectors. Besides healthcare, the railway planning in The Netherlands is studying the soft preferences of their crew since a national strike (Abbink et al., 2005). Negotiations led to a new set of scheduling rules ('Sharing-Sweet-and-Sour' rules) aimed at increasing the quality of the schedules in terms of workers' preferences. Breugem (2020) explored the trade-off between fairness and attractiveness (measured by these rules) of schedules.

In preference scheduling, the satisfaction of a nurse ($i$) for a given schedule ($j$) is often denoted by a value, say $P_{ij}$ (Bard and Purnomo, 2005; Dowsland, 1998). However, the formulation of this value as a function of the shifts assigned to nurse ($i$) and the personal preference profile of this nurse ($i$) is rarely presented. This research aims to gain insight into formulations of a satisfaction taking as input the assigned shifts to a nurse and personal preferences to return a personalised satisfaction score.

### 2.1.2 Objective

The formulation of the objective in the Nurse Scheduling Problem (NSP) often contains multiple aspects. For example, Legrain, Bouarab and Lahrichi (2015) use an objective with three components in a weighted combination. First, the aim is to minimise the alternation of shift types. Second, to minimise the violation of cover requirements. Third, preferences should be adhered to as well as possible. This third part is a simple summation of all shifts assigned per nurse and multiplied by a binary parameter "wants to (not) work this shift". Therefore, this formulation of the problem requires us to know whether a nurse would like to work a certain shift. In this application, planners ask nurses to fill in their preferences every planning cycle through a simple spreadsheet (Figure 2.1).

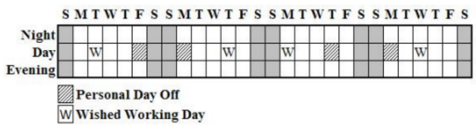



Figure 2.1: Example of schedule annotated with nurse preferences
(Legrain, Bouarab and Lahrichi, 2015)

Besides preferences per shift, nurses can also have preferences that are independent of specific days but are more about patterns in the schedule. For example, the number of consecutive shifts. Independent of the specific days a nurse is assigned to work, each block of consecutive shifts should not be longer (or shorter) than a specific number of days. Warner (1976) designs a survey to ask nurses about such preferences directly.

### 2.1.3 Fairness

Literature on fairness in optimisation objectives often mentions Rawls' Theory of Justice (Rawls, 1971). According to this theory, a fair distribution is determined by the worst-off person as *inequality is justified only when it improves the welfare of the worst off.* Therefore, the objective should be to maximise the satisfaction of the worst-off (most unsatisfied) nurse. Other approaches to fairness could be to optimise the average satisfaction of all nurses, the spread between minimum and maximum satisfaction, or the average deviation of the mean (Chen and Hooker, 2023).

## 2.2 Solution approaches

Approaches to solve the Nurse Scheduling Problem generally belong to one of two groups: exact methods and heuristics. Exact methods solve the problem to find an optimal solution, but require lots of computation time. For large problem instances, exact methods might never be able to find an optimal solution within reasonable running times (one hour) or more. Therefore, heuristics can be preferred to provide an acceptable solution within reasonable time.

### 2.2.1 Exact methods

Small instances of the nurse scheduling problem can be solved by a mathematical (multiple-choice) programming approach to assign a schedule out of a set of potential schedules per nurse (Warner, 1976). However, this approach does not solve problems with a larger scheduling horizon unless the problem is split into scheduling problems with small horizons and each problem is solved separately. Other examples of exact methods such as integer programming implementations can be found in Glass and Knight (2010) and M'Hallah and Alkhabbaz (2013). To reduce the computation time, a solver can also be supplied with an initial solution as a warm start (Rahimian, Akartunalı and Levine, 2017; Hesaraki, Dellaert and Kok, 2020).

### 2.2.2 Heuristics

Literature on the Nurse Scheduling Problem describes lots of previous work on heuristics such as the use of a Variable Neighbourhood Search (Lü and Hao, 2012). In a Variable Neighbourhood Search approach, the solver starts with constructing an initial schedule. Then, based on some predefined neighbourhoods, small changes are made to this initial schedule to iteratively look for improvements. A common neighbourhood is a swap neighbourhood. In a swap neighbourhood, swaps are made between shifts assigned to nurse A and nurse B such that the assigned shifts to both on a specific day are swapped. The process could iterate over all days in the scheduling period to look for improvements. Swaps can also be made within a schedule per nurse. For example, when a nurse was assigned a day shift on Monday and a day off on Tuesday, these could be swapped. At every iteration, the resulting schedule after swapping is checked for any violations of the hard constraints before comparing its objective value to the best-known objective until then.

Variable Neighbourhood Search heuristics can also be combined with integer programming (Rahimian, Akartunalı and Levine, 2017) or a stochastic approach (Tassopoulos, Solos and Beligiannis, 2015). Another type of heuristic that is commonly used is the Genetic Algorithm which is inspired by the process of natural selection(Ayob et al., 2013; Burke et al., 2001a). The performance of this heuristic is highly dependent on proper tuning of its parameters.

Sometimes, a neighbouring solution would improve the objective for one nurse but at the same time worsen the solution for another nurse. Therefore, an improvement in the total objective would require more changes. These changes can be represented by a chain of swaps. Making such a chain requires heuristics to select the next swap to add to the chain and when to stop the chain as described by Burke et al. (2013). Using this approach, Burke et al. (2013) were able to outperform previously published approaches. Since the optimisation of crew satisfaction should preferably not affect the already planned capacity, the chain implementation of swaps could be well suited for the problem to be solved in this thesis.

## 2.3 Summary

To summarise, there exists literature on including nurse preferences in the nurse scheduling problem. However, previous work often lacks an explanation of the measurement of nurse satisfaction or does not allow personalised preferences, but only generalised. Therefore, this thesis aims to gain insight in the indicators that affect an individual nurse's satisfaction score. Additionally, insights should be gained into the effect of adhering to such preferences at the cost of coverage or the satisfaction of other nurses. Therefore, literature on fairness presents several criteria for a fair distribution of satisfaction among nurses and solution approaches are presented to solve the scheduling problem including satisfaction. When possible, exact methods should be used to measure the exact cost of including satisfaction in terms of lost capacity or fairness trade-offs. However, when instances are too large to solve using an exact method, even with a warm start, in reasonable time, a heuristic such as a Variable Neighbourhood Search should be used instead.

# Chapter 3

# Problem description

The Nurse Scheduling Problem (NSP) is about matching nurses with shifts to be worked (per day). This chapter describes the input for the scheduling process and describes the set of indicators used to model nurses' schedule satisfaction based on previous research (Rooijen, 2023).

## 3.1 Input

The input to the nurse scheduling process, as considered in this thesis, is a set of days with cover requirements for all shift types; a set of shift types; a set of contracts with labour agreements; a set of nurses with requests for certain shifts (or days) on or off and other personal preferences. Except for the personal preferences input, all input is taken from benchmark instances to allow for comparable results to other academic literature on the nurse scheduling problem (Curtois and Qu, 2014). These instances are described in more detail in the remainder of this chapter.

### 3.1.1 Scheduling period

The scheduling period is defined by the number of weeks that should be planned. In the benchmark instances, this period ranges from two weeks to a year. Based on interviews, nurses prefer to receive their schedules three months in advance (Rooijen, 2023). This reduces the number of incidental wishes as nurses can plan their personal events around their work. Therefore, we consider benchmark instances with a scheduling period up to 12 weeks. Instances 1, 2, and 3 have a scheduling period of two weeks, instances 11 and 12 of four weeks, instance 14 of six, instance 16 of eight, and instance 18 of 12 weeks.

### 3.1.2 Shift types

Shifts are defined by a start time and duration. For example, a typical day shift starts at 9:00 and lasts for 8 hours until 17:00. However, the scheduling problem can also include early or late day shifts, starting at 6:00 or 14:00 respectively. Additionally, nurses can work a night shift of 10 hours from 22:00 till 8:00. In instance 14, the early day shifts start at 8:00 instead of 6:00 but also last 8 hours till 16:00.

Most instances include an early day shift (E), a day shift (D), a late day shift (L), and a night shift (N) described in Table 3.1. However, in instances 11 and 12, there can be different types of E, D, and N shifts with the same starting times and duration but requiring different skills. Therefore, these shifts are denoted as day 1 (D1), day 2 (D2) etc.

Table 3.1: Shift types

| Shift type | start time | end time | duration (hrs) |
|---|---|---|---|
| E, E1, E2, E3 | 6:00 | 14:00 | 8 |
| D, D1, D2, D3 | 9:00 | 17:00 | 8 |
| L, L1, L2, L3 | 14:00 | 22:00 | 8 |
| N, N1 | 22:00 | 8:00 | 10 |

### 3.1.3 Nurses

Nurses are assigned a certain contract specifying the number of contract hours they work. Additionally, nurses can have work agreements specifying the number of shifts nurses have to work per shift type. For example, nurses can be exempt from working night shifts when they are pregnant or reach a certain age. Table 3.2 shows the number of nurses per instance grouped into fulltime and parttime nurses depending on if they work more or less than 25 hours per week.

Table 3.2: Nurses by contract type

| instance | weeks | nr. nurses | fulltime | parttime |
|---|---|---|---|---|
| 1 | 2 | 8 | 8 | 0 |
| 2 | 2 | 14 | 10 | 4 |
| 3 | 2 | 20 | 15 | 5 |
| 11 | 4 | 50 | 50 | 0 |
| 12 | 4 | 60 | 50 | 10 |
| 14 | 6 | 32 | 27 | 5 |
| 16 | 8 | 20 | 20 | 0 |
| 18 | 12 | 22 | 22 | 0 |

### 3.1.4 Cover requirement

For every day in the scheduling period, a cover requirement is specified per shift type. For example, the scheduling process should result in 10 nurses working a day shift (starting at 9:00) on 01-08-2023. Usually, this requirement is a minimum capacity required to cover expected labour demand. Therefore, planning more nurses than required is preferred over planning less than the required number. In the benchmark problem, a penalty of 100 is assigned to every unassigned shift (less than required) and a penalty of 1 is assigned to every shift above the required number. Chapter 4 explains the calculation of these penalties in more detail.

### 3.1.5 Shift on/off requests on specific days

The input from the benchmark instances also includes a set of requests to (not) work certain shifts on specific days. Each of these requests is assigned a weight by the nurse to represent relative importance. These weights range from one to three. However, none of these requests are hard constraints since nurses should request official leave if they want a day off. These requests are only preferences and will be included in the satisfaction score. Nonetheless, nurses who can be scheduled during Monday-Sunday have the right to choose one recurring weekday off (see Section 3.2). This day is defined per nurse as a fixed assignment in the problem instance.

### 3.1.6 Work agreements

The benchmark instances define a set of work agreements as a contract which is then assigned to a nurse. These contracts can include personally agreed upon terms as well as terms defined by law or collective labour agreements. However, since the schedule satisfaction score will take into account the personal preferences per nurse, personalised contracts become obsolete. The schedule should only adhere to one type of contract which holds for all nurses and is defined by law and/or collective labour agreements. These are presented in Section 3.2.

## 3.2 Hard constraints

In the nurse scheduling problem, a set of hard constraints defines the set of feasible schedules. First, in a feasible schedule, a nurse can only be assigned to work one shift per day. The following hard constraints are taken from Curtois and Qu (2014).

- Certain shift types cannot be assigned following others, for example, a nurse cannot work the night shift starting on Monday (finishing Tuesday morning) and work the day shift on Tuesday. This is also referred to as “forward rotation” in other literature and labour agreements. It means nurses should get at least 16 hours off between assigned shifts.
- Nurses can only work a limited number of consecutive shifts before they have a day off (this number can vary per nurse depending on the contract).
- Nurses have to work at least a specified number of consecutive shifts (this number can vary per nurse depending on the contract).
- Nurses have to get at least a specified number of consecutive days off after each block of assigned shifts (this number can vary per nurse depending on the contract).
- Nurses work a limited number of weekends per scheduling period depending on their contract (working either Saturday or Sunday also counts as working a weekend)
- Nurses get to request days off throughout the scheduling period for vacation or something else, these are considered hard constraints as opposed to the requests in Section 3.1.5.

## 3.3 Multiple objectives

Within the set of feasible schedules, we want to find the *optimal* schedule. However, the quality of a schedule is subjective to multiple perspectives. First, a planner aims to meet the coverage requirements of the department as closely as possible. Second, the nurses should be sufficiently satisfied with the schedule to improve job retention in the long run. Therefore, this problem is multi-objective: coverage and crew satisfaction.

A solution (schedule) is evaluated based on two penalty types. First, a penalty is added for every unassigned or over-assigned shift. Here, the assumption is made that assigning too few nurses on a shift is worse than too many. Therefore, an unassigned (required but not assigned to any nurse) shift gets a higher penalty than an over-assigned (not required but assigned to a nurse) shift. These penalties do not depend on the (type of) nurse. Second, nurse satisfaction is measured based on penalties assigned when the schedule violates nurses' personal preferences. These preferences are studied using a survey which is described next in Chapter 4. This chapter also explains the calculation of the satisfaction penalties.

The coverage penalties can be seen as vertical penalties as they are measured per day (column). The satisfaction penalties can be considered per nurse (row). When evaluating a schedule, all individual schedule satisfaction scores are considered. To ensure fair incorporation of all these individual scores into the problem's objective, the Rawlsian Theory of Justice suggests the use of a MinMax criterion (Barsotti and Koçer, 2022).

The aim of the optimisation is to create schedules that improve the satisfaction of the worst-off nurse while maintaining the best possible level of coverage. Additionally, the trade-off is analysed when coverage is allowed to worsen at the benefit of crew satisfaction.

# Chapter 4

# Measuring nurse preferences

To answer the first research question, a survey has been designed to ask nurses working in hospitals all over The Netherlands about their personal scheduling preferences and the relative weight they assign to each of these preferences. This chapter describes the survey design and results before explaining the personalized calculation of satisfaction penalties per nurse.

## 4.1 Methodology

The survey is done using the online survey platform Qualtrics. The questions are based on the themes resulting from the coding of the interviews done in previous research (Rooijen, 2023). A link to the (digital) survey is shared with the hospital by account managers of ORTEC through an email with information about the survey, the use and storage of the data, and other information required for informed consent. The email also includes contact information in case nurses or their managers have questions about the survey.

The survey uses mostly closed questions since the aim is to gather data to use in the mathematical optimisation problem. The questions are direct and specifically ask about preferences such as the number of preferred minimum consecutive working days. However, the survey concludes with an open question asking the respondent for any other factors that may impact their schedule satisfaction and were not covered by the survey questions to allow them to share scheduling aspects previous questions might have missed.

To research the scheduling preferences of nurses, the target population is nurses who work in Dutch hospitals. This population consists of 218000 nurses at the start of 2023 according to Statistics Netherlands (CBS, 2023). However, the survey was shared through account managers at ORTEC so the sample consisted of nurses who work in a hospital that is using ORTEC software. The survey collected responses from May 5th, 2023 to June 29th, 2023, and collected 301 responses.

The responses are cleaned by removing incomplete responses and responses from employees outside of the target group (technicians, dietitians, etc.). After cleaning, the response data is statistically analyzed to explore patterns, trends, and correlations.

## 4.2 Results

After the removal of 32 respondents with other roles (dietitians, technicians, etc.), 19 incomplete responses, and 6 test responses, the sample consisted of 244 responses. The removed roles are specified in Appendix A.

### 4.2.1 Demographics

Most respondents (56%) worked between 25-32 hours per week according to their contract. The second largest group of respondents (33%) worked less than 25 hours a week and 11% works more than 32 hours per week. To explore patterns in preferences related to the number of working hours per week, nurses are grouped into parttime (24 or less hours/week) and fulltime (25 or more hours/week) nurses. On average, respondents have 19 years of experience working as a nurse with a minimum of 0 and a maximum of 57 years (both occur only once).

### 4.2.2 Consecutiveness and workload division

First, nurses are asked two questions about their preferred division of their workload throughout a (Monday-Sunday) week. Results show that, generally, 2/3 of nurses prefer to work their hours per week between Monday and Sunday instead of compensating hours. For example, with compensation, nurses might work five shifts in the first two weeks of the month and only three shifts in the last two weeks of the month. Also, generally, 2/3 of nurses prefer to work their shifts between Monday and Sunday consecutively instead of split into two (or more) blocks.

Table 4.1: Workload division

| | yes | no |
|---|---|---|
| Preference for working all contract hours on a Monday-Sunday basis | 165 (68%) | 79 (32%) |
| Preference for working all shifts per Monday-Sunday week consecutively | 159 (65%) | 85 (35%) |

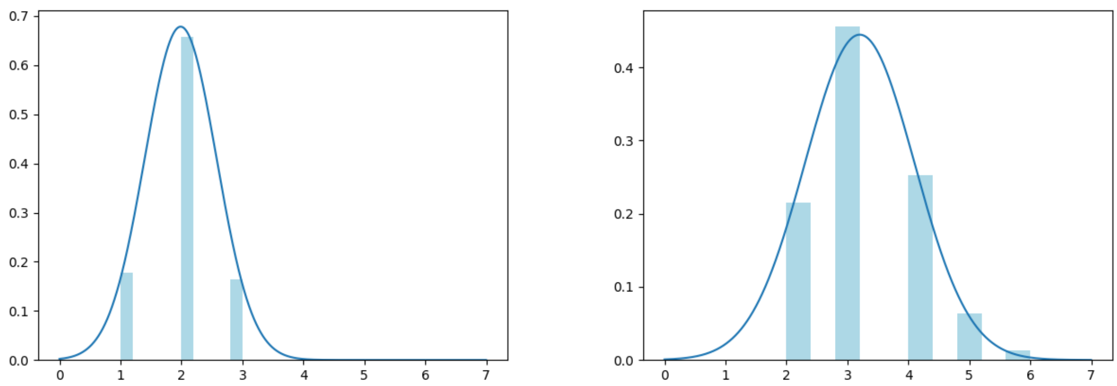
Nurses also answered questions about their preferences for a minimum and a maximum number of consecutive working days. These results are in line with the results above on working all shifts between Monday and Sunday consecutively. Nurses can be grouped based on a fulltime contract type when working 25 or more hours per week and parttime if they work less than 25 hours per week. Table 4.2 shows the consecutiveness preferences for nurses grouped by contract type. The consecutiveness preferences indeed increase with the number of contract hours.

Table 4.2: Consecutiveness preferences per contract type

| preference | contract | min | max | mean | std dev |
|---|---|---|---|---|---|
| min | parttime | 1 | 3 | 1.99 | 0.59 |
| | fulltime | 1 | 7 | 2.61 | 0.87 |
| max | parttime | 2 | 6 | 3.20 | 0.90 |
| | fulltime | 2 | 10 | 4.63 | 1.19 |

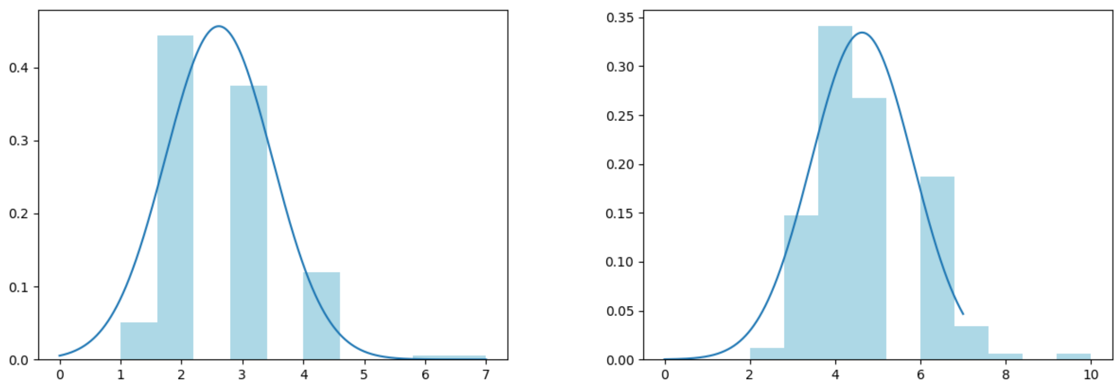
Parttime nurses, on average, prefer to work consecutive blocks of at least 1.99 shifts and at most 3.20 shifts. Given that parttime nurses should at most work 24 hours per week, this aligns with their preferences. Also for fulltime nurses, the consecutiveness preferences do not seem to raise a conflict with the preference to work all shifts consecutively and all contract hours between Monday and Sunday. Nonetheless, it might be difficult to adhere to these preferences in combination with capacity demands and other preferences. Chapter 7 explores such effects and trade-offs.

To explore the effects of including nurse satisfaction on the optimisation results, consecutiveness preferences will have to be simulated as they currently do not exist in the benchmark problem instances (Curtois and Qu, 2014). Based on the histogram of the survey results and the probability density functions of Normal distributions with corresponding mean and standard deviation values, simulating preferences using Normal distributions seems acceptable (Figures 4.1 and 4.2). As consecutive preferences are measured in numbers of days, the simulated values are discretized by rounding to the nearest integer.




(a) Minimum (days) (b) Maximum (days)

Figure 4.1: Consecutiveness preferences distribution for parttime nurses




(a) Minimum (days) (b) Maximum (days)

Figure 4.2: Consecutiveness preferences distribution for fulltime nurses

### 4.2.3 Shift types

Nurses are asked about their general preferences for shift types. Most nurses prefer to work a day shift which is in line with results from previous research (Rooijen, 2023). Day shifts are generally more intense but they allow for a good work-life balance which makes them preferable for most nurses over evening or night shifts. However, a large group of nurses also stated no preference for any of the shift types. The 11% of nurses who specified other preferences mainly stated a preference for variability in their textual answers (see Appendix A for the written answers). When asked about variability, 66% of nurses prefer variability in their assigned shift types.

Table 4.3: Preferred shift type

| | day | evening | night | no preference | other |
|---|---|---|---|---|---|
| Preferred shift type | 41.39% | 24.59% | 4.51% | 18.44% | 11.07% |

Based on the forward rotation rules specified in labour agreements, nurses are not allowed to work certain shift combinations. For example, when a nurse works a night shift on Sunday, planners cannot assign a day shift to the same nurse on Monday. This affects the common shift types assigned at the beginning and ending of a block. When asked about their preferred shift types to begin and end a block with, nurses prefer to start with a day shift and end a block with an evening shift (Table 4.4). Compared to Table 4.3, where only 4.51% of nurses preferred to work a night shift, actually 30.74% of nurses prefers to work a night shift when they are specifically asked about shift types to end a block with (Table 4.4). Based on interviews (Rooijen, 2023), nurses realise that night shifts are part of the job and have to be covered by the workforce.

Table 4.4: Preferred shift types at beginning and ending of a block

| | day | evening | night |
|---|---|---|---|
| Preferred shift type at the beginning of a block | 81.15% | 18.44% | 0.41% |
| Preferred shift type at the end of a block | 25.82% | 43.44% | 30.74% |

### 4.2.4 Weekend shifts

Regarding the scheduling of weekend shifts, most nurses prefer to work weekends spread throughout the month (57%) although a large group specifies no preference (32%). When working in the weekends, most nurses prefer to work a day shift (41%), 33% has no preference, 23% prefers an evening shift and only 3% prefer a night shift. These results clearly show a general preference for working day shifts, also in the weekend, but it also indicates a potential improvement in nurse satisfaction for a minor group of nurses who do prefer to work the night shift. The results are comparable to the results in Table 4.3, so working in weekends does not seem to affect the preferred shift type.

### 4.2.5 Night shifts

In the sample, 199 out of 244 respondents were working night shifts. This means 45 respondents are excluded from working the nights shifts possibly because of age or other contractual agreements. When asked about the scheduling of blocks of night shifts, 42% of nurses preferred to work isolated blocks of only night shifts whereas 58% preferred to combine their night shifts with also a day or evening shift. The second group thus prefers some variability in the shift types per block of working days. Before working a night shift, most nurses prefer to work an evening shift (Table 4.5).

Table 4.5: Preference for shift before night shift

| Before working a night shift, I prefer to be assigned... | choice count |
|---|---|
| a day shift | 40 (20%) |
| an evening shift | 96 (48%) |
| no preference | 63 (32%) |

### 4.2.6 Requests

Nurses can request to (not) work a specific shift because of personal reasons. These requests can be incidental or recurring. When nurses submit a request, they can assign a weight to each request to communicate relative priority. For example, a specific day off for a wedding might be worth sacrificing a recurring day off to play sports once. Based on the survey results, 70% of nurses seem to have more incidental requests than recurring requests. Also, most nurses seem to submit only 0-5 requests per month (Table 4.6). In this question, a recurring request for example for sports training on Monday evening counts as four requests per month.

Table 4.6: Number of requests (per month)

| In an average month, you submit ... requests | parttime | fulltime |
|---|---|---|
| 0-5 | 66 (85%) | 134 (82%) |
| 5-10 | 10 (13%) | 23 (14%) |
| 10+ | 2 (2%) | 6 (4%) |

### 4.2.7 Priorities of preferences

After the questions about specific preferences, nurses are asked to sort the types of preferences based on importance for their schedule satisfaction in two final questions. First, nurses ordered the five types (consecutiveness, shift types, night shifts, weekend shifts, requests) based on importance. Most nurses selected the adherence to requests as most important for their satisfaction. Second most important for most nurses is the consecutiveness of blocks of shifts. Third most important is the (variability in) types of assigned shifts followed by the planning of weekend shifts. Least important seems to be the planning of night shifts (Table 4.7).

Table 4.7: Top 5 most important preferences to affect schedule satisfaction

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Requests | **138 (61%)** | 46 (20%) | 18 (8%) | 9 (4%) | 15 (6%) |
| Consecutiveness | 45 (20%) | **71 (32%)** | 66 (29%) | 23 (10%) | 21 (10%) |
| Shift types | 28 (12%) | 56 (25%) | **76 (34%)** | 44 (19%) | 22 (10%) |
| Weekends | 10 (5%) | 39 (17%) | 31 (14%) | **80 (35%)** | 66 (29%) |
| Nights | 5 (2%) | 14 (6%) | 35 (15%) | 70 (31%) | **102 (45%)** |

Second, nurses were asked to divide 50 points over the five types of preferences to indicate their relative importance. Figure 4.3 shows that, like before, most nurses care mostly about the adherence to requests and consecutiveness. In the next chapter, both are used to define a formula for nurse schedule satisfaction.

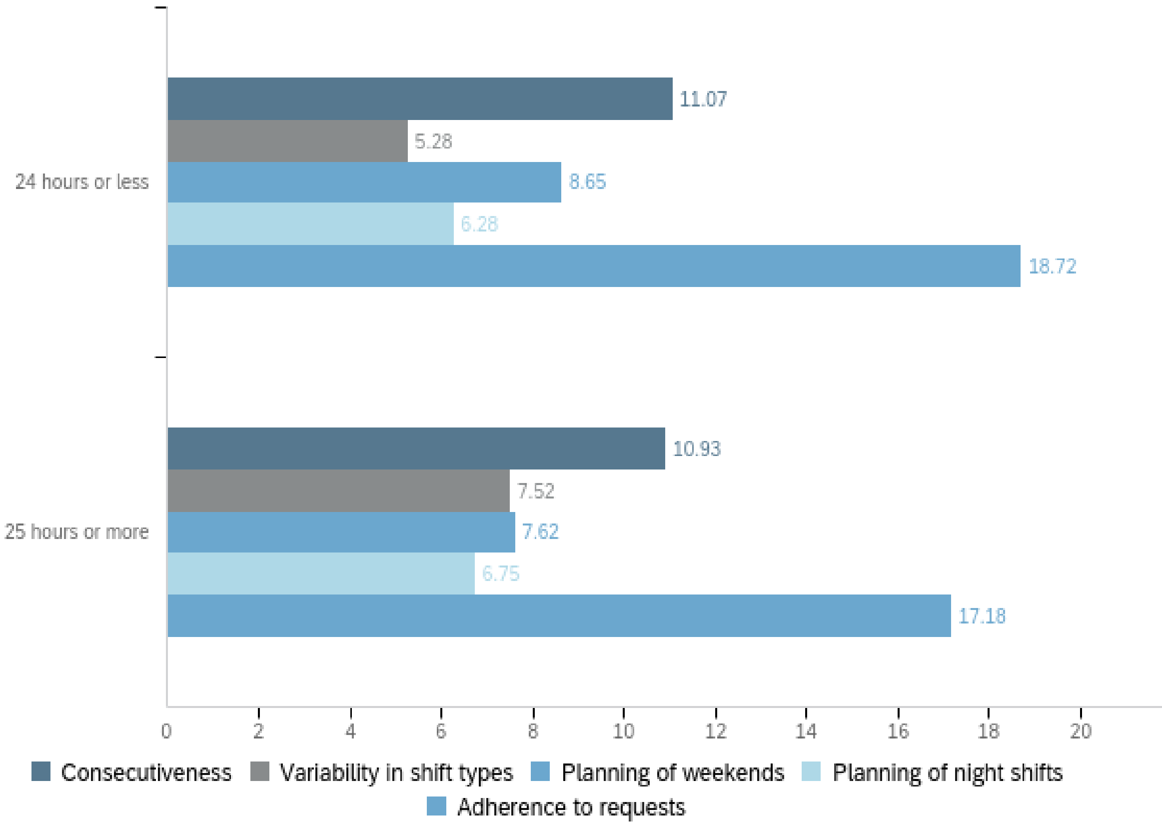



Figure 4.3: Average weight assigned to satisfaction indicator (out of 50)

## 4.3 Comparison to Dutch labour laws and agreements

Certain scheduling preferences can conflict with Dutch labour law and collective labour agreements. For example, according to the Collective Labour Agreement (CAO) for nurses in The Netherlands, nurses can only work up to five shifts per Monday-Sunday week unless they personally agree upon more. Nurses with a preference for more than five consecutive shifts should thus change their work agreement personally. Also, according to the CAO, nurses who can be assigned to work from Monday till Sunday get to select a recurring day off on a weekday (Monday-Friday).

Finally, according to the CAO, nurses can be assigned a maximum of seven consecutive working days. Comparing this to the survey results (Table 4.2), the CAO conflicts with nurses who prefer a maximum consecutiveness of 8, 9 or 10 shifts. In the survey, out of 244 respondents only two nurses have such a preference. Assuming a normal distribution of the maximum consecutiveness preferences, this implies not even 1% of nurses would have a preference above seven. Additionally, research shows that working long consecutive blocks increases the risk of making errors in patient care (Lockley et al., 2007). Therefore, a hard limit of a maximum of seven consecutive shifts seems reasonable.

## 4.4 Comparison to benchmark instances data

The benchmark problem instances include data on the minimum and maximum number of consecutive shifts allowed per nurse. These are used to specify the hard constraints. Table 4.8 shows the descriptive statistics of the parameter values for all instances. Compared to the results of the survey, some nurses seem to have preferences that are now infeasible because of the hard constraints (Table 4.2). For example, a fulltime nurse with a preference for seven consecutive shifts can never get the preferred schedule (in terms of consecutiveness) because of the hard constraint setting a maximum of six consecutive shifts in the problem instance. Additionally, when compared to the Dutch labour laws and agreement, nurses are allowed to work a maximum of seven consecutive shifts. Therefore, nurse satisfaction can be improved by relaxing these hard constraints depending on personalised consecutiveness preferences.

Table 4.8: Benchmark instances consecutiveness data

| | | min | max | mean | std dev |
|---|---|---|---|---|---|
| min. nr. of consecutive days | parttime | 1 | 2 | 1.4 | 0.49 |
| | fulltime | 2 | 3 | 2.03 | 0.17 |
| max. nr. of consecutive days | parttime | 3 | 5 | 4.75 | 0.66 |
| | fulltime | 4 | 6 | 5.16 | 0.43 |

The benchmark problem also includes data on requests for working (or not) specific shift types on specific days and some fixed days off where nurses do not work any of the shift types on that day. The benchmark problems include more requests per month, on average, per nurse than the most common survey answer of 0-5 requests per month per nurse.

## 4.5 Summary

This chapter describes the results from a survey designed to gain insights into the personal preferences of nurses. In the next chapter, these results are transformed into a mathematical formulation of nurse scheduling satisfaction to take into account during the optimisation process. Based on the priorities assigned by nurses (Table 4.7) most nurses selected the requests and consecutiveness as their top two priorities. The mathematical formulation will therefore focus on these two indicators of satisfaction. Focusing on two indicators instead of using all five aids interpreting the effects of changing the objective on the optimisation results later on.

# Chapter 5

# Mathematical formulation

This chapter presents a mathematical formulation of the problem described in Chapter 3 extended with the preferences described in Chapter 4. The formulation from Curtois and Qu (2014) is adapted to include nurse preferences measurements. The objective now includes optimisation of nurse satisfaction which is a function of personalised preference parameters as well as weights. These parameters are described in Section 5.2 following definitions of the sets used in Section 5.1. Then, Section 5.3 defines the decision variables and Section 5.4 explains the satisfaction function expressed using these decision variables. Section 5.5 and 5.6 describe how this satisfaction function is incorporated in the problem's objective. Finally, Section 5.7 presents the complete mathematical (IP) formulation.

## 5.1 Sets

| | |
|---|---|
| $D$ | set of days in the scheduling period $\{1, ..., h\}$ |
| $W$ | set of weekends in the scheduling period $\{1, ..., h/7\}$ |
| $I$ | set of employees |
| $T$ | set of shift types |
| $R_t$ | set of shift types that cannot be assigned directly after shift type $t$ |
| $N_i$ | set of days nurse $i$ cannot be assigned to work on |

## 5.2 Parameters

The mathematical formulation of the problem requires two types of parameters. The first type of parameters contain information about the hard constraints.

| | |
|---|---|
| $h$ | number of days in the scheduling period |
| $l_t$ | length of shift of type $t$ in minutes |
| $m_{it}^{max}$ | maximum nr. of shifts of type $t$ that can be assigned to nurse $i$ |
| $b_i^{min}$ | minimum nr. of minutes nurse $i$ must work during the scheduling period |
| $b_i^{max}$ | maximum nr. of minutes nurse $i$ must work during the scheduling period |
| $c_i^{min}$ | minimum nr. of shifts nurse $i$ must work consecutively |
| $c_i^{max}$ | maximum nr. of shifts nurse $i$ must work consecutively |
| $o_i^{min}$ | minimum nr. of consecutive days off nurse $i$ must be assigned |
| $a_i^{max}$ | maximum nr. of weekends nurse $i$ can work |

The second type of parameter is about preferences and penalties. These parameters are required to measure the objective value of a solution.

| | |
|---|---|
| $pc_i^{min}$ | preferred minimum nr. of shifts nurse $i$ wants to work consecutively |
| $pc_i^{max}$ | preferred maximum nr. of shifts nurse $i$ wants to work consecutively |
| $u_{dt}$ | cover requirement for shift of type $t$ on day $d$ |
| $v^{min}$ | penalty assigned per under-assigned shift |
| $v^{max}$ | penalty assigned per over-assigned shift |
| $q_{idt}$ | penalty for violation of shift on request for shift of type $t$ on day $d$ for nurse $i$ |
| $p_{idt}$ | penalty for violation of shift off request for shift of type $t$ on day $d$ for nurse $i$ |

The penalties per request are scaled such that the sum of all penalties assigned per nurse equals 1. This is done to improve fairness between nurses who submit many or only a few requests.

## 5.3 Decision variables

The problem is modelled using five decision variables where the variable $x_{idt}$ measures if nurse $i$ is working a shift of type $t$ on day $d$. The other decision variables are required to calculate the objective value or check if a hard constraint is violated.

| | |
|---|---|
| $x_{idt}$ | 1 if nurse $i$ is working shift type $t$ on day $d$, 0 otherwise |
| $k_{iw}$ | 1 if nurse $i$ is working weekend $w$, 0 otherwise |
| $c_{idr}$ | 1 if nurse $i$ is working $r$ consecutive shifts starting day $d$, 0 otherwise |
| $y_{dt}$ | total nr. of shifts of type $t$ assigned below the preferred cover for day $d$ |
| $z_{dt}$ | total nr. of shifts of type $t$ assigned above the preferred cover for day $d$ |

## 5.4 Satisfaction function

The satisfaction function $P_i$ takes the shifts assigned to nurse $i$ and calculates a satisfaction score based on the nurse's preferences.

$$P_i = \alpha_i * \text{consecutivenessPenalty}_i + (1 - \alpha_i) * \text{requestPenalty}_i \tag{5.1}$$

The weight $\alpha_i$ represents the relative importance of each concept to nurse $i$. They differ based on personal situations, for example, two nurses might have the same preferences regarding consecutiveness but also have requests for shifts off. Nurse A can assign more weight to the requests whereas nurse B might care more about consecutiveness. Then, even though both nurses have the same preferences, their satisfaction scores could differ when consecutiveness is met but requests are not.

### 5.4.1 Consecutiveness

Consecutiveness is measured by counting the number of consecutive shifts per block. The decision variable $c_{idr}$ is equal to 1 if nurse $i$ works a consecutive block of $r$ shifts starting on the day $d$. Therefore, the summation of $c_{idr}$ per nurse over all $r$ values outside of this nurse's preferences is the total number of blocks per scheduling period with a consecutiveness outside of the preferences.

$$\text{consecutivenessPenalty}_i = CP_i = \sum_{r=1}^{pc_i^{min}-1} (pc_i^{min} - r) c_{idr} + \sum_{r=1+pc_i^{max}}^{c_i^{max}} (r - pc_i^{max}) c_{idr} \tag{5.2}$$

The penalty per block is calculated by taking the difference between the number of consecutive days per block and the preferred consecutiveness of the nurse. This implies that a block of six consecutive shifts yields a penalty of one when a nurse prefers to work a maximum of only five consecutive shifts but a penalty of three if a nurse prefers to work a maximum of only three consecutive shifts. The penalty thus increases with the distance between the actual consecutiveness of the block and the nurse's preferences. The total consecutiveness penalty per nurse $i$ for a scheduling period is the sum of penalties of all blocks in the nurse's schedule.

### 5.4.2 Requests

A second indicator of schedule satisfaction is the number of violated requests for shifts on/off. Nurses are less satisfied with a schedule when their requests are not met. Therefore, we count the number of times preferences to (not) work a specific day or shift are violated. Then, the calculation of satisfaction penalties due to request violations becomes a summation of the scaled weights assigned to violated requests per nurse $i$.

$$\text{requestPenalty}_i = RP_i = \sum_{d \in D} \sum_{t \in T} q_{idt}(1 - x_{idt}) + \sum_{d \in D} \sum_{t \in T} p_{idt} x_{idt} \tag{5.3}$$

As stated in Section 3.2, nurses also get to request days off for vacations or other personal reasons. These requests are limited by an agreed-upon (contractual) number of days off and are hard constraints. This type of request, on the other hand, is a request for a day on/off but the employer is not obliged to adhere to the request. Therefore, it affects nurse satisfaction and adds to the satisfaction penalties but violations do not affect the feasibility of a solution.

## 5.5 Objective including crew satisfaction

The objective including crew satisfaction combines minimization of both the coverage penalties and the crew satisfaction penalties.

$$\min \quad \gamma_1 * \max_{i \in N} P_i + \gamma_2 * \sum_{i \in N} P_i + \sum_{d \in D} \sum_{t \in T} y_{dt} v^{min} + \sum_{d \in D} \sum_{t \in T} z_{dt} v^{max} \tag{5.4}$$

### 5.5.1 Coverage penalty

$$\text{coveragePenalty} \quad = \quad \sum_{d \in D} \sum_{t \in T} y_{dt} v^{min} + \sum_{d \in D} \sum_{t \in T} z_{dt} v^{max} \tag{5.5}$$

The vertical part of the objective function is defined by the difference in the capacity planned to work versus the required capacity. This capacity is specified per day per shift. Therefore, this penalty part of the objective is measured per shift per day by adding penalties for over- or under-staffing. When a shift is understaffed by one (nurse), a penalty of $v^{min}$ is added, and when a shift is overstaffed with one (nurse), $v^{max}$ is added. Currently, these are set to 100 and 1 respectively as it is much worse to be understaffed than overstaffed.

### 5.5.2 Satisfaction penalty

$$\text{satisfactionPenalty} \quad = \quad \gamma_1 * \max_{i \in N} Pi + \gamma_2 * \sum_{i \in N} P_i = \quad \gamma_1 * \theta_1 + \gamma_2 * \sum_{i \in N} P_i \tag{5.6}$$

The horizontal part of the objective function aggregates the individual satisfaction penalties per nurse into one score. To incorporate fairness, we choose to minimize the satisfaction penalty of the worst-off nurse, the one most dissatisfied. To minimise the worst-off score, the maximisation needs to be linearised by using an auxiliary constraint and variable $\theta_1$ which should be higher than all $P_i$ such that it equals $\max_{i \in N} P_i$.

$$\theta_1 \geq \quad P_i \qquad \forall i \in N \tag{5.7}$$

If the objective would only be to minimize the value of the worst-off nurse, the number of nurses with that same value is not penalized. As we would like to improve crew satisfaction, the overall sum of dissatisfaction should be minimized as well. Therefore, $\gamma_1$ and $\gamma_2$ are both set to 1. However, these parameters can be adjusted based on scheduling objectives and policy.

### 5.5.3 Adding $\beta$ to explore trade-off

To explore the trade-off between crew satisfaction and meeting the cover requirements, the objective should be a convex combination of both. By increasing the (relative) weight $\beta$ on the crew satisfaction part of the objective, the schedule should prioritize schedules that adhere to nurse preferences over meeting coverage requirements. The edge cases of $\beta$ values of 0 and 1 yield schedules with the best possible coverage and crew satisfaction, respectively.

$$\min \quad \beta\left(\gamma_1 * \theta_1 + \gamma_2 * \sum_{i \in N} P_i\right) + (1-\beta)\left(\sum_{d \in D}\sum_{t \in T} y_{dt} v^{min} + \sum_{d \in D}\sum_{t \in T} z_{dt} v^{max}\right) \tag{5.8}$$

## 5.6 MIP Formulation

The objective and hard constraints form an Mixed Integer Programming (MIP) formulation of the nurse scheduling problem. The objective (5.8) is as defined in Section 5.5.3 and the following constraints must be satisfied (mathematical formulation is presented on page 27).

Constraint 5.9 ensures that each nurse only works one shift per day, this can be one of any of the shift types. Every nurse also has to work a certain amount of hours in the scheduling period. Constraint 5.10 checks if the total number of worked hours in the scheduling period is within a certain range around this number. Forward rotation is ensured by Constraint 5.11. Here, $R_t$ is the set of shift types that cannot follow a shift of type $t$. Next, every nurse $i$ can have a limit on the number of shifts of type $t$ that can be scheduled in the scheduling period (5.12). This handles cases when nurses are exempt from working night shifts for example.

Constraints 5.13 and 5.14 check the maximum number of weekends nurses are allowed to work during the scheduling period. Fixed days off are defined in Constraint 5.15 where $N_i$ is the set of days off for nurse $i$ due to holidays for example. Constraints 5.16 and 5.17 check the maximum and minimum number of consecutive shifts allowed per nurse. Additionally, Constraint 5.18 checks the minimum number of consecutive days off. Constraint 5.19 defines the number of under- and overassigned shifts to calculate the coverage penalty. Constraint 5.20 defines the consecutiveness variable as explained in Section 5.4.1 and is used in 5.21 to calculate the satisfaction penalty per nurse. Additionally, an auxiliary constraint is used to linearize the maximisation of the satisfaction penalties (5.22). Finally, the decision variables are specified.

$$\sum_{t \in T} x_{idt} \leq 1 \qquad \forall\ i \in I, d \in D \tag{5.9}$$

$$b_i^{min} \leq \sum_{d \in D} \sum_{t \in T} l_t x_{idt} \leq b_i^{max} \qquad \forall\ i \in I \tag{5.10}$$

$$x_{idt} + x_{i(d+1)u} \leq 1 \qquad \begin{array}{r} \forall\ i \in I, d \in \{1, ..., h-1\}, \\ t \in T, u \in R_t \end{array} \tag{5.11}$$

$$\sum_{d \in D} x_{idt} \leq m_{it}^{max} \qquad \forall\ i \in I, t \in T \tag{5.12}$$

$$k_{iw} \leq \sum_{t \in T} x_{i(7w-1)t} + \sum_{t \in T} x_{i(7w)t} \leq 2k_{iw} \qquad \forall i \in I, w \in W \tag{5.13}$$

$$\sum_{w \in W} k_{iw} \leq a_i^{max} \qquad \forall\ i \in I \tag{5.14}$$

$$x_{idt} = 0 \qquad \forall\ d \in N_i, i \in I, t \in T \tag{5.15}$$

$$\sum_{j=d}^{d+c_i^{max}} \sum_{t \in T} x_{ijt} \leq c_i^{max} \qquad \forall\ i \in I, d \in \{1, ..., h - c_i^{max}\} \tag{5.16}$$

$$\sum_{t \in T} x_{idt} + (s - \sum_{j=d+1}^{d+s} \sum_{t \in T} x_{ijt}) + \sum_{t \in T} x_{i(d+s+1)t} \geq 1 \qquad \begin{array}{r} \forall\ i \in I, s \in \{1, ..., c_i^{min} - 1\}, \\ d \in \{1, ..., h-(s+1)\} \end{array} \tag{5.17}$$

$$2 - \sum_{t \in T} x_{idt} + \sum_{j=d+1}^{d+s} \sum_{t \in T} x_{ijt} - \sum_{t \in T} x_{i(d+s+1)t} \geq 1 \qquad \begin{array}{r} \forall\ i \in I, s \in \{1, ..., o_i^{min} - 1\}, \\ d \in \{1, ..., h-(s+1)\} \end{array} \tag{5.18}$$

$$\sum_{i \in I} x_{idt} - z_{dt} + y_{dt} = u_{dt} \qquad \forall\ t \in T, d \in D \tag{5.19}$$

$$c_{idr} := \begin{cases} 1 \ \text{ if } \ 2 - \sum_{t \in T} x_{i(d-1)t} - \sum_{t \in T} x_{i(d+r)t} \\ \qquad\qquad + \sum_{d}^{d+r-1} \sum_{t \in T} x_{idt} = r + 2 \\ 0 \ \text{ else} \end{cases} \qquad \forall\ i \in N, d \in \{1, ..., h-(r+1)\} \tag{5.20}$$

$$P_i = \alpha_i * \mathrm{CP}_i + (1 - \alpha_i) * \mathrm{RP}_i \qquad \forall i \in I \tag{5.21}$$

$$\theta_1 \geq P_i \geq 0 \qquad \forall i \in I \tag{5.22}$$

$$x_{idt} \in \{0, 1\} \qquad \forall\ i \in N, d \in D, t \in T \tag{5.23}$$

$$k_{iw} \in \{0, 1\} \qquad \forall\ i \in N, w \in W \tag{5.24}$$

$$c_{idr} \in \{0, 1\} \qquad \forall\ i \in N, d \in D, r \in \{1, ..., c_i^{max}\} \tag{5.25}$$

$$y_{dt}, z_{dt} \geq 0 \qquad \forall\ d \in D, t \in T \tag{5.26}$$

# Chapter 6

# Solution approach

## 6.1 Exact MIP solution

The mathematical formulation of Chapter 5 is solved using a CPLEX 22.1.1 implementation in Python 3.10.0. The running time is limited to one hour for all instances. Therefore, only some instances can be solved to optimality.

### 6.1.1 Warm start

First, the problems are solved using an objective without nurse satisfaction to find a solution that meets the coverage requirements as well as possible (within the feasible set). Then, nurse satisfaction is added to the objective to search for schedules that improve nurse satisfaction. To reduce running time, the solutions to maximise coverage are used as a warm start for solving the satisfaction problem. Also, the coverage penalty is constrained to be at least as high as in the warm start solution. This constraint reduces running time since it reduces the solution space by removing all schedules with coverage below the best possible solution.

## 6.2 Variable Neighborhood Search Heuristic

The formulation of an objective function presented in Chapter 5 is also used to evaluate solutions in a Variable Neighbourhood Search. This meta heuristic is implemented using the AutoRoster software developed by Staff Roster Solutions (2023). This chapter describes the solution approach used to solve the scheduling problem and find the optimal schedule to balance capacity coverage and nurse satisfaction.

The solver initially applies a constructive heuristic to create an initial schedule. Then, it generates new schedules by swapping shifts between nurses and evaluates these schedule using the objective function (Chapter 5). Based on the objective value, the solver returns the schedule with the lowest objective value. The solver takes as input a maximum running time and, optionally, a lower bound. The search terminates when the objective equals this lower bound or the maximum running time is reached. An outline of the approach is presented in Appendix C.

### 6.2.1 Constructive heuristic

The search is initialised by using a greedy approach. Starting with a set of shifts to be assigned, we assign each shift to the nurse that would get the smallest gain in penalty or highest loss. The search can be restarted using different initial solutions by randomisation of the order of shifts to assign. This approach is taken from Curtois and Qu (2014).

### 6.2.2 Neighbourhoods

Three types of neighbourhoods are implemented to iteratively look for improvements in the objective value. First, swaps can be made (horizontally) within one nurse's schedule. Second, shifts can be added to or removed from a nurse's schedule. Finally, (blocks of) shifts can be swapped completely between two nurses. The length of the blocks to be swapped, added or removed are of variable length. The maximum block length is a parameter that is set to 5 (Burke et al., 2013).

**Swapping shifts within nurse's schedule**

Per nurse, shifts can be swapped such that a shift of type 'D' used to be assigned to a nurse on Wednesday but is now swapped with a shift of type 'L' on Friday (Table 6.1). This swap changes the consecutiveness of the first block from three to two and introduces a single working day into the schedule. Generally speaking, this reduces the quality of a schedule. However, this swap might remove a request violation when the nurse would like to have the Wednesday off. Depending on the $\alpha_i$ weight assigned by this nurse, this swap could improve the roster quality. However, for a nurse who prefers long blocks of consecutive shifts and has a high $\alpha_i$, this swap would decrease the roster quality.

Table 6.1: Example of horizontal swap

| | M | T | W | T | F | S | S |
|---|---|---|---|---|---|---|---|
| before swap | D | D | D | | | | |
| after swap | D | D | | | L | | |

**Adding or removing shifts per nurse**

Per nurse (horizontal row), a shift can be added or removed per day to explore solutions which might improve upon the coverage penalty. Due to swapping shifts, there might be an opportunity to assign a previously unassigned shift to a nurse. Also, it might be beneficial to remove a shift for a certain nurse if it would improve the roster quality (satisfaction) as part of a chain of swaps. In the example (Table 6.2), the roster quality will be improved by adding a shift if the cover requirement was not met on Thursday before. Similar to the horizontal swap, nurse's schedule satisfaction can improve or decrease after the additional assigned shift depending on personal preferences for consecutiveness and requests.

Table 6.2: Example of adding a shift

| | M | T | W | T | F | S | S |
|---|---|---|---|---|---|---|---|
| before add | D | D | D | | | | |
| after add | D | D | D | L | | | |

**Swapping shifts between nurses**

Besides making changes (horizontally) per nurse, this neighbourhood searches for improvements in the schedule by swapping blocks between nurses. Table 6.3 shows an example of a single shift swapped between nurses A and B on Friday. Nurse A used to work five consecutive (week)days whereas nurse B used to work only on Saturday-Sunday. In case nurse B has requested a Saturday off and nurse A prefers to work a maximum of four consecutive days, this swap could improve nurse A's satisfaction score. Another swap affecting nurse B's schedule should be added to try and improve the total objective.

Table 6.3: Example of swapping one shift between nurses

| | nurse | M | T | W | T | F | S | S |
|---|---|---|---|---|---|---|---|---|
| before swap | A | D | D | D | D | D | | |
| | B | | | | | | D | D |
| after swap | A | D | D | D | D | | | |
| | B | | | | | D | D | D |

During the search, depending on a predefined parameter for the maximum block size, the algorithm also explores larger block sizes to swap. An example of a swap of five consecutive shifts is visualised in Table 6.4. Both examples show that the coverage per day does not change as a results of swaps between employees. Therefore, these swaps can only change the satisfaction scores.

Table 6.4: Example of swapping three shifts between nurses

| | nurse | M | T | W | T | F | S | S |
|---|---|---|---|---|---|---|---|---|
| before swap | A | | | | | E | E | E |
| | B | | | D | D | D | | |
| after swap | A | | | D | D | D | | |
| | B | | | | | E | E | E |

### 6.2.3 Search Strategy

After initialising the algorithm with the constructive heuristic, the algorithm iteratively searches for improvements in the objective value by exploring the three neighbourhoods. However, sometimes a single swap between employees would not improve the objective value but a chain of sequential swaps would. This is an intuitive approach which works similar to manually changing a shift in one nurse's schedule (because of a new shift request for example) and sequentially making other changes until you reach an improvement in objective value. The length of the chain of swaps is limited by the depth parameter of the search algorithm. When the depth parameter is set to one, this search method works just like a regular local search with only swapping (or adding/removing) shifts when it yields an immediate decrease in objective value. It is recommended to use a relatively small depth value to prevent extremely long chains of swaps such as 100. Similar to Burke et al. (2013), we found best results using a maximum depth of 40. An example chain of seven swaps is visualised in Figure 6.1.

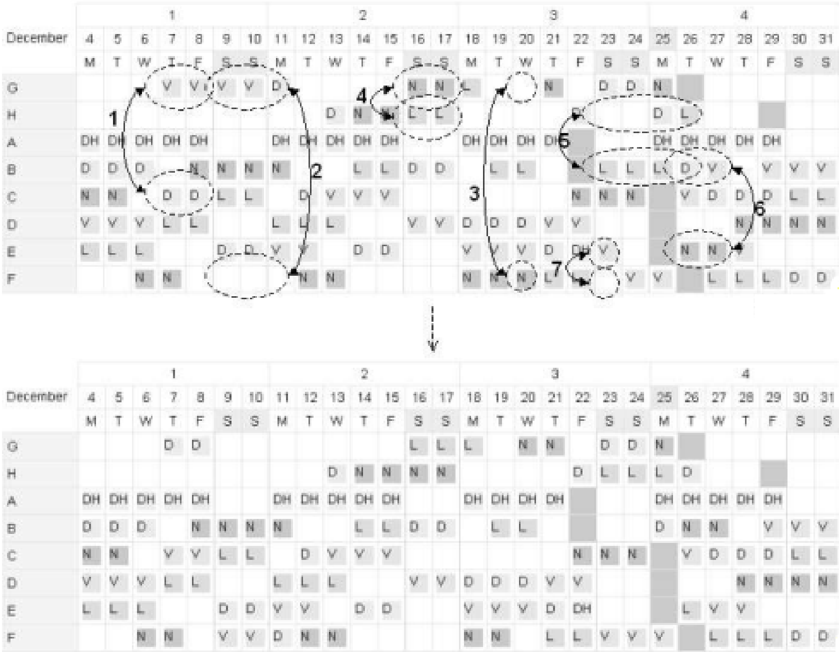


Figure 6.1: Example of swaps in a chain (Burke et al., 2013)

**Selection rule**

After initialising a solution using the greedy approach (Section 6.2.1), an unvisited neighbour is selected based on the neighbourhoods explained in Section 6.2.2. If this neighbour already yields a lower (total) objective value than the current solution, the current solution is updated and we start a new search iteration if time allows. If the personal penalties do not decrease for both of the nurses involved in the swap (or add/remove) or the maximum depth parameter is set to 1, we do not explore any additions to the chain but move on to another neighbour of the current solution. However, when the selected neighbour solution improves the penalty for only one nurse that is involved in the swap but not the other, we aim to add another swap to the chain such that we can improve the total objective.

In this case, say nurse A's schedule improved based on the swap and nurse B's schedule worsened based on this first swap. To find a next swap to add to the chain, we are only going to consider swaps involving nurse B and all other employees (C) to look for the second swap to add to the chain. A swap is only selected as addition to the chain if the resulting neighbour of that swap has a lower penalty than the current best solution, *ignoring the change in the other's (nurse C) penalty.* So, we only consider moves that improve the schedule of the worsened nurse B in the last move added to the chain when searching for the next move. When we find such an improving swap, it could worsen the schedule of the other nurse (C) such that we start another search to add a swap that improves this nurse's (C) schedule until we reach the maximum allowed depth. However, if we find a schedule that improves the overall objective, we add it as the final move of this chain and update the overall best solution. If time allows, we start a new search iteration.

### Heuristics to reduce running time

When setting the depth too high, the required running time will become too long as the heuristic gets stuck in long chains. To decrease the running time, two heuristics can be used to reduce the number of neighbours to consider. First, in the **violation flag heuristic**, all days which need repairing after either the addition, removal or swapping of shifts, in order to improve upon any violations are flagged during penalty recalculations (Burke et al., 2013). Then, only swaps that involve at least one of these days are tested to see if adding them to the chain would improve the solution's objective value. So, we only focus on parts of the schedule that need repairing when considering what to add to the chain, this approach is a common heuristic also used in the tabu search approach to solve the nurse scheduling problem, see for example Nonobe and Ibaraki (1998).

In the second heuristic, called the **worsened days heuristic**, we keep track of the days that were worsened since the last swap in the chain. For example, when a shift is removed which leads to violation of the minimum consecutiveness in the new schedule, the day of the removed shift is labeled as the worsened day, as the change on this day caused the increase in the penalty. When selecting a neighbour, we now only consider swaps that affect one of these worsened days. Compared to the violation flag heuristic, the set of available neighbours to select from is now smaller as days which contain violations will be ignored if they were not affected by the last swap in the chain (Burke et al., 2013).

Depending on the allowed maximum running time, a choice is made to use either the violation flag or worsened days heuristics. If the remaining run time is less than a set number of minutes, we switch from using the violation flag to the worsened days heuristic. We set this to 5 minutes.

# Chapter 7

# Computational results

This chapter presents the effects of including nurse satisfaction in the objective. To add preference data to the benchmark problem instances, preferences for minimum and maximum consecutiveness values are drawn from Normal distributions with $\mu$ and $\sigma$ from Table 4.2. The preference weights $\alpha_i$ are also simulated by a Normal distribution ($\mu = 0.5, \sigma = 0.5$) truncated on [0, 1]. The requests for (not) working specific shifts are already included in the problem instances. To be able to compare solution approaches and perform a sensitivity analysis, we fix one set of simulated preferences to use in the results. However, Section 7.1.3 presents results for multiple simulation runs to show that results do not only hold for this one set of fixed preferences.

First, results using the exact method are presented to provide insights in the effect of including crew satisfaction in the objective for the problem instances. Thereafter, results of the Variable Neighborhood Search are presented. These results together are used to answer the first research question. To answer the second, Section 7.3 presents results for when $\beta$ is varied between 0 and 1 to explore the trade-off between coverage and crew satisfaction. Finally, the chapter is concluded with a sensitivity analysis and summary.

## 7.1 Including crew satisfaction using exact method

All MIP results are obtained using an Intel Core i7 2.8 GHz processor and 16GB RAM.

### 7.1.1 Fixed preferences

Table 7.1 shows the exact results obtained from the MIP using the fixed set of simulated preferences. As expected, including the satisfaction reduces the crew satisfaction penalties (crew dissatisfaction) heavily. These results and fixed preferences will be used in the remaining sections to compare results of both methods and several implementations. Runtime is presented in total number of seconds and the gap is the MIP gap. The coverage column presents the total coverage penalty as defined in Equation 5.5. The worst and total column present the maximum and sum of the dissatisfaction scores of all nurses as defined in Equations 5.1 and 5.6. The total objective value of the solution is the sum of the coverage, worst and total column (Equation 5.4).

Table 7.1: MIP results for fixed preferences

| | excl. warm start | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | excl. satisfaction | | | | | incl. satisfaction | | | | |
| instance | time | gap | coverage | worst | total | time | gap | coverage | worst | total |
| 1 | 0.31 | 0 | 600 | 2 | 6.488 | 1.25 | 0 | 600 | 1 | 2.548 |
| 2 | 30.16 | 0 | 800 | 4 | 11.62 | 21.86 | 0 | 800 | 1 | 3.785 |
| 3 | 39.20 | 0 | 1000 | 4 | 24.648 | 887 | 0 | 1000 | 1.77 | 8.67 |
| 11 | 1349 | 0 | 3423 | 6 | 66.102 | 3600 | 0.061 | 3626 | 2.496 | 21.735 |
| 12 | 3600 | 0.024 | 4100 | 10 | 84.526 | 3600 | 0.573 | 9317 | 7.6 | 50.211 |

### 7.1.2 Warm start

As explained in Section 6.1.1, adding a warm start could reduce the runtime of the MIP as it is already provided with a schedule that meets the best possible coverage. Table 7.2 shows that with a warm start, we still cannot solve instances 11 and 12 to optimality. However, compared to not using a warm start (Table 7.1), the solutions to instances 11 and 12 now do have the best possible coverage value and the gap is reduced. For instances 14, 16, and 18 we are unable to find a warm start solution (optimizing coverage only) within one hour.

Table 7.2: MIP results using fixed preferences using warm start

| | incl. warm start | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | excl. satisfaction | | | | | incl. satisfaction | | | | |
| instance | time | gap | coverage | worst | total | time | gap | coverage | worst | total |
| 1 | 0.203 | 0 | 600 | 2 | 5.807 | 1.078 | 0 | 600 | 1 | 2.548 |
| 2 | 7.781 | 0 | 800 | 5 | 12.232 | 26.36 | 0 | 800 | 1 | 3.785 |
| 3 | 32.10 | 0 | 1000 | 4 | 21.371 | 490 | 0 | 1000 | 1.77 | 8.67 |
| 11 | 9.36 | 0 | 3423 | 4 | 60.432 | 3600 | 0.01 | 3423 | 4 | 33.163 |
| 12 | 3600 | 0.000 | 4001 | 9 | 82.062 | 3600 | 0.018 | 4000 | 9 | 70.872 |

### 7.1.3 Simulation results

The scheduling problem is solved using the objective function without satisfaction (only coverage penalty, $\beta = 0$) and the new objective including the satisfaction scores ($\beta = 0.5$).

Figure 7.1 shows the coverage penalty divided by 100 such that it shows the number of unassigned shifts (green, same results from solving with $\beta = 0$ and $\beta$=0.5), the results using the objective excluding satisfaction (red, calculating satisfaction scores in hindsight), and the objective including satisfaction (orange, results from solving with $\beta = 0.5$) for instance 1. The coverage penalty is the same for all runs (6 unassigned shifts). The red area shows that in every simulation run, not including crew satisfaction in the objective leads to a higher satisfaction penalty thus a worse objective value.

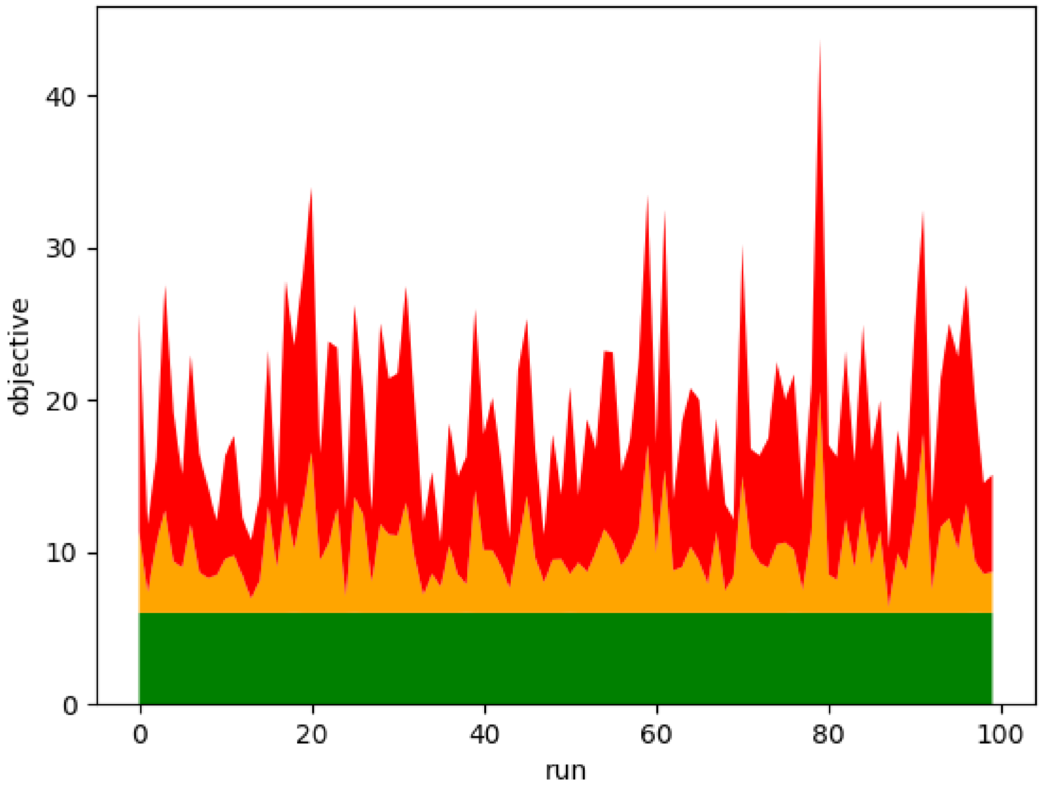
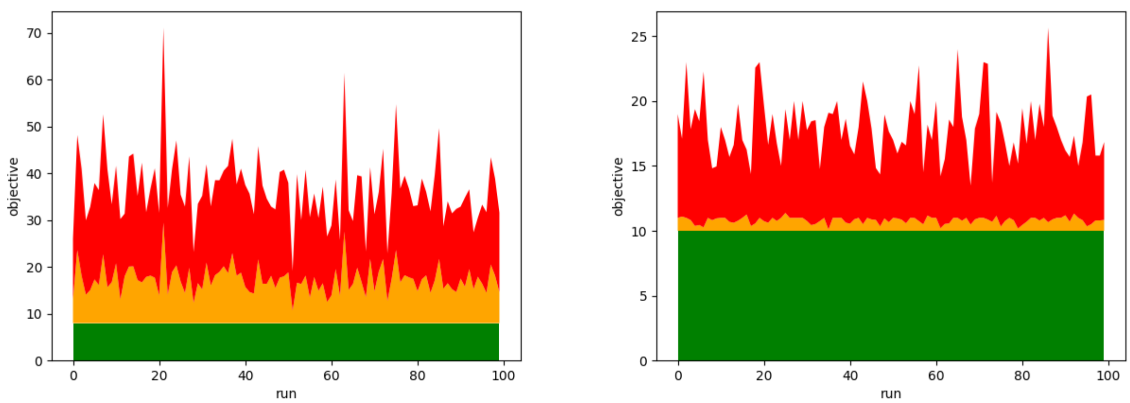



Figure 7.1: Simulation results for instance 1 ($v^{min}$=1 and $v^{max}$ =100)

The simulation results for instances 2 and 3 are visualised in Figure 7.2. Again, we see that the crew satisfaction part of the objective improves by including the satisfaction penalties in the objective at every simulation run. Also, the coverage penalties are the same so satisfaction does not come at a cost in terms of capacity coverage. The warm start and settings of the coverage penalties ($v^{min}$=1 and $v^{max}$ =100) ensure that the result after including satisfaction does not sacrifice this capacity coverage.

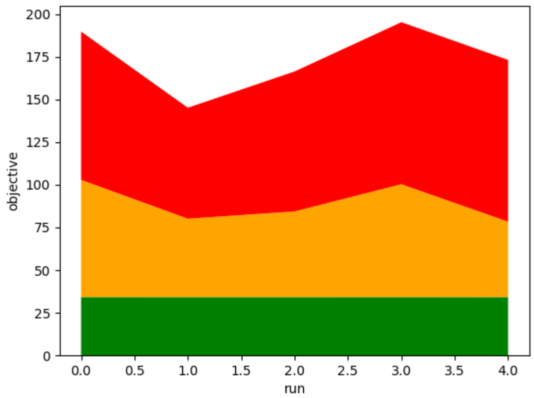



(a) Instance 2

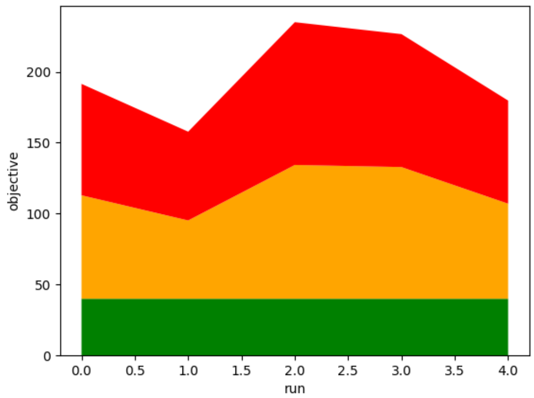
(b) Instance 3

Figure 7.2: Simulation results per instance ($v^{min}$=1 and $v^{max}$ =100)

Also in the results for instances with a scheduling period of four weeks, we see an improvement in the worst-off satisfaction score for all simulation runs when including crew satisfaction in the objective. For instances 11 and 12, again, the coverage penalties stay the same. However, due to the size of the problem instances, we could run fewer simulation runs.




(a) Instance 11




(b) Instance 12

Figure 7.3: Simulation results per instance ($v^{min}$=1 and $v^{max}$ =100)

So, the results show that crew satisfaction can be improved at no cost in terms of coverage by including it in the objective function of the Nurse Scheduling Problem. This has been tested using multiple simulation runs to ensure positive results are not simply one case of easy preferences.

## 7.2 Including crew satisfaction using heuristic

After solving the scheduling problem including crew satisfaction with the exact method, this section presents results using the Variable Neighborhood Search (VNS) approach. This approach is based on Burke et al. (2013) and is used to obtain results on the same benchmark problem instances (Curtois and Qu, 2014). These results are reproduced using the selected set of eight benchmark instances and the version of the VNS algorithm created by Staff Roster Solutions and used by ORTEC. Reproduction results show some differences with Curtois and Qu (2014) but these differences seem to be due to randomness in the search (Table B.1). In this study, we use the default settings of a maximum search depth of 40 and runtimes of 10 and 60 minutes based on Burke et al. (2013) and Curtois and Qu (2014).

### 7.2.1 Heuristic results

Results using the heuristic show that, again, including crew satisfaction improves the satisfaction levels. Especially for larger instances, VNS finds better schedules within one hour than the MIP. However, on the smaller instances, the exact MIP solution is better than the VNS solution. For instance 1, both solution approaches find the same (optimal) solution. Nonetheless, for instances 14, 16, and 18, the exact method is not able to return any feasible schedule within one hour whereas the heuristic still does. Therefore, the VNS is fit to solve the larger instances.

Table 7.3: VNS results including crew satisfaction ($\beta = 0.5$)

| | 10min | | | 60min | | |
|---|---|---|---|---|---|---|
| instance | coverage | worst | total | coverage | worst | total |
| 1 | 600 | 1 | 2.548 | 600 | 1 | 2.548 |
| 2 | 900 | 0.333 | 0.965 | 900 | 0.333 | 0.965 |
| 3 | 1000 | 11.633 | 3 | 1000 | 2.36 | 10.773 |
| 11 | 3928 | 5 | 28.387 | 3827 | 5 | 27.36 |
| 12 | 5100 | 6.025 | 39.073 | 4900 | 6.025 | 38.386 |
| 14 | 1740 | 6.166 | 30.745 | 1740 | 6.157 | 30.754 |
| 16 | 3968 | 9.266 | 30.593 | 3968 | 8.555 | 29.984 |
| 18 | 6682 | 16.535 | 74.832 | 6177 | 14.326 | 60.955 |

### 7.2.2 Results coverage only

When comparing the VNS results to the MIP results, we see that the VNS solution approach does not find the optimal coverage penalties for most instances. However, results for $\beta = 0$ show that VNS is able to find better coverage values when we discard satisfaction in the optimization objective. Therefore, the VNS solution approach is not focused on prioritizing coverage penalty improvements over satisfaction improvements during the search. It would require more runtime to find the optimal coverage penalties and get the same coverage results as the exact MIP.

Table 7.4: VNS results for coverage only ($\beta = 0$)

| instance | MIP | 10min | 60min |
|---|---|---|---|
| 1 | 600 | 600 | 600 |
| 2 | 800 | 900 | 800 |
| 3 | 1000 | 1000 | 1000 |
| 11 | 3423 | 4332 | 3726 |
| 12 | 4000 | 5600 | 4900 |
| 14 | - | 1942 | 1841 |
| 16 | - | 4170 | 3867 |
| 18 | - | 6480 | 6278 |

## 7.3 Trade-off coverage and crew satisfaction

By varying $\beta$ between 0 and 1, the objective varies between solely optimising for coverage or solely crew satisfaction. The $\beta$ value determines whether the objective is dominated by one or the other so, at certain $\beta$ values, it becomes "worth it" to increase satisfaction at the cost of coverage or vice versa. Figure 7.4 shows the different solutions obtained by varying $\beta \in (0, 1)$ with steps of 0.1. This range is exclusive to prevent edge cases to be arbitrarily high. For example, at $\beta = 0$ we find the minimum number of unassigned shifts but the worst-off nurse's satisfaction penalty can be arbitrarily high. Using $\beta = 0.01$ instead makes results more reproducible as you will get the same worst-off score at every run. The number of unassigned shifts and worst-off score are scaled such that the edge cases ($\beta = 0.01$ and $\beta = 0.99$) yield 1 on the number of unassigned shifts ($\beta = 0.01$) and the worst-off score ($\beta = 0.99$). This allows us to plot the results for all instances in the same figure (Figure 7.4). Each dot represents a solution and is plotted by its number of unassigned shifts and dissatisfaction score of the worst-off nurse. However, varying $\beta$ leads to a limited set of different schedules so only a few data points. It is difficult to improve on the undercoverage due to limited contract hours and hard constraints such as forward rotation and consecutiveness.

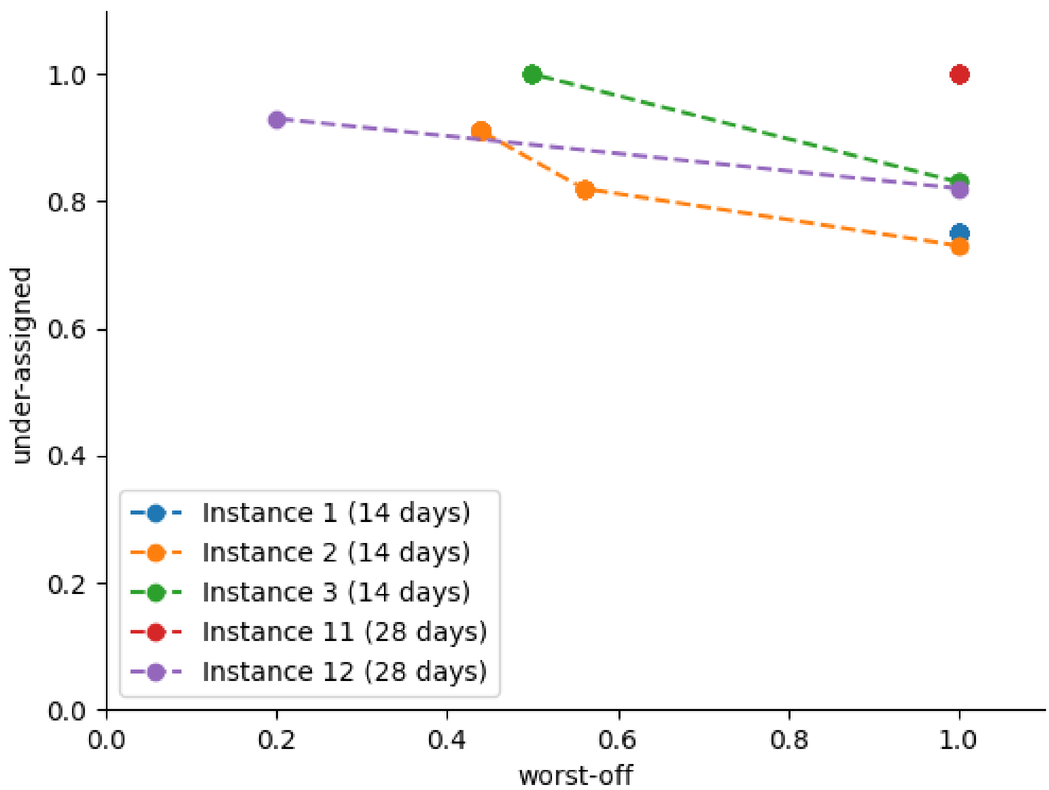



Figure 7.4: Results for varying $\beta \in (0, 1)$ per instance ($v^{min} = 1$ and $v^{max} = 100$, 1 run)

## 7.4 Sensitivity analysis

### 7.4.1 Relaxing hard consecutiveness constraints

Sometimes nurse preferences require exceptions to agreements such as the Dutch CAO. Often nurses are allowed to work, for example, more consecutive shifts than agreed upon by the Union if they prefer to do so. Therefore, some hard constraints can be relaxed which increases the solution space and could improve the optimal objective. However, it could also increase the running time or gap if the running time limit is reached. For this analysis, the hard constraint parameters $c_i^{min}$ and $c_i^{max}$ are relaxed if nurse $i$ had such exceptional preferences. This applied to only 10% of the nurses at most.

For all instances that can be solved to optimality within one hour, we see an improvement in the worst and/or total dissatisfaction score after relaxation (Table 7.5). However, for instances 11 and 12, we cannot find an exact solution within one hour and this does not apply.

Table 7.5: MIP effect of relaxing hard constraints in line with preferences

| | incl. warm start | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | before relaxation | | | | | after relaxation | | | | |
| instance | time | gap | coverage | worst | total | time | gap | coverage | worst | total |
| 1 | 1.078 | 0 | 600 | 1 | 2.548 | 2.719 | 0 | 600 | 0.938 | 2.542 |
| 2 | 26.36 | 0 | 800 | 1 | 3.785 | 48.64 | 0 | 800 | 0.731 | 2.986 |
| 3 | 489.5 | 0 | 1000 | 1.77 | 8.67 | 573.8 | 0 | 1000 | 1.77 | 7.164 |
| 11 | 3600 | 0.01 | 3423 | 4 | 33.163 | 3600 | 0.015 | 3423 | 4 | 49.928 |
| 12 | 3600 | 0.018 | 4000 | 9 | 70.872 | 3600 | 0.018 | 4000 | 9 | 69.558 |

### 7.4.2 Varying fairness metrics

Next, we explore the formulation of fairness in the objective function by comparing three different options. First, a focus on only the worst-off nurse is implemented by setting $\gamma_1 = 1$ and $\gamma_2 = 0$ in the objective (5.9). Second, a focus on only the total sum of satisfaction penalties is implemented by setting $\gamma_1 = 0$ and $\gamma_2 = 1$. A third option is combining both with equal weight, by setting $\gamma_1 = 1$ and $\gamma_2 = 1$. Table 7.6 shows the optimization results for these settings.

Table 7.6: Tuning results for fairness metrics $(\gamma_1, \gamma_2)$

| instance | objective (min) | $\gamma_1$ | $\gamma_2$ | worst | total | MIP gap |
|---|---|---|---|---|---|---|
| 1 | worst off | 1 | 0 | 1 | 2.956 | 0 |
| 1 | total dissatisfaction | 0 | 1 | 1 | 2.548 | 0 |
| 1 | both | 1 | 1 | 1 | 2.548 | 0 |
| 2 | worst off | 1 | 0 | 1 | 6.77 | 0 |
| 2 | total dissatisfaction | 0 | 1 | 2 | 3.785 | 0 |
| 2 | both | 1 | 1 | 1 | 3.785 | 0 |
| 3 | worst off | 1 | 0 | 1.5 | 11.847 | 0 |
| 3 | total dissatisfaction | 0 | 1 | 3 | 8.66 | 0 |
| 3 | both | 1 | 1 | 1.77 | 8.67 | 0 |
| 11 | worst off | 1 | 0 | 2 | 40.519 | 0 |
| 11 | total dissatisfaction | 0 | 1 | 7 | 31.318 | 0.003 |
| 11 | both | 1 | 1 | 4 | 33.163 | 0.01 |
| 12 | worst off | 1 | 0 | 6 | 67.362 | 0.049 |
| 12 | total dissatisfaction | 0 | 1 | 8 | 54.055 | 0.327 |
| 12 | both | 1 | 1 | 9 | 70.872 | 0.018 |

Results show that optimizing the score of the worst off nurse leads to a higher total dissatisfaction score. When the worst off score is obtained for one nurse, the scores for all other nurses are not minimized further after they reach this score. Therefore, a smaller total dissatisfaction score can be obtained by setting $\gamma_2 = 1$. For smaller instances, assigning both equal weights ($\gamma_1 = 1, \gamma_2 = 1$) leads to the same total dissatisfaction score as optimizing for total dissatisfaction only ($\gamma_1 = 0, \gamma_2 = 1$). Nonetheless, the satisfaction penalty of the worst off nurse is smaller. For larger instances, assigning both equal weights of 1 leads to a slightly higher score on both total and maximum dissatisfaction but is a middle ground between both edge cases.

### 7.4.3 Varying weights of under- and overcoverage

Based on interviews with planners, an underassigned shift should yield a higher penalty than an overassigned shift. However, this analysis shows the result of assigning equal weights to an underassigned and overassigned shift. As we reduce the weight of an underassigned shift from 100 to 1, we increase the relative importance of the satisfaction scores. This implies that reducing one of the satisfaction measures by one now leads to the same improvement in the objective as reducing the number of unassigned shifts by one. Table 7.7 shows that assigning weights of one to all components of the objective (underassigned, overassigned, worst-off, and total dissatisfaction) reduces the satisfaction penalties but increases the coverage penalty. This analysis is done using the instances that can be solved to optimality within one hour only to analyse exact outcomes.

Table 7.7: Results with $v^{min} = 1$ and $v^{max} = 1$

| | $v^{min} = 1$ and $v^{max} = 1$ | | | | | $v^{min} = 100$ and $v^{max} = 1$ | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| instance | time | gap | coverage | worst | total | time | gap | coverage | worst | total |
| 1 | 1.157 | 0 | 7 | 0.72 | 1.475 | 1.078 | 0 | 600 | 1 | 2.548 |
| 2 | 9.078 | 0 | 9 | 0.54 | 2.393 | 26.36 | 0 | 800 | 1 | 3.785 |
| 3 | 650.9 | 0 | 12 | 1.18 | 5.273 | 490 | 0 | 1000 | 1.77 | 8.67 |

## 7.5 Summary

Based on Section 7.1, the effect of including crew satisfaction in the objective function is, as expected, an improvement in crew satisfaction. This improvement however, never has an effect on the coverage penalties of the optimal solutions. Only in larger instances that cannot be solved by the exact method within the running time of one hour, the coverage penalties can increase when including crew satisfaction. However, the results show that crew satisfaction can be improved by including it in the objective at no cost in terms of coverage.

Section 7.2 shows similar results for the smaller instances using a Variable Neighborhood Search (VNS) heuristic. Nonetheless, the heuristic is also able to return feasible solutions to the larger instances within a runtime of one hour. Section 7.3 showed the trade-off between coverage and crew satisfaction is limited by a set of feasible schedules. It is not possible to measure a marginal cost of improving undercoverage by one shift in terms of worst off satisfaction penalties. This is reasonable as the solution space is constrained by labour rules and contracts. This chapter concludes with a sensitivity analysis showing the effect of relaxing some hard constraints, varying the fairness metrics and the weights for the coverage penalties per under- and overassigned shift.

# Chapter 8

# Conclusion

The main research question answered in this thesis is:

**What is the effect of incorporating nurses' personal scheduling preferences into the Nurse Scheduling Problem?**

The two most important indicators of nurse schedule satisfaction are the adherence to requests made by nurses to (not) work specific shifts and the consecutiveness of assigned shifts in the schedule. When nurses are assigned too many consecutive shifts per block, their schedule satisfaction decreases as they cannot balance their workload with enough rest. However, the maximum number of preferred consecutive shifts differs per nurse because of personal differences. The same applies to a preference for a minimum number of consecutive days. Additionally, the importance of requests versus the consecutiveness of shifts differs per person. Therefore, including these personal preferences in the objective function of a nurse scheduling problem requires input from the nurses. In this thesis, nurse preferences are studied based on interviews and a survey. Based on the survey results, nurse preferences are simulated to explore the effect of including crew satisfaction in the objective function. Violation of the preferences are translated into penalties which are minimised. Besides minimizing the preference violations, the main aim of the nurse scheduling problem is to minimize the difference between planned nurses and required. Here, assigning too few nurses is considered worse than too many.

To make the results comparable to other research on the nurse scheduling problem, we use the data of benchmark instances provided by Curtois and Qu (2014). To solve the problem formulation, two methods are used. Because the scope of this thesis is scheduling problems with a maximum scheduling period of 12 weeks, most problem instances can be solved by a Mixed Integer Programming formulation using a CPLEX 22.1.1 implementation. However, as larger instances cannot be solved by the exact method, the second method is a Variable Neighborhood Search (VNS) heuristic. This method iteratively makes small changes in the solution to look for improvements in the objective value. While one change might not lead to an improvement, sometimes a chain of changes can. Therefore, the heuristic takes a specified maximum depth and explores chains of changes until this maximum depth.

The effect of including crew satisfaction in the objective function using the exact solution methods shows that on every instance, the satisfaction of the crew can be improved without hurting the coverage penalties. Therefore, it does not cost anything in terms of coverage penalties to improve the satisfaction of the crew. Results of the heuristic also show improvement in crew satisfaction but not as much as the solution of the exact method. However, for scheduling problems with a longer scheduling horizon ($\geq$ 6 weeks) the heuristic could still provide a feasible solution within one hour whereas the exact solution method cannot.

## 8.1 Suggestions for further research

Further research could move into three directions. First, more data should be collected on personal scheduling preferences of nurses and how they affect nurse job satisfaction. This research only focuses on nurses working in Dutch hospitals. With further research, a feedback mechanism could be implemented to continuously evaluate the fit of the objective compared to the needs of the nurses and the preference settings.

Second, further research could focus on the formulation of the scheduling problem including nurse satisfaction. For example, we currently ignore all shifts assigned in a previous scheduling period when calculating employee hard and soft constraints. This could have an effect on, for example, the consecutiveness penalty of a nurse $i$. Currently, we assume a nurse is not working the days before and after the current scheduling period. Nonetheless, a nurse could have worked the day(s) before the start of this new scheduling period which affects the consecutiveness of the schedule. Therefore, the measurement of the penalties could be improved. Regarding fairness, taking historical shifts into account could also prevent a nurse from receiving two bad schedules in a row.

Finally, a third direction for further research could be tailoring the VNS heuristic to the objective including crew satisfaction as opposed to the objective in Curtois and Qu (2014). The heuristic was developed to solve the benchmark instances with the benchmark objective. However, as we have made some changes in the objective formulation, the heuristic could be tailored to this objective to explore improvements. For example, the heuristic should exploit all possible swaps that affect the coverage first before exploring satisfaction related swaps.

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# Appendix A

# Survey

## A.1 Removed roles specification

Table A.1: Removed roles from survey respondents during cleaning

| |
|---|
| Anesthesiemedewerker |
| Applicatiebeheerder |
| Apothekers assistent |
| baliemedewerker |
| beveiliging |
| Business analist |
| coordinator Martini Flex |
| Facilitaire Dienst |
| functioneel beheerder |
| Installatietechnicus |
| Jurist |
| Kwaliteit coördinator |
| MBB'er (4x) |
| mdw bloedafname |
| medisch secretaresse |
| Operatieassistent |
| Planbureau medewerker |
| planner (3x) |
| procescoördinator |
| PROMs en onderzoeksmedewerker |
| Radiodiagnostisch laborant (2x) |
| Teamleider (2x) |
| Voedingassistent |
| zorgbeveiliger |
| Zorgcoordinator |

## A.2 Shift type preferences

Table A.2: Answers for 'other' shift type preference (mostly about variability)

| |
|---|
| Afhankelijk van prive situatie |
| zo min mogelijk nachten |
| Avond en nacht |
| Dag en avond |
| Liefst geen nacht, avond of dag maakt niet uit |
| Dag en daarop avond |
| In schoolvakanties voorkeur voor late dienst, anders geen voorkeur |
| dag of nacht |
| Alle 3 verdeelt over het rooster |
| Dag of laat |
| Dag en avond |
| Liefst dag en late. Geen nachten of 1 |
| Weekend dag en doordeweeks laat |
| afwisseling van alle diensten |
| variatie |
| dag en nacht/ geen liefhebber van late diensten |
| dag en avond |
| Alles in afwisseling |
| als er maar afwisseling in dag en avonddiensten zijn , vind ik het prima |
| liefst geen late ivm thuissituatie, nachten en dag geen voorkeur |
| alle diensten zijn wel OK, maar niet meer dan 2 dagdiensten achter elkaar. |
| Liefst dagdiensten in het weekend en ld en nacht door de week. |
| Voorkeur voor dag of avond |
| Vooral goed verdeeld, maar niet te veel dezelde achter elkaar |
| lieve rmeer avond en nacht dan dag |
| Vooral voorkeur voor afwisseling |
| goede afwisseling |
| dag en avond |
| van alle diensten bij voorkeur max 2 achter elkaar |

## A.3 Additional questions

Table A.3: Consecutiveness preferences

| | min | max | mean | st dev | variance |
|---|---|---|---|---|---|
| Preferred minimum nr. of consecutive shifts (per block) | 1 | 7 | 2.41 | 0.84 | 0.70 |
| Preferred maximum nr. of consecutive shifts (per block) | 2 | 10 | 4.19 | 1.29 | 1.67 |

Next, nurses are asked to divide 20 points over two options to get insights into their priorities. This question is based on previous research on nurse preference scheduling by Warner, 1976.

Table A.4: Preference for single days on/off

| | min | max | mean | std dev | variance |
|---|---|---|---|---|---|
| single day on (off-on-off) | 0 | 20 | 10.40 | 5.59 | 31.22 |
| single day off (on-off-on) | 0 | 20 | 9.6 | 5.59 | 31.22 |

Table A.5: Number of requests (per month)

| In an average month, how many requests would you submit | choice count |
|---|---|
| 0-5 | 200 (83%) |
| 5-10 | 33 (14%) |
| 10+ | 8 (3%) |

Table A.6: Incidental vs. structural requests

| Do you mainly have... | choice count |
|---|---|
| incidental requests (birthday, parties, private appointments, etc.) | 168 (70%) |
| structural requests (recurring sports training, babysitter, etc.) | 73 (30%) |

Table A.7: Incidental vs. structural requests

| Do you mainly have... | 24 hours or less | more than 24 hours |
|---|---|---|
| incidental requests | 50 | 118 |
| structural requests | 28 | 45 |

Table A.8: Preference for scheduling of weekends

| When you are working two weekends in a month, ... | choice count |
|---|---|
| I prefer to work them consecutively | 5 (2%) |
| I prefer to work them spread throughout the month (biweekly) | 138 (57%) |
| I have no preference | 101 (41%) |

Table A.9: Preference for shift type in weekend

| When working in the weekend, I prefer to be assigned... | choice count |
|---|---|
| a day shift | 100 (41%) |
| an evening shift | 56 (23%) |
| a night shift | 8 (3%) |
| no preference | 80 (33%) |

Table A.10: Variability in shift types per block

| | yes | no |
|---|---|---|
| Preference for variability in assigned shift types per block | 160 (66%) | 84 (34%) |

# Appendix B

# Reproduction

Table B.1: VNS reproduction (Curtois and Qu, 2014)

| instance | ORTEC 10min | 2014 10min | diff | ORTEC 60min | 2014 60min | diff |
|---|---|---|---|---|---|---|
| 1 | **607** | **607** | 0 | **607** | **607** | 0 |
| 2 | 924 | 923 | 1 | 832 | 837 | -5 |
| 3 | 1004 | 1003 | 1 | 1003 | 1003 | 0 |
| 11 | 4163 | 3967 | 196 | 3855 | 3661 | 194 |
| 12 | 5388 | 5611 | -223 | 4690 | 5211 | -521 |
| 14 | 2305 | 2542 | -237 | 2014 | 1847 | 167 |
| 16 | 4048 | 4343 | -295 | 3736 | 4048 | -312 |
| 18 | 7312 | 6404 | 908 | 6545 | 6404 | 141 |

# Appendix C

# Pseudocode VNS

Let
$penalty_r$ = the penalty for roster $r$.
$penalty_{r,n}$ = the penalty for the schedule of nurse $n$ in roster $r$.

0. set best roster := the current roster
1. set current roster := an unvisited neighbour
   in neighbourhood for best roster
2. if no unvisited neighbour available
     stop and return best roster
3. if $penalty_{\text{current roster}} < penalty_{\text{best roster}}$
     goto 0.
4. if neither of the penalties decrease for
   the individual schedules of the two employees
   involved in the swap OR maximum depth $<= 1$
     goto 1.
5. set E1 := the employee with increased penalty
   set current depth := 1
6. In the neighbourhood for the current roster
   where considering swaps of blocks between
   employee E1 and all other employees (E2)
   set current roster := neighbouring roster with
   lowest penalty where
   $penalty_{\text{neighbour}} < penalty_{\text{best roster}}$ or
   $penalty_{\text{neighbour}} - penalty_{\text{neighbour, E2}} +$
   $penalty_{\text{current roster, E2}}$
   $< penalty_{\text{best roster}}$
7. if no such neighbour
     goto 1.
8. else if current roster's penalty $<$ best roster's penalty
     goto 0.
9. else if current depth $<$ a preset maximum depth
     set E1 := E2
     set current depth := current depth + 1;
     goto 6.
10. else
     goto 1.

Figure C.1: Variable Neighbourhood (Depth) Search Outline (Burke et al., 2013)