Nurse Rostering Problem, Scheduling, Healthcare, Metaheuristics, Logistics Approach

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CHALLENGES FOR NURSE ROSTERING PROBLEM AND OPPORTUNITIES IN HOSPITAL LOGISTICS

In the last 45 years nurse scheduling has received considerable attention in the research community. Nurse rostering can be described as a task of finding a duty roster for a set of nurses in such a way that the rosters comply with work regulations and meet the management's requests. The objective varies from minimizing the costs of float nurses or minimizing under-staffing to maximizing the degree to which the nurses' requests are met. In logistics, one aspect is optimization of the steady flow of materials through a network of transport links and storage nodes, and the other is, coordination of a sequence of resources, such as staffing and scheduling clinical resources. The period up to 2000 is characterized by using mathematical programming and objective functions to solve nurse rostering problem. In the period after 2000 the focus of researches aimed at solving nurse rostering and scheduling problem becomes implementation of meta-heuristics and multi-objective functions. The aim of this paper is to present the latest researches conducted in last ten years.

1. INTRODUCTION

Traditional approaches to addressing the challenges of clinical staffing and scheduling aren't always effective in modern complex healthcare environment. Many staffing offices are chaotic, budgets are frequently over-run, and staffing levels too often fail to match demands. More state legislatures are mandating specific nurse staffing levels, and many nurses are dissatisfied with their work schedules.

Logistics refers to management of the flow of goods, information, and other resources, including people, between the point of origin and the point of consumption in a way that meets all parties' requirements. Two different logistics aspects must be satisfied. The first is optimization of the steady flow of materials through a network of transport links and storage nodes. And the other is a coordination of a sequence of resources, such as staffing and scheduling clinical resources.

The nurse rostering problem (NRP) is a well-known NP-hard scheduling problem that aims at allocating the required workload to the available staff nurses at healthcare organizations to meet the operational requirements and a range of preferences. The NRP is a two-dimensional timetabling problem that deals with the assignment of nursing staff to shifts across a scheduling

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period subject to certain constraints [4]. The NRP with higher dimensions (more nurses, more constraints) is denoted as CNRP which is short for Chinese Nurse Rostering Problem. CNRP contains many nurses across a longer duration and various constraint sets, which requires trade-off results between quality and computational time [10].

Duty rosters can be generated manually by nursing officers for each hospital unit. However, scheduling nurses has always been difficult. The main reason lies in the fact that hospitals need to be staffed 24 hours a day over seven days a week. In addition, in many hospitals, nurses are allowed to request pre-set shifts, while other nurses are scheduled around these pre-set shifts. The NRP involves producing a periodic (weekly, fortnightly, or monthly) duty roster for nursing staff, subject to a variety of hard/soft constraints such as legal regulations, personnel policies, nurses' preferences and many other requirements that may be hospital-specific.

New technologies developed over the past few years aim to promote more effective scheduling and staffing. Computerized schedules, which began as rudimentary spreadsheet tools, have evolved into sophisticated, algorithmically driven applications that allow staff to self-schedule from home, view and offer availability for extra shifts, and modify staffing requirements based on continual census feed.

Period up to 2000 is characterized by using mathematical programming and objective functions. In the period after 2000 focus of researches aimed at solving nurse rostering and scheduling problem becomes implementation of meta-heuristics and multi-objective functions. The aim of this paper is to present the most cutting edge researches conducted in the period from 2004 onwards.

The rest of the paper is organized in the following way: Section 2 provides a short overview of the modeling of the nurse rostering problem and Section 3 describes the solution approaches available for this problem: general methods, classical heuristics methods and metaheuristics. Section 4 presents practical applications of nurse rostering and scheduling problem and the evaluation of some different approaches and Section 5 provides some conclusions and some points for future work.

2. MODELLING THE NURSE ROSTERING PROBLEM

The nurse rostering problem is commonly described by a nurse day view, a nurse-task or nurse-time slot view and a nurse-shift pattern view. A nurse-day view is a direct depiction of two-dimensional duty rosters (Table 1).

2.1. DECISION VARIABLE

Accordingly, the decision variables can be defined for each nurse on each day as ν_{ij}, where $1 \leq i \leq N$ indexes the nurses and $1 \leq j \leq P$ indexes the days within a scheduling period. The domains of these variables consist of on-duty shifts and free shifts. On-duty shifts may include any number of shifts per day, but it is common to use only a morning shift (A) of eight working hours, an afternoon shift (P) of eight working hours, and a night shift (N) of eight working hours. Free shifts include day-off (O), compensation-off (CO), public holiday (PH), vacation leave (VL), study day (SD), maternity leave (ML). Thus, the decision variables can typically take on 10 or more values, which increase computational efforts.

In [9] is used a reduction of variable domains. The idea is to set all values of the free shifts to 0. In the general situation, when there are Z shifts per day, ν_{ij} can take $Z + 1$ possible value:

$$\nu_{ij} = \begin{cases} 0 & \text{nurse } i \text{ is off duty on day } j, \\ 1 & \text{nurse } i \text{ works shift 1 on day } j, \\ 2 & \text{nurse } i \text{ works shift 2 on day } j, \\ \vdots & \\ Z & \text{nurse } i \text{ works shift } Z \text{ on day } j. \end{cases} \tag{1}$$

The values of the free shifts are reduced to one value (F). There is only the morning shift (A), the afternoon shift (P) and the night shift (N), so that the decision variable will take on four possible values:

$$\nu_{ij} = \begin{cases} 0 & \text{nurse } i \text{ is off duty (F) on day } j, \\ 1 & \text{nurse } i \text{ works shift (A) on day } j, \\ 2 & \text{nurse } i \text{ works shift (P) on day } j, \\ 3 & \text{nurse } i \text{ works shift (N) on day } j. \end{cases} \tag{2}$$

Table 1. Nurse-day view.

Nurse-ID	Mon	Tue	Wen	Thu	Fri	Sat	Sun
N-01	A (1)	P (2)	N (3)	F (0)	F (0)	A (1)	P (2)
N-02	P (2)	N (3)	F (0)	F (0)	A (1)	P (2)	N (3)
N-03	N (3)	F (0)	F (0)	A (1)	P (2)	N (3)	F (0)
N-04	F (0)	F (0)	A (1)	P (2)	N (3)	F (0)	F (0)
N-05	F (0)	A (1)	P (2)	N (3)	F (0)	F (0)	A (1)
N-06	A (1)	P (2)	N (3)	F (0)	F (0)	A (1)	P (2)

Table 1 shows part of a weekly roster which indicates the shifts allocated to the nurses, in a nurse-day view.

2.2. CONSTRAINTS

Constraints that commonly occur with NRP can generally be divided into two classes: hard constraints and soft constraints. Hard constraints usually include coverage requirements: for example, staff demands per day per shift type per skill category; while soft constraints are usually those involved with time requirements on personal schedules – a nurse cannot work more than one shift per day; all shift type demands during the planning period must be met.

The goal is always to schedule resources to meet the hard constraints while aiming at a high quality result with respect to soft constraints. Commonly occurring soft constraints are listed: 1) Nurses workload (minimum/maximum); 2) Consecutive same working shift (minimum/maximum/exact number); 3) Consecutive working shift/days (minimum/maximum/exact number); 4) Nurse skill levels and categories; 5) Nurses' preferences or requirements; 6) Nurses free days (minimum/maximum/consecutive free days); 7) Free time between working shifts (minimum); 8) Shift types assignments (maximum shift type, requirements for each shift types); 9) Holidays and vacations (predictable), annual leave; 10) Working weekend (complete weekend); 11) Constraints among groups/types of nurses, (nurses not allowed to work together or nurses who must work together); 12) Shift patterns; 13) Historical record, e.g., previous assignments; 14) Other requirements in a shorter or longer time period other than the planning time period; 15) Constraints among shifts (shifts cannot be assigned to a person at the same time); 16) Requirements of (different types of) nurses or staff demand for any shift (minimum/maximum/exact number).

The soft constraint lists some papers which have one or more of the constraints described above. It can bee seen that constraints 1, 3, 5, 6, 7, 8, 10, 14 and 16 are common in NRP. In particular, it is note that constraint 16 must be covered in any solution. Other soft constraints can include having identical shift types on the weekend, balance in workload, assigning complete weekends and patterns enabling specific cyclic constraints.

2.3. OBJECTIVE FUNCTIONS

Typically, with optimization problems models that use standard objective functions can be found, such as those for mathematical programming (MP) models. In other models, we find target or evaluation functions that are used to guide the generation of results or to evaluate results. In [7], the objective function is defined:

$$\sum_{i=1}^{n} \sum_{j \in F(i)} p_{ij} x_{ij} \rightarrow \min, \tag{3}$$

where p_{ij} is the penalty cost of nurse i working on shift pattern j, x_{ij} is the decision variable with a nurse-shift view and $F(i)$ is the set of feasible shift patterns for nurse i, where the purpose is to minimize the total penalty cost for all nurses. This total is subject to minimization, since the total penalty needs to be as low as possible. The best schedule is thus one where this value of total penalties of nurses working is lowest.

In [1] such a function where the penalty is proportional to the number of uncovered shifts for the problem could be found, and is used to evaluate the fitness of solutions. In [15], a function that will minimize the cost of schedules and the penalty for violating shift balance could be found. Some of the goals for optimization include: minimum staffing requirements, minimum desired staffing requirements, maximum satisfaction of nurses' preferences or their special requests, and so on. In general, optimization using MP can be classified in three categories: single-objective MP, multi-objective MP, and MP-based near-optimal approaches.

3. SOLUTION APPROACHES TO THE NRP

Generally, a quick approach to solving the NRP could be used, where the aim is to generate an acceptable schedule while there can also be more thorough approaches depending on the problem and the needs of the hospital. Moreover, nurse rostering should be balanced against sensitivity to changes, since hospitals are very dynamic environments.

Studies of nurse rostering problems date back to the early 1960s. Most of the researchers adopted convention optimization approaches to generate solutions with minimum cost. They are always able to obtain the optimal solution if there is no time limit. However, the methods were only effective with small-scale NRP with simple constraints since they strongly relied on the particularity of the problems [10].

Pre-planning and post-planning the NRP are always options and part of sensitivity analysis. In pre-planning, it is possible to set hard constraints to preferred requirements and minimum requirements and, in post-planning, it is possible to add shift types to preferred requirements. Optimal solutions derived from techniques with high computing times are usually less valuable than one that is based on a flexible algorithm or user intuitive application.

In general, there are two basic types of scheduling used for the NRP: cyclic and non-cyclic scheduling. In cyclic scheduling, each nurse works in a pattern which is repeated in consecutive scheduling periods, whereas, in non-cyclic scheduling, a new schedule is generated for each scheduling period. Cyclic scheduling was first used in the early 1970s due to its low computational requirements and the possibility for manual solution. The algorithms for the NRP, generally, deal with either cyclic scheduling or non-cyclic scheduling.

3.1. GENERAL METHODS

In the past decades, many approaches have been proposed to solve NRP as they are manifested in the different models. The three commonly used general methods are MP, heuristics and Artificial Intelligence (AI) approaches. Most heuristic approaches focus on solving cyclic scheduling problems, while MP and AI approaches can be found to be used on both cyclic and non-cyclic problems.

3.2. CLASSICAL HEURISTICS APPROACHES

Many heuristic approaches were straightforward automation of manual practices, which have been widely studied and documented [12]. Basic heuristics can include: Shuffling and Greedy Shuffling. In the first, the problem is solved for the worst schedule and then the quality is improved by exchanging a part of this schedule with a part from another person's schedule. Many human-inspired approaches can be found in Greedy Shuffling type algorithms which work by calculating all the shuffles for all personnel and listing them with the highest cost benefit first. This is repeated as many times as possible.

3.3. METAHEURISTICS APPROACHES

For combinatorial problems, exact optimization usually requires large computational times to produce optimal solutions. In contrast, heuristic approaches can produce satisfactory results in reasonably short times. In the recent years, metaheuristics including: tabu search algorithm (TS), genetic algorithm (GA) and simulated annealing (SA), have been proven as very efficient in obtaining near-optimal solutions for a variety of hard combinatorial problems including the NRP.

TS approaches have been widely used to solve many combinatorial problems. Some TS approaches have been proposed to solve the NRP. TS is a search that moves iteratively from one solution to another by moves in a neighborhood space with the assistance of an adaptive memory. This memory forbids solution attribute changes recorded in the short-term memory to be reused. How long a restriction is in effect depends on the tabu tenure. In TS, a move, for example, can take on an assigned shift type from one nurse to another on the same day and the move is not allowed (tabu) if, for example, the person does not belong to the skill category required or if there is already an assignment for that shift type.

In TS, hard constraints remained fulfilled, while solutions move in the following way: calculate the best possible move which is not tabu, perform the move and add characteristics of the move to the tabu list. In [7] is used TS with strategic oscillation to tackle the NRP in a large hospital. The objective is to ensure enough nurses on duty at all times while taking account of individual preferences and requests for days off.

GAs, which are stochastic meta-heuristics, have also been used to solve the NRP. In GA, the basic idea is to find a genetic representation of the problem so that 'characteristics' can be inherited. Starting with a population of randomly created solutions, better solutions are more likely to be selected for recombination into new solutions. In addition, new solutions may be formed by mutating or randomly changing old ones.

In the context of NRP, for crossover and mutation, the best personal schedule from each of the parents can be selected, a random selection from the personal schedule of parents can be selected, or we can select the best events in a schedule. Some of the best solutions in each generation are kept while others are replaced by newly formed solutions. In [11] GA for example, a problem with multiple criteria with the concept of a Pareto optimality scheme is used for the evaluation of the multi-criteria objective function.

Harmony Search Algorithm (HSA) is a meta-heuristic algorithm inspired by the improvisation on Jazz musicians. The investigative research issues presented in [8] of the parameter settings in HSA and application of HSA to effectively solve complex NRP. Due to the well-known fact that most NRP algorithms are highly problem (or even instance) dependent, the performance of our proposed HSA is evaluated on two sets of very different nurse rostering problems. The first set represents a real world dataset obtained from a large hospital in Malaysia. Experimental results show that proposed HSA produces better quality rosters for all considered instances than a genetic algorithm, implemented herein.

The development of decision support systems acceptable for nurse rostering practitioners still presents a daunting challenge. Building on an existing nurse rostering problem, a set of fairness-based objective functions recently introduced in the literature has been extended. To this end, a generic agent-based cooperative search framework utilizing new mechanisms is described, aiming to combine the strengths of multiple metaheuristics. These different metaheuristics represent individual planners' implicit procedures for improving rosters. The framework enables to explore different ways of assessing nurse rosters in terms of fairness objectives [13].

Due to the problem of slow convergence of the basic HSA, the study presented in [2] attempts to enhance basic Harmony Search Algorithm, called EHSA. This is done by using a semi cyclic shift patterns in the initialization step to generate the initial harmonies (population) rather than using a fully random mechanism in basic HSA. Furthermore, a dynamic mechanism was employed in EHSA to update the parameter values of harmony memory considering rate and pitch adjusting rate instead of fixed values in basic HSA.

The paper [5] presents a new variant of the HSA, called Geometric Selective Harmony Search. The main differences between the proposed variant and the original formulation of Harmony Search are the integration of a selection procedure in the improvisation phase, a new memory consideration process that makes use of a recombination operator, and the integration of a new mutation operator. Geometric Selective Harmony Search is compared to the original Harmony Search, with another existing variant called Improved Harmony Search, and with two existing selection-based HSA. The experimental study was conducted on 20 benchmark problems belonging to the CEC 2010 suite, one of the most well-known benchmark sets.

4. DISCUSSION AND PRACTICAL APPLICATIONS

In order to bridge the gap from a purely academic problem to actual application in hospitals, still much has to happen. Only few of the published efforts were actually used in real-world hospital environments. Two notable examples are the ANSOS system which was during the early 1990s applied in over 750 hospitals [16] and more recently [3] who developed an automated scheduling tool which was applied in over 40 different Belgian hospitals.

There are some professional software tools which help nurse leadership to organize more effective nurse scheduling. One of them is called 'ScheduleAnywhere', and it is used in more than 100 hospitals [19]. 'Shiftboard' is another popular professional software which is a great fit for nurse scheduling problem [20]. The third software package is 'Drools Planner' which is renamed to 'OptaPlanner' [18]. 'OptaPlanner' is open source software, released under the Apache Software License. It is 100% pure Java^{TM}, runs on any JVM and is available in the Maven Central Repository.

Solving the nurse rostering problem is so significant that several international competitions, in which teams of scientists and researchers have participated, have been organized. The idea of organizing a nurse rostering competition derives from the interest aroused by the two timetabling competitions, ITC 2002 and ITC 2007 [17]. The main objective of INRC 2010 was to generate new approaches to the associated problem by attracting researchers from different areas of research. As with many cases in the past, significant advancements have been made in research areas by attracting multi-disciplinary approaches and comparing them on a common ground.

The First International Nurse Rostering Competition (INRC 2010) aimed at developing interest in the general area of rostering and timetabling, while providing researchers with models of the problems faced which incorporate a significant number of real world constraints [14]. The features of the algorithm are often tuned to the available running time, the three tracks represented different challenges to the participants:

- *Sprint*: Required a solution in a few seconds, typical for interactive use.
- *Middle Distance*: Required the solution in a few minutes and simulated the practical situation in which the problem has to be solved a few times during a solving session.
- *Long Distance*: Granted the solver many hours of running time and simulated overnight solving.

Seven teams participated in this competition – *Solvers*. In the first round – *Sprint* – all seven teams qualified. In the second round – *Middle Distance* – 5 teams qualified. The – *Long Distance Track* – granted the solver about ten hours of running time and simulated overnight solving. The fifteen instances of this track consisted of 50 nurses. The planning horizon was 28 days. In the third part of competition, *Long Distance*, only four *Solvers* qualified.

It is interesting to mention some other views on NRP. In [6], H. Simon the 1978 Nobel economics, argued that human beings are irrational. This view was that people try to be rational but that human ability to be so is very limited, especially given the complexity of the world - or given the prevalence of uncertainty. This means that often the main constraint on decision-making is not the lack of information but our limited capability to process the information that we have. Given limited human rationality, we are developing mental 'shortcuts' that allow us to economize mental capabilities. These are known as heuristics, or intuitive thinking, and can take different forms: rule of thumb, common sense or expert judgment. Underlying all these mental devices is the ability to recognize patterns, which allows us to abandon a large range of alternatives and focus on a small, manageable but most promising range of possibilities. This point of view is absolutely different from trends on which the researches in the last decade have been focused.

In many cases optimization techniques have been successfully used on problems which are essentially 'hard'. On the other hand, once problems have a significant number of 'soft' i.e. human features, optimization techniques are less suitable, if not unsuitable. Optimization methods in such problems, and for the use of heuristics for 'satisfying', against optimizing could possibly be better. Maybe after 45 years of trying optimizing, one should consider that 'optimization' techniques may be less appropriate solutions.

5. CONCLUSION AND FUTURE WORK

The long period of 45 years, hasn't diminished interest in one of the most important combinatorial optimization problems, nurse rostering and scheduling problem. The aim of this paper is to present the latest researches, on metaheuristics, conducted in last ten years. The period up to 2000 is characterized by using metaheuristics methods such as: tabu search algorithm, genetic algorithm, and simulated annealing method. But, the latest decade is characterized by using other metaheuristics methods, and the most significant would be: Harmony Search Algorithm, Enhanced Harmony Search Algorithm, and Geometric Selective Harmony Search.

The significance of nurse rostering and scheduling problem is mirrored in continuous existence of some professional software tools which help nurse leadership to organize more effective nurse scheduling. Further more, organizing a nurse rostering competition in 2010 says even more about the importance of NRP.

Our future researches will focus on creating hybrid metaheuristics model combined by intuitive thinking which will efficiently solve NRP. The model will be tested with original real world dataset obtained from the Oncology Institute of Vojvodina in Serbia.

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