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Greedy Constructive Heuristic and Local Search Algorithm for Solving Nurse Rostering Problems

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Abstract—**The Nurse Rostering Problem (NRP) is one of the NP-hard problems that are difficult to solve for optimality. NRP deals with the distribution of working shifts to the staff nurses at healthcare organizations under given rules. Normally, NRP aims at generating a duty roster that satisfies all of the hard constraints (mandatory) and as many soft constraints (optional) as possible. This work introduces a greedy constructive heuristic algorithm, based on building two patterns of two-week's duration that satisfies all of the hard constraints and several soft constraints. The first pattern is designed mainly to fulfill the night shift coverage whilst the second pattern is concerned with morning and evening shifts only. If the solution is not feasible (for example the coverage is not met), a repairing mechanism algorithm is applied until a feasible solution is reached. Simulated Annealing (SA) is then used to improve the constructed solution. A real dataset from Universiti Kebangsaan Malaysia Medical Center (UKMMC) is used in this work to test the proposed approach. Currently, the duty roster at UKMMC is still constructed manually. Promising results have been obtained and presented in this paper.**

Keywords: Nurse Rostering, Greedy Constructive Heuristic, Simulated Annealing and Scheduling.

I. INTRODUCTION

The Nurse Rostering Problem (NRP) is one the timetabling problems that are concerned with the distribution of the shift assignments among the available staff nurses to fairly fulfill the operational requirements for a particular period. Typically, the nurses are assigned to work one of the following shifts: (i) morning (M), (ii) evening (E), (iii) night (N) or (iv) day off (O).The distribution of these shifts mainly comply with the staff preferences, the policy laid down by the administration and the labor agreement clauses[1]. The complexities and the challenges of nurse rostering problems arise from the fact that a large variety of constraints exist, some of which contradict each other. The nurses' duty roster is a timetable that consists of the shift assignments and rest days of staff nurses at healthcare organizations. Normally, hospitals are divided into several wards; each ward has its own staff nurses who are working at the same ward. The head nurse is the one who is responsible of producing and managing the duty rosters of each ward.

In the literature of timetabling, many approaches and methods have been used to solve NRP. Several overview articles have been published which summarized the progress in the area of nurse rostering, such as [2-4].For example [2], provides a thorough overview of proposed approaches and methods up to 2004. Based on the survey paper of [2], the proposed method is classified into, heuristics, meta-heuristics and artificial intelligence. Meta-heuristic approaches show a different rate of success in solving time tabling problems in general and NRP specifically[2]. Meta-heuristic approaches have been proposed to solve NRP through methodology such as variable neighborhood [5], tabu search [6], simulated annealing [7], genetic algorithm [8] and others [9, 10]. Heuristic approaches are usually considered as the fastest approximate methods that can produce solutions from scratch by adding opportunely defined solution components to an initially empty partial solution. This is accomplished until a solution is complete or other stopping criteria are fulfilled; this is known as a greedy approach[11].

In [12], a simulated annealing and a simple local search heuristic are merged to produce cyclical schedules for personnel in continuously operating organizations. A Simulated Annealing algorithm and Genetic algorithm are used to solve staff scheduling in[13]. A simulated annealing is also used in [7] to improve the initial solution that was constructed based on the shift patterns approach. In [7] they used a group of one-week feasible patterns to construct the nurse duty roster for a two-week duration, while in this work, we only used two patterns of two-week periods to fill up the time slots for each nurse.

The aim of this paper is to present our proposed constructive approach that uses a greedy shift pattern approach and simulated annealing to solve NRP at UKMMC.

II. UKMMC NURSE ROSTERING PROBLEM

In this paper we are solving the same problem in [7], as to solve the NRP at Universiti Kebangsaan Malaysia Medical Center(UKMMC). UKMMC is an educational hospital which belongs to the National University of Malaysia. The hospital has more than 1300 nurses attending about 900 beds. There are three shifts a day; two day-time shifts of 7 hours each (morning and evening) and a 10-hour long night shift. The nurses are also categorized as either senior or junior.

So far, the manual method scheduler is still used at UKMMC to generate fourteen-day duty rosters for their staff nurses. In fact, many hospitals still use a manual scheduler around the world which is a frustrating and time consuming task[2].

In [14], an exploration study is made of NRP at UKMMC and a mathematical model is presented, including hard and soft constraints and other related aspects to UKMMC NRP in their paper. For more details about UKMMC NRP refer to [7,14].

A. UKMMC Hard and Soft Constrains

Constraints in NRPs are usually classified into two groups: hard and soft constraints, which vary significantly with respect to official regulations and individual requirements, depending on individual organizations and countries [2]. Hard constraints have to be satisfied to get feasible solutions whilst soft constraints are desirable to be satisfied but not mandatorily, and thus can be violated [15]. The quality of the produced roster is dependent on the total penalty average; a lower total penalty indicates the better duty roster.

Hard constraints are:

H1. Coverage of shifts must be at least for the demanded number of nurses.
H2. Nurses cannot work more than one shift a day.
H3. A rest day must be included, with at least two days per two-week period for every nurse.
H4. At least one senior nurse is presented for every shift.
H5. There must be no isolated working days.
H6. The minimum working load is 10 days for each two-week period and the maximum is 12 days.
H7. The maximum span of consecutive working load is 4 days.
H8. If the nurse has four consecutive night shifts this must be followed by two rest days.

The soft constraints are:

S1. Attempt to give an equal number of working days and rest days for every nurse.
S2. Attempt to give each nurse at least one rest day in the weekend during the two-week duty roster.
S3. Attempt to give four consecutive morning shifts followed by one day off.
S4. Attempt to give four consecutive evening shifts followed by one day off.
S5. Attempt to give an evening shift after the rest days that follow the night shift pattern.

B. Coverage Demand

Coverage demand is among the most important constraints that need to be satisfied. In the UKMMC datasets, the coverage demand is different from one shift to another and from the weekdays to the weekends. Table 1 presents the coverage demand of the UKMMC datasets.

TABLE 1 THE MINIMUM COVERAGE DEMAND.

			Weekdays (Mon-Fri)			Weekend (Sat-Sun)		
Dataset	nurses	Senior nurses	Morning	Evening	Night	Morning	Evening	Night
CICU	11	8	3	3	2	2	2	2
SGY5	18	11	4	4	3	4	4	2
MD1	19	12	4	4	3	4	4	2
N50	50	31	10	10	10	10	10	10
GCIU	73	38	16	16	15	15	15	14

C. Objective function

Generally, the objective function is used to measure the quality of the produced duty roster. In this work, the objective function is a minimization-based method that attempts to reduce the total penalty occurring due to the violation of soft constraints as in [14]. Each soft constraint is weighted according to its importance. There is no standard weight for the soft constraints and as in [16], the weights of each soft constraint are set based on the discussion with the head nurses at UKMMC. Usually, the higher weight is used to indicate the higher value and importance of the specific soft constraints to be satisfied which are shown in table2.

TABLE2 THE WEIGHT OF EACH SOFT CONSTRAIN

No.	Soft constraints	Weight of violation
S1	Give an equal number of working days and rest days for every nurse.	100
S2	Give each nurse at least one rest day in the end of the week during the two-week.	100
S3	Give four consecutive morning shifts followed by one day off.	10
S4	Give four consecutive evening shifts followed by one day off.	10
S5	Give an evening shift after the rest day that follows night shift.	1

Table 3 shows an example of some shift sequences for the problem.

TABLE3 SAMPLE FOR SHIFT SEQUENCES

Shift Sequence	Penalty	Comment
NNNNOOE	0	Satisfy S5
MMMMO	0	Satisfy S4
EEMMO	10	M not allowed to follow E
MMEEO	10	E not allowed to follow M
NNNNOOM	1	M not allowed to follow days off that followed night shifts

Note: where M=morning shift, E=evening shift, N=night shift, O=day off.

An example of calculating the total penalty for the soft constraint (S1) violations is presented in table 4 where two nurses have different working load.

TABLE 4. SAMPLE FOR CALCULATION OF S1

Nurse	Total working days	Total No. of days off	Violation of S1
N1	11	3	100

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N2	10	4	0
	Total penalty of S1		100

Note: If total working days <10 violation is 100

Table 5 shows an example demonstrating how to calculate penalty for S2.

TABLE 5. SAMPLE TO CALCULATE S2

Nurse	Total No. of days off on weekend	Violation of S2
N1	1	0
N2	0	100
	Total penalty of S2	100

Note: If total No. of days off <1 violation is 100

III. A CONSTRUCTIVE SHIFT PATTERN APPROACH

In this work, we have three main stages to construct the initial solution; the first stage is a preprocessing stage where the shift patterns we built. In the second stage, those shift patterns are allocated to each nurse until the required constraints are satisfied. In the final stage, a repairing mechanism is used if the constructed roster from the allocation stage is not feasible.

A. Preprocessing stage

In this stage, we have designed two shift patterns for a two-week period.

The first pattern is built based on the following rules:

1. As it is difficult to satisfy H8 (night shifts), the first part of the first pattern consists of four consecutive night shifts followed by two days off. The first part of the pattern also satisfies other constraints such as H2, H5 and H7.
2. The second part of the pattern (four consecutive evening shifts followed by a day off) satisfies the constraints H2, H5, H7 and S4 (evening).
3. The last part is completed by 2 morning shifts (MM) in order to make this pattern inclusive of all the possible shifts (2 morning, 4 evening, 4 night and 4 days off).

The second pattern is built based on the following rules:

1. The first part is satisfying the constraints H2, H5, H7 and S3 (morning shift); 4 consecutive morning shifts are followed by one day off.
2. The second part of the pattern (four consecutive evening shifts followed by a day off) satisfies the constraints H2, H5, H7 and S4 (evening).
3. The last part is completed by 3 morning shifts (MMM), this pattern including day shift patterns only (7 morning, 4 evening and 3 days off).

B. Allocation stage

The allocation stage starts by allocating the first pattern (rotating) to the first nurse and shifting the pattern for four positions, then allocating it to the next nurse until the minimum coverage demands of night shift on all days of the entire schedule period are met. Refer to figure 1 for more explanations about the allocation process.

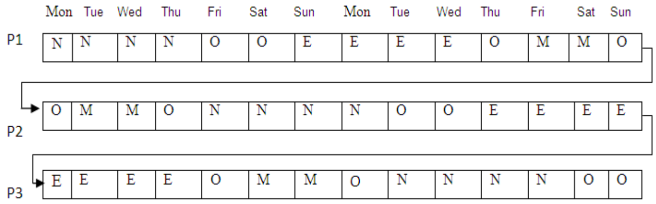

FIGURE 1. EXAMPLE FOR DISTRIBUTION THE FIRST PATTERN

Then the allocation of the second pattern is done in the same way as the allocation of the first pattern until the coverage demand of the morning and evening shifts is fulfilled. Refer to figure 2 for more explanation about the allocation process.

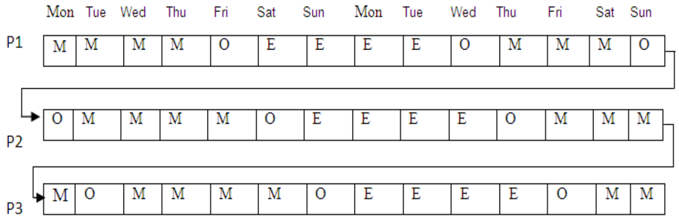

FIGURE 2. EXAMPLE FOR DISTRIBUTION OF THE SECOND PATTERN

C. Repairing Stage

In this stage, we check the minimum coverage demand. If it is not reached then we use a repairing mechanism algorithm to check the coverage constraints, and distribute senior nurses to fulfill the constraint H4. Refer to figure 3, for more details about the construction procedure and repairing mechanism.

```
DN= number of minimum coverage demand for night shifts;
CN= the maximum number for consecutive night shifts;
Repeat
    Repeat
        Set the first Pattern;
        Rotate the first pattern CN positions
    Until DN is met
    Repeat
        Set the second pattern
        Rotate the second pattern one position
Until (number of nurses is reached)
To (number of nurses)

Check Coverage:
Repeat
   Repeat
        If (required coverage is not reached)
            (Swap rest day with working day)
   To (All days of the period)
To ((requested coverage is reached) or (all nurses have been checked))
Repeat
 Repeat
      (Check hard constraints)
      (Take from extra shift to cover a missed shift)
  To (All days of the period)
To (all nurses have been checked)
```

FIGURE 3. INITIAL SOLUTION CONSTRUCTIVE PROCEDURE

IV. SIMULATED ALGORITHM OPTIMISER

The Simulated Annealing (SA) algorithm is inspired by the process of solid material that is initially heated and then cooled in order to develop particular characteristics. In optimisation problems this principle is applied in order to avoid local optima in the search space. There must be an existing initial solution in order to apply SA to develop this initial solution. The SA procedure works by moving from the current solution candidate to another neighbor candidate based on some criterion that accepts this move if it develops the current objective value or leaves it without any change based on predefined moves. At this stage, we are trying to reach the global optimal solution which is the best duty roster found so far in this work. In SA, a solution in the neighborhood is chosen randomly, and then evaluated. Three neighborhood moves are used in this work such as in [17-20]. These moves are:

1. Swap single shift between two days of a single nurse e.g. a day off and a day worked were swapped, thus not affecting the cover constraints but potentially affecting the other constraints and objectives.
2. Swapping of single shift between two nurses on the same day e.g. evening shift is swapped by morning shift.
3. Change of single shift to another single shift type of a single nurse, for example a working day is changed to a day off. Refer to figure 4 for the simulated annealing procedure.

Procedure SIMULATED_ANNEALING;

Determine initial candidate solution s
Set initial temperature T according to annealing schedule
While termination condition not satisfied:
    Probabilistically choose a neighbor
    s' of s
  If s' satisfies probabilistic acceptance criterion
    (Depending on T):
    $s := s'$
Update T according to annealing schedule

FIGURE 4. THE SIMULATED ANNEALING PROCEDURE

The procedure of simulated annealing is the standard simulated annealing as in[21].

V. EXPERIMENTAL RESULT

For the parameter settings that are used in this work [22], temperature t=2000, cooling rate α=o.98, $\pi = 0.001$with probability function $=e^{\Delta f/t}$, stopping criteria are to meet t<π or get the best solution so far.

The work used a real world data of 6 different datasets from UKMMC covered in the experiments. We ran our experiments by the utilization of an Intel Core i3-350M processor 2.26 GHz with 4 GB RAM and windows 7, 64-bit operating system. The codes were implemented using Microsoft Visual C++ 6.0. The results were obtained by running every dataset for 30 times and taking the mean of the result.

The mean of total cost/minimum penalty for 10 run times, and the results obtained for 5 data sets in UKMMC are presented in table 6.

			Initial solution	**Improved solution**		
No.	**Dataset**	**No. of nurses**	**average Penalty**	**Average Penalty**	**Number of iterations**	**Time (Sec)**
1	CICU	11	680	12	300	90
2	SGY5	18	920	10	410	121
3	MD1	19	930	10	425	185
4	N50	50	2960	31.6	520	210
5	GCIU	73	3810	45.0	716	280

TABLE 6. EXPERIMENTAL RESULT OF UKMMC DATASET

VI. DISCUSSION

Here we are summarizing the computational experiments that were executed on NRP datasets from UKMMC. The results in table 6 include the initial penalty of each dataset in the constructive stage and after applying simulated annealing (SA). For the improvement stage, we notice that, the number of iterations increased as the number of nurses in each dataset increased. The average of construction time varied between 90 seconds and 280, which is considered as a reasonable time in comparison with the construction times in the literature, which in some situations take hours. So, it is obvious that our algorithm has obtained a good quality solution for all of the datasets that it was applied to. The effectiveness of simulated annealing is shown as it can greatly reduce the total penalty of the initial solution.

VII. CONCLUSION AND FUTURE WORK

This paper has considered a real-world nurse rostering problem (UKMMC), which has a highly constrained search space. Several methods have been proposed for this problem, which have either struggled to find feasible solutions and produce high quality solutions efficiently in terms of the objective function. In this paper, we proposed a greedy constructive heuristic algorithm towards constructing an initial solution, and then applied simulated annealing to improving the solution by using 3 neighborhood structures. Experimental results on UKMMC NRP demonstrated the high performance and consistency of this approach. In future work we will compare our approach with other constructive algorithms, and implement it at other benchmark datasets.

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