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A Hyperheuristic Approach to Belgian Nurse Rostering Problem

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1 Introduction

Nurse rostering problem involves the assignment of shifts to nurses with respect to several constraints like workload, legal restrictions, and contractual agreements [7]. The complexity of the problem attracts many researchers around the world. Since the labour regulations, workload requirements, and contractual agreements differ from country to country, the models and solution methods differ as well [7].

A reference model for nurse rostering problem is introduced in [11] to categorize the problem at hand. The solution methods to tackle the nurse rostering problems are as diverse as the problem definitions. Petrovic and Vanden Berghe propose several criteria to compare these solution methods in [13]. Constraint programming [4], case-based reasoning [1], and hybrid meta-heuristic methods [6] can be given as examples to the solution methods that are proposed to cope with the nurse rostering problem.

This study is focused on the nurse rostering problem in Belgium. The instances of nurse rostering problem in Belgium are very diverse. Problem properties like workload, number of nurses, schedule periods, and contractual agreements vary among different institutions as well as among the wards within the same institution. A generic model that covers the different aspects of the problem is presented in [3].

Variable Neighbourhood Search (VNS) conducts a search on different neighbourhoods of the problem domain [9]. Bilgin et al. propose six different neighbourhoods on the generic model for the nurse rostering problem in Belgium. Several neighbourhood sets are composed from different combinations of these neighbourhoods. These sets are deployed within a VNS algorithm. The resulting solution method performed satisfactory on real world problem instances, and it is deployed within a commercial personnel planning software [3].

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Hyperheuristics are high level search strategies like metaheuristics. The main defining property of hyperheuristics is that they operate on a set of heuristics instead of operating directly on the search space of the problem [5]. Hyperheuristics try to benefit from the strengths of each heuristic, and try to avoid the weaknesses of them. Improving hyperheuristics are iterative methods that select and execute a heuristic at each iteration and either accept or decline the new state of the candidate solution. Several heuristics and metaheuristics are deployed as the selection method and the acceptance criterion in such a setting [12]. Dowsland et al. used simulated annealing as the acceptance criterion and applied the resulting hyperheuristic to the problem of determining shipper sizes for storage and transportation [8]. Kendall and Mohamad used great deluge as the acceptance criterion to tackle the channel assignment problem in cellular communication [10]. In this study, simulated annealing and great deluge acceptance criteria are deployed in hyperheuristics to tackle the problem at hand.

Heuristics based on the neighbourhoods proposed in [3] are deployed by the hyperheuristics in this study. The heuristics used involve a tournament strategy. At each call, they evaluate a fixed number of random solutions in the neighbourhood of the current solution, and return the solution with the best fitness value. This fixed number is referred as tournament factor in the remainder of the paper.

In [3], a neighbourhood set that chooses between two different neighbourhood sets according to the input problem instance is presented. The criterion to decide between the two sets was the existence of secondary skill types of nurses. This neighbourhood set was among the best performers on most of the problem instances. Therefore, the heuristic set that is used in this study is composed from the corresponding heuristics according to the same criterion.

The solution methods are evaluated empirically on the real world benchmarks that are also used in [3]. The performance of the methods are compared with the performance of the methods presented in [3]. Simulated annealing hyperheuristic performed significantly better on most of the test cases.

The remainder of the paper is structured as follows: the problem definition and model is introduced in Section 2, the solution method is described in Section 3, experiments are presented in Section 4, and the paper is concluded in Section 5.

2 Problem Definition and Model

The problem addressed in this paper is defined in detail in [3], and it can be categorized as ASBI|RVNO|PLO according to the notation introduced in [11]. The search space of the problem is defined by the schedule period, skill types, shift types, and nurses. The parameters of each dimension of the search space is user-defined. Nurses are defined with their own individual contracts. Shift types are defined by their start and end times, rest time before and after, and the effective job times.

The solution of the problem, the roster, consists of a set of assignments. An assignment is defined by a shift type that is assigned to a nurse on a particular day and for a particular skill type of her. Several hard and soft constraints are applied to the problem (Table 1). The non-trivial constraints like horizontal and coverage constraints also involve user parameterization to a high degree. Most of the constraints that are defined on shift types are defined on a set of compatible shift types instead of a single shift type [3].

Hard Constraints	Soft Constraints
Single Assignment Start Per Nurse Per Day	Coverage Constraints
No Overlap between Assignments	Assignment to the Primary Skill
Honour Skill Types	Rest Times
Operations on Defined Assignments Only	Requests
Schedule Locks	Horizontal Constraints

Table 1 Constraints

3 Solution Method

Dowsland et al. combined simulated annealing as an acceptance criterion with tabu search as the selection method in a hyperheuristic [8]. Simulated annealing acceptance criterion accepts all improving and equal quality moves. The remaining moves are accepted with a probability that decreases throughout the execution. Simulated annealing is combined with simple random selection method in this study.

Kendall and Mohammad used great deluge as an acceptance criterion in a hyperheuristic [10]. The selection method they have used is the simple random. Similar to simulated annealing, all improving and equal quality moves are accepted by great deluge. However, the worsening moves are accepted only if they are less than a variable called the deluge value. The deluge value is decreased throughout the execution.

There are six problem-specific neighbourhoods defined in [3]: *assign shift*, *delete shift*, *single shift-day*, *change assignment based on compatible shift type*, *change assignment based on compatible skill type*, and *general assignment change*. VNS algorithm presented in [3] carried out a search in a steepest-descent fashion with few exceptions over these neighbourhoods. In this study, a heuristic over each neighbourhood is defined. These heuristics check a fixed number of solutions in the neighbourhood of the current solution and return the one with the best fitness value at each iteration. This strategy is referred to as tournament strategy, and the number of solutions checked at each iteration is referred to as the tournament factor.

Bilgin et al. experimented with six different neighbourhood sets in [3]. A decision criterion based on the existence of the secondary skill types of nurses that chooses between two different neighbourhood sets is found out to be the most promising way of the composition of the neighbourhood set overall. This decision criterion chooses the neighbourhood set that is composed of *assign shift*, *delete shift*, *single shift-day*, and *general assignment change*, and adds *change assignment based on compatible skill type* to this set, if the nurses have secondary skill types. The heuristic set that is deployed in this study is composed using the same strategy.

4 Experiments

4.1 Experimental Settings

Experiments are carried out on the same data set, in the same way and under the same conditions as in [3] to enable comparisons between the results from both studies. The data set is collected from six different wards in two hospitals. It reflects the diversity of the problem properties among different wards and institutions. Three different scenarios are considered for each data set: normal, overload, and absence. Overload scenario

Emergency	Normal		Overload		Absence	
VNS-*	11234.05	178.80	26871.33	258.42	21175.67	19.12
SA-6-128	**10922.50**	**199.16**	26836.33	142.09	**21146.67**	**0.00**
SA-6-256	11038.50	316.31	**26633.50**	**108.87**	**21146.67**	**0.00**
GD-6-128	12087.17	765.41	27382.17	228.44	21149.17	2.64
GD-6-256	11501.83	354.71	26903.67	132.96	21151.17	9.26

Table 2 Emergency Results

Geriatrics	Normal		Overload		Absence	
VNS-*	5132.17	293.30	11484.50	398.61	8999.83	282.10
SA-6-128	**3706.50**	**64.92**	**9686.33**	**57.76**	**8140.00**	**0.00**
SA-6-256	**3765.50**	**100.95**	**9647.67**	**38.64**	**8140.00**	**0.00**
GD-6-128	3824.50	97.19	9915.00	80.52	**8140.00**	**0.00**
GD-6-256	3813.17	101.93	9820.50	81.02	**8140.00**	**0.00**

Table 3 Geriatrics Results

Reception	Normal		Overload		Absence	
VNS-*	22234.67	197.33	53414.17	228.00	28648.67	120.74
SA-6-128	**21705.67**	**186.75**	**52893.17**	**136.32**	**28126.67**	**0.00**
SA-6-256	**21622.17**	**183.87**	**52981.67**	**74.05**	**28126.67**	**0.00**
GD-6-128	21990.17	147.59	**52889.67**	**123.07**	28223.17	113.73
GD-6-256	**21792.67**	**216.03**	53119.17	218.94	**28165.67**	**94.77**

Table 4 Reception Results

Meal Preparation	Normal		Overload		Absence	
VNS-*	3018.80	36.10	**10982.10**	**35.41**	5448.33	116.53
SA-6-128	**2994.70**	**39.29**	11011.20	39.58	**4925.17**	**49.38**
SA-6-256	**2967.73**	**45.32**	**10942.50**	**31.63**	**4912.33**	**38.31**
GD-6-128	3117.13	27.26	11122.90	40.46	**4954.17**	**48.72**
GD-6-256	3089.03	55.50	11074.70	53.18	4978.17	53.23

Table 5 Meal Preparation Results

refers to a situation where the number of requested nurses is higher than the normal scenario. Absence scenario refers to rescheduling of a roster due to unforeseen absence of a nurse for a week. The input data, a sample output and penalty report from each ward-scenario couple are published in [2].

The algorithms are implemented in C#. MS Visual Studio 2005, Professional Edition is used to carry out the experiments. The experiments are carried out on MS Windows Server 2003 Enterprise Edition SP 2 and Intel Pentium 4 CPU with 2.40 GHz and 2.00 GB of RAM.

Psychiatry	Normal		Overload		Absence	
VNS-*	8706.00	134.43	10643.00	65.50	12819.00	255.45
SA-6-128	8248.00	93.90	**9995.00**	**90.95**	**11786.00**	**170.18**
SA-6-256	**8117.00**	**98.78**	**10021.00**	**127.06**	**11804.00**	**139.54**
GD-6-128	8410.00	76.74	10223.00	204.56	12034.00	272.40
GD-6-256	8253.00	181.78	10196.00	180.26	12060.00	99.44

Table 6 Psychiatry Results

Palliative Care	Normal		Overload		Absence	
VNS-*	50201.25	1137.85	51217.50	685.19	56626.50	557.74
SA-6-128	**48955.25**	**717.77**	51109.00	932.06	**55020.50**	**117.38**
SA-6-256	**48983.25**	**1063.56**	50709.50	740.64	**55008.50**	**228.98**
GD-6-128	**48438.50**	**682.60**	51161.75	815.27	**54997.50**	**191.93**
GD-6-256	49677.00	1159.21	50786.00	681.97	**55048.00**	**157.19**

Table 7 Palliative Care Results

4.2 Experimental Results

The objective of the experimentations is to compare the performances of the hyperheuristics with the performance of the variable neighbourhood search. For this comparison, the results of the best performing variable neighbourhood search settings from [3] are used. Only the best results on each problem instance is taken for the comparison from the paper [3].

Hyperheuristics are denoted with X-i-j in Tables 2-7. 'X' denotes the hyperheuristic type: SA for simulated annealing, GD for great deluge. The selection method used in the experiments is simple random. Same heuristics set is used in hyperheuristics throughout the experiments carried out in this study. This heuristic set is denoted with 6, and it is based on the neighbourhood set 6 in [3]. 'j' refers to the tournament factor of the heuristics.

The average fitness values over ten runs and their standart deviations are given in Tables 2-7. Wilcoxon test has been used to detect statistically significant variances between the results. The confidence level is 95%. In Tables 2-7, data that are highlighted with bold characters denote the best results and the results that are not significantly worse than the best results.

Hyperheuristic algorithms performed significantly better than the VNS algorithms on 16 out of 18 problem instances. VNS algorithms performed as good as hyperheuristics only on palliative care and meal preparation wards, both overload scenarios. Simulated annealing hyperheuristic with the tournament factor 256 was among the best performers on 17 out of 18 problem instances. Same hyperheuristic with the tournament factor 128 was among the best performers on 15 out of 18 problem instances. Great deluge hyperheuristic with the tournament factor 128 was among the best performers on 6 out of 18 problem instances, and same hyperheuristic with the tournament factor 256 on 5 out of 18 problem instances. Experimental results suggest that simulated annealing hyperheuristic with the tournament factor 256 is the most promising solution method on the nurse rostering problem introduced in [3].

5 Conclusions

Nurse rostering problem in Belgian hospitals was tackled successfully with a VNS algorithm in a previous study [3]. In the same study, the composition of the neighbourhood set based on problem properties was proposed. In this study, tournament heuristics based on the neighbourhoods from the previous study are implemented. One of the neighbourhood sets was composed according to the fact whether the nurses had secondary skill types or not. This set was among the best performing neighbourhood sets on most cases. The heuristics set used in this study is also composed according to this logic.

In this study, simulated annealing and great deluge hyperheuristics are used to deploy the tournament heuristics set. Two different tournament factors, 128 and 256, are experimented with. The results of the best performing VNS methods reported in [3] are clearly improved by hyperheuristic methods on 16 out of 18 cases. On the remaining two cases hyperheuristic variants performed as good as the best performing VNS variant. As a conclusion, simulated annealing hyperheuristic with the tournament factor 256 performs best on overall.

Further hyperheuristics are planned to be experimented over the heuristics set at hand. The objective of the future work will be to study the relationships with the problem instance properties and the solution method performances. These way, selection of the most appropriate solution method and the parameter according to the problem input will be possible.

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