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Nurse and Paramedic Rostering with Constraint Programming: A Case Study*

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Abstract. The nurse rostering problem consists in generating a configuration of daily schedules for a set of nurses satisfying a set of constraints. The problem is known to be computationally challenging as it must consider different requirements such as minimal area or floor allocations, different skills, working regulations, as well as personnel wishes. The literature presents several successful work devoted to this problem, however there still is limited evidence about real cases of nurse rostering, in particular solved with constraint programming. The aim of this paper is to illustrate a real case study involving the design of a constraint programming solution for nurse rostering. The solution is devoted to a set of mid-size Chilean hospitals where nurse rostering is done manually using a very uncommon shift sequence called the "fourth shift" system. We present a classic model and a global constraint-based model that can be applied generically to any fourth shift health care center.

Key words: Rostering, Constraint Programming, Heuristic Search.

1. Introduction

Nurse rostering problems (NRPs) corresponds to a class of scheduling problem commonly found in health care centers. The idea is to produce a configuration of

*This paper is an extended and improved version of [19] daily schedules for a set of nurses satisfying a set of constraints. The problem presents a great challenge for researchers and personnel managers in hospitals. Indeed, different requirements must be taken into account such as minimum number of nurses, different skills, legal regulations that may vary from one country to another, as well as unexpected personnel needs. There exist different generic and commercial solutions, however they hardly meet the requirements of all hospital, clinics, and health care centers in general due to the wide variety of constraints. As a result, health centers tend to implement a tailored system that satisfies their specific needs or simply to design rosters by hand. However, manually rostering is expensive in terms of time and effort, and commonly fails to satisfy the complete set of needs that are critical for the health care center operation.

In this paper, we study the real case of six mid-size Chilean health care centers: Ciudad del Mar Clinic Center, Child Hospital, Carlos Van Buren Hospital, Miraflores Clinic Center, Reñaca Clinic Center, and Valparaíso Clinic Center. All centers have similar size and features. They have between 30-50 nurses, 30-50 paramedics, 5-10 chief nurses, and receive 1000-2000 patients per month. The centers are also organized in similar areas: Urgency, Medical Center, Operating Rooms, Intensive-care Unit, and Hospitalization. As in most of Chilean hospitals, they use the "fourth shift" system, which is a very uncommon working shift system. In the six centers, the main administrative processes are already automated. However, nurse rostering is done manually, which is error-prone and time consuming. Therefore, a main goal is to design an automated system for roster generation.

The literature presents a large list of work devoted to NRPs. Classical operational research methods such as linear, integer, and goal programming were early employed to solve such a problem [22, 17, 28]. A main problem in this context is that nurse rostering may have several or application-specific constraints to allow for a suitable mathematical programming formulation. Evolutionary computing has also been strongly involved in scheduling, and particularly in rostering problems. Solutions to NRPs based on metaheuristics propose the use of tabu search [13, 5], simulated annealing [27], genetic algorithms [3, 2], and scatter search [6]. Constraint programming is another optimization technique used for nurse rostering, some examples can be seen in [1, 4, 23] and [24]. The efficient use of global constraints for an efficient NRP is reported in [16] Constraint programming has also been combined with other incomplete techniques for instance, with local search [21], with variable neighborhood search [20], and tabu search [15].

Although there is a large list of successful work devoted to NRP, there still exist limited knowledge and research experience about real cases of nurse rostering solved with constraint programming. In this paper, we focus on presenting a real case of nurse rostering based on the study of six mid-size health care centers. We model the NRP as a Constraint Satisfaction Problem (CSP) and then we solve it via state-of-the-art Constraint Programming (CP) techniques. We present two models, one based on logical relations and other one based on global constraints, specially the regular constraint. Both models have been implemented in the Ecl^{i}ps^e solver and generate suitable rosters within some seconds instead of manually some days. We believe that this work will be useful to increase the experience in real cases of nurse rostering as well as to future NRP researchers.

The outline of this paper is as follows: Section 2 gives an overview of CP and related solving techniques. A real case of nurse rostering based on the study of the six aforementioned health care centers is described and modeled in Section 3. A second model based on regular constraints is described in Section 4. Some experiments are presented in Section 5. Finally, we conclude and give some directions for future work.

2. Constraint Programming

Constraint Programming is a relatively modern technology for solving constraint satisfaction and constraint optimization problems. It has arisen as a combination of techniques mainly coming from the operational research domain, artificial intelligence, and programming languages. The last 20 years CP has been successfully applied in different application areas, for instance to express geometric coherence in computer graphics, for the conception of complex mechanical structures, to ensure and/or restore data consistency, to locate faults in electrical engineering, and even for sequencing DNA in molecular biology [14].

In CP, a problem is formulated as a CSP. This representation mainly consists in a sequence of variables attached to domain, and a set of constraints. Formally, a CSP P is defined by a triple $P = \langle X, D, C\rangle$ where:

- X is an n-tuple of variables $X = \langle x_1, x_2, \ldots, x_n\rangle$.
- D is a corresponding n-tuple of domains $D = \langle d_1, d_2, \ldots, d_n\rangle$ such that $x_i \in d_i$, and d_i is a set of values, for $i = 1, \ldots, n$.
- C is an m-tuple of constraints $C = \langle c_1, c_2, \ldots, c_m\rangle$, and a constraint c_j is defined as a subset of the Cartesian product of domains $d_{j_1} \times \cdots \times d_{j_{n_j}}$, for $j = 1, \ldots, m$.

A solution to a CSP is an assignment $\{x_1 \to a_1, \ldots, x_n \to a_n\}$ such that $a_i \in d_i$ for $i = 1, \ldots, n$ and $(a_{j_1}, \ldots, a_{j_{n_j}}) \in c_j$, for $j = 1, \ldots, m$.

2.1. CSP Solving

CSPs are commonly solved by building on the fly a tree data structure. This structure contains the potential solutions and it is explored by using a backtracking-based procedure. In general two main phases are involved: enumeration and propagation. The enumeration phase instantiates variables in order to create branches of the tree, while the propagation phase attempts to prune the tree by filtering from domains the unfeasible values. This is possible by using the so-called consistency properties (see [7] for a detailed description about constraint propagation).

A general procedure for solving CSPs is depicted in Algorithm 1. The idea is to generate partial solutions until a result is reached, applying backtracking when inconsistencies are found. The algorithm has as input the set of constraints and domains. Then, a while loop encloses a set of actions to be performed until success (*i.e.* a solution is reached) or a failure is detected (*i.e.* no solution is found). The first two enclosed actions correspond to the variable and value selection. The third action is a call to a propagation procedure, which is responsible for attempting to prune the tree. Finally two conditions are included to perform backtracks. A shallow backtrack corresponds to try the next value available from the domain of the current variable, and the backtracking returns to the most recently instantiated variable that has still values to reach a solution.

Algorithm 1

Input: $\mathcal{C}$, $\mathcal{D}$

```
While ¬success or failure do
  Variable_Selection(D)
  Value_Selection(D)
  Propagate_C(D)
  If empty_domain_in_future_var
    Shallow_Backtrack()
  If empty_domain_in_current_var
    Backtrack()
End While
```

3. The NRP model

As we have mentioned, the six health care centers studied present similar features and organization. In particular, they use the uncommon "fourth shift" system, which does not fit at all with the typical 8 hours-shift system (e.g. 8:00→16:00; 16:00→24:00; 24:00→8:00) used in NRP models of most of research papers and hospitals over the world. The "fourth shift" system considers only two shifts per day, denoted as:

- Day Shift (D): starts at 8:00 AM and ends at 8:00 PM.
- Night Shift (N): starts at 8:00 PM and ends at 8:00 AM.

The problem considers nurses, paramedics but also chief nurses. The "fourth shift" system applies over those three group of workers. However, a different shift sequence applies over chief nurses, to be explained in subsection 3.3. Hence, the model to be presented is composed of three group of constraints:

- Nurses constraints
- Paramedic constraints
- Chief nurses constraints

Nurse, paramedic and chief nurses constraints are equivalent for the six hospitals, so, we illustrate only one constraint formulation. This formulation works for the six hospitals, and can slightly be modified to be adapted to any "fourth shift"-based hospital.

3.1. Nurses constraints

Following the "fourth shift" system for nurses, shifts are assigned in the following order: Day 1: D, Day 2: N, Day 3: Off, Day 4: Off. A complete planning considers 28 days (see Fig. 1) as it corresponds to the lowest common multiple of 4 (a cycle of nurse shifts) and 7 (the week). Hence, for a nurse $i \in \{1, \ldots, nurses\}$ and a day $j \in \{1, \ldots, 28\}$, we consider the following set of variables, where 0 denotes day off, 1 denotes day shift, and 2 denotes night shift.

$$V_{i,j} \in \{0, 1, 2\}$$

The sequence: Day 1: D, Day 2: N, Day 3: Off, Day 4: Off, is modeled by means of four constraints.

1. A day shift must be followed by a night shift, for $i \in \{1, \ldots, nurses\} \wedge j \in \{1, \ldots, 27\}$
$$(V_{i,j} = 1 \Rightarrow V_{i,j+1} = 2)$$
2. A night shift must be followed by an off day, for $i \in \{1, \ldots, nurses\} \wedge j \in \{1, \ldots, 27\}$
$$(V_{i,j} = 2 \Rightarrow V_{i,j+1} = 0)$$
3. Two off days must be followed by a day shift, for $i \in \{1, \ldots, nurses\} \wedge j \in \{1, \ldots, 26\}$
$$(V_{i,j} = 0 \wedge V_{i,j+1} = 0) \Rightarrow (V_{i,j+2} = 1)$$
4. A night shift must be followed by two off days, for $i \in \{1, \ldots, nurses\} \wedge j \in \{1, \ldots, 26\}$
$$(V_{i,j} = 2) \Rightarrow (V_{i,j+1} = 0 \wedge V_{i,j+2} = 0)$$

Then, we include the `occurrences` global constraint to ensure the required amount per day of day shifts, night shifts, and off nurses*. The global constraint `occurrences` $(Value, Vars, N)$ ensures that $Value$ occurs N times in the $Vars$ list. Let V_j denote the set of variables $\{V_{1,j}, \ldots, V_{nurses,j}\}$ for $j \in \{1, \ldots, 28\}$:

5. $nurses/2$ nurses must be off per day
$$\texttt{occurrences}(0, V_j, nurses/2)$$
6. $nurses/4$ day shifts per day
$$\texttt{occurrences}(1, V_j, nurses/4)$$

*Let us note that the amount of shifts required per day are regulated by administrative criteria of each Hospital.

7. $nurses/4$ night shifts per day

$$\texttt{occurrences}(2, V_j, nurses/4)$$

	1	2	3				…				26	27	28
1	0	0	1	2	0	0	…	1	2	0	0	1	2
2	0	0	1	2	0	0	…	1	2	0	0	1	2
	1	2	0	0	1	2	…	0	0	1	2	0	0
⋮							⋮						
	0	1	2	0	0	1	…	2	0	0	1	2	0
nurses	2	0	0	1	2	0	…	0	0	1	2	0	0

1	2	0	0	1	2	0	…	0	0	1	2	0	0
2	2	0	0	1	2	0	…	0	0	1	2	0	0
	1	2	0	0	1	2	…	1	2	0	0	1	2
⋮							⋮						
	1	2	0	0	1	2	…	1	2	0	0	1	2
paramedics	2	0	0	1	2	0	…	0	0	1	2	0	0

1	0	0	1	1	2	1	…	0	1	1	2	1	1
2	0	0	1	1	2	1	…	0	1	1	2	1	1
⋮							⋮						
chief_nurses	1	1	0	2	0	2	…	1	1	0	2	0	2

Fig. 1. Example of roster generation.

In the studied hospitals, there are nurses holding a senior position that have the faculty to impose some preferences on the schedule. Let us note that preferences are commonly handled with soft constraints. However, preferences here correspond to hard constraints, so they are handled as simple linear constraints. As for the six hospitals, preferences are similar and handled in the same way, we will illustrate only one case (Valparaśo Clinic Center), which is shown below.

8. Nurse 3 prefers not to be off on day 1

$$V_{3,1} \neq 0$$

9. Nurses 6 and 12 prefer to start with a day shift

$$V_{6,1} = 1 \ \wedge \ V_{12,1} = 1$$

10. Nurse 10 prefers to be off the third weekend of the cycle

$$V_{10,20} = 0 \ \wedge \ V_{10,21} = 0$$

11. Nurse 11 prefers to be off the second weekend of the cycle

$$V_{11,13} = 0 \ \wedge \ V_{11,14} = 0$$

12. Nurse 13 prefers to be off the first and second Sunday of the cycle

$$V_{13,7} = 0 \ \wedge \ V_{13,14} = 0$$

13. Nurse 15 prefers to be off the first two days of the cycle

$$V_{15,1} = 0 \ \wedge \ V_{15,2} = 0$$

3.2. Paramedics constraints

For paramedics, shifts are assigned in the same way: Day 1: D, Day 2: N, Day 3: Off, Day 4: Off. Thus, the constraints are analogous. For preferences, we illustrate below the case of senior paramedics from Valparaíso Clinic Center for $P_{i,j} \in \{0, 1, 2\}$.

1. Paramedic 3 prefers not to be off on day 1

$$P_{3,1} \neq 0$$

2. Paramedic 6 prefers to be off the third weekend of the cycle

$$P_{6,20} = 0 \ \wedge \ P_{6,21} = 0$$

3. Paramedic 8 prefers to be off the second weekend of the cycle

$$P_{8,13} = 0 \ \wedge \ P_{8,14} = 0$$

4. Paramedic 11 prefers to be off the first and second Sunday of the cycle

$$P_{11,7} = 0 \ \wedge \ P_{11,14} = 0$$

3.3. Chief nurses constraints

As mentioned before, chief nurses are not tied to the same nurse and paramedic shift sequence. They have night or day weeks, that is, they must take either 4 D per week or 3 N per week. The shifts are assigned in order to balance the total amount of workers per day. Hence, for a chief nurse $i \in \{1, \ldots, chief\_nurses\}$ and a day $j \in \{1, \ldots, 28\}$, we consider an analogous set of variables $X_{i,j} \in \{0, 1, 2\}$ and the following set of constraints.

1. Let X_j denote the set of variables $\{X_{1,j}, \ldots, X_{chief\_nurses,j}\}$ for $j \in \{1, \ldots, 28\}$. If the occurrence of N is less than D for a determined day the chief nurse take a night shift. Then, for $j \in \{1, \ldots, 28\}$:

$$(\texttt{occurrences}(1, V_j, N) \ \wedge \ \texttt{occurrences}(2, V_j, D) \ \wedge \ (N < D) \\ \wedge \ \texttt{occurrences}(2, X_j, S)) \Rightarrow \ (S = D - N)$$

2. If the occurrence of D is less than N for a determined day, the chief nurse take a day shift.

$$(\texttt{occurrences}(1, V_j, N) \ \wedge \ \texttt{occurrences}(2, V_j, D) \ \wedge \ (N > D)$$
$$\wedge \ \texttt{occurrences}(1, X_j, S)) \Rightarrow \ (S = N - D)$$

Let us note that if $D = N$ does not matter the shift of the chief nurse. The following constraints ensure specific regulations of the health care centers for chief nurses.

3. $nurses/2$ chief nurses per day, for $j \in \{1, \ldots, days\}$

$$\texttt{occurrences}(1, X_j, nurses/2) \ \vee \ \texttt{occurrences}(2, X_j, nurses/2)$$

4. No more than three consecutive day shifts, for $i \in \{1, \ldots, chief\_nurses\} \ \wedge \ j \in \{1, \ldots, days - 3\}$

$$(X_{i,j} = 1 \ \wedge \ X_{i,j+1} = 1 \ \wedge \ X_{i,j+2} = 1) \Rightarrow \ (X_{i,j+3} = 0)$$

5. Four day shifts or three night shifts per week, and two days off, for $j \in \{1, \ldots, days\}$

$$(\texttt{occurrences}(1, X_j, 4) \ \vee \ \texttt{occurrences}(2, X_j, 3)) \ \wedge \texttt{occurrences}(0, X_j, 2)$$

4. The NRP model including regular constraints

In this section we present a second model for the problem based on regular constraints. A regular constraint is a special global constraint that allows one to enforce a sequence of variables to take a value defined by a finite automaton. This constraint is known to be useful for solving different types of NRP [16]. In this particular case of NRP, the regular constraint can be used to model the shift sequence: Day 1: D, Day 2: N, Day 3: Off, Day 4: Off, described in subsection 3.1. In order to introduce such a global constraint, let us define $M = (Q, \sum, \delta, q_0, F)$ as a Deterministic Finite Automaton (DFA), where:

- Q is a finite set of states.
- $\sum$ is the input alphabet.
- $\delta : Q \times V \to Q$ is the transition function.
- q_0 is the initial state.

- $F \subseteq Q$ is the set of final states.

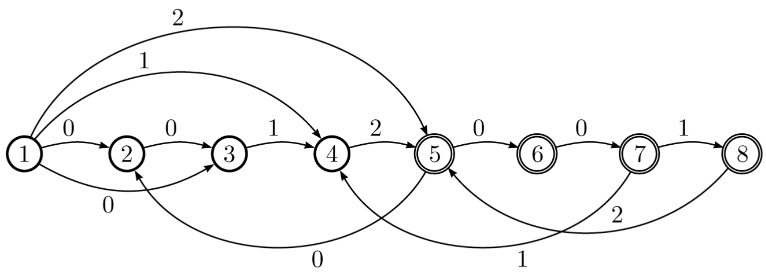

Fig. 2. DFA for modeling the sequence: Day 1: D, Day 2: N, Day 3: Off, Day 4: Off.

We have implemented the regular constraint in Ecl^{i}ps^e, which has the form:

$$\texttt{regular}(\delta, q_0, F, X)$$

The constraint enforces that the sequence of values in array X, which must belong to $\sum$, is accepted by the DFA $M = (Q, \sum, \delta, q_0, F)$.

Then, recalling that nurses and paramedics must follow the sequence: Day 1: D, Day 2: N, Day 3: Off, Day 4: Off, for a 28 days schedule; we identify four sequences that can appear in the whole planning. We represent those sequences as four regular expressions:

```
(0012)+,(0120)+,(1200)+,(2001)+,
```

where 0 denotes day off, 1 denotes day shift, and 2 denotes night shift. The DFA supporting those regular expressions is depicted in figure **??**. The corresponding regular constraint written in Ecl^{i}ps^e is shown below.

```
regular([[0, 1, 2],[0, 2, 3],[1, 3, 4],[2, 4, 5],
         [0, 5, 6],[0, 6, 7],[1, 7, 8],[0, 1, 3],
         [1, 1, 4],[2, 1, 5],[0, 5, 2],[1, 7, 4],
         [2, 8, 5]], 1,[5,6,7,8],X)
```

where δ is composed of a set of transitions of the form $[s, q_a, q_b]$ denoting that a symbol $s \in \sum$ is consumed when a transition from state q_a to state q_b is carried out.

Next, we include the same occurrence constraints (nurse constraints 5,6, and 7) to ensure the required amount per day of day shifts, night shifts, and off nurses.

$$\texttt{occurrences}(0, V_j, nurses/2)$$
$$\texttt{occurrences}(1, V_j, nurses/4)$$
$$\texttt{occurrences}(2, V_j, nurses/4)$$

Likewise, we include the same constraints for handling the nurse preferences (constraints 8 to 13).

$$V_{3,1} \neq 0$$

$$V_{6,1} = 1 \ \wedge \ V_{12,1} = 1$$

$$V_{10,20} = 0 \ \wedge \ V_{10,21} = 0$$

$$V_{11,13} = 0 \ \wedge \ V_{11,14} = 0$$

$$V_{13,7} = 0 \ \wedge \ V_{13,14} = 0$$

$$V_{15,4} = 0 \ \wedge \ V_{15,2} = 0$$

Constraints related to the paramedic shift sequence are analogous and can be modeled via regular constraints in the same way. The remaining constraint about paramedic preferences and chief nurses are equivalent.

5. Experiments

We have performed a set of experiments in order to illustrate the scalability of the proposed solution. For each model, we have tested 6 instances (see Table 1) denoted as xN+yP+zCN, where x is the number of nurses, y the number of paramedics and z the number of chief nurses. The last 6 instances are implemented by using regular constraints. We consider a portfolio of six enumeration strategies coming from the combination of two well-known variable ordering heuristics and three value ordering heuristics, which are described below:

- Variable ordering heuristics:
  - First-Fail (FF): the variable with the smallest domain size is selected.
  - Round Robin (RR): variable are selected in the order they appear in the list.
- Value ordering heuristics:
  - Min: values are tried in increasing order.
  - Middle: values are tried beginning from the middle of the domain.
  - Max: values are tried in decreasing order.

Both models have been implemented in the Ecl^{i}ps^e solver. The experiments have been performed on a 3.06GHZ Intel Core2 Duo with 2GB RAM computer running Ubuntu considering a stop criterion of 1000 seconds. Results show the scalability of both models. Rosters are generated in less than 1 second for 72 workers, in less than 3 seconds for 288 workers, and in about 8 seconds for 576 workers. A small overhead can be appreciated in the use of regular constraints, which is explained by the computation of the DFA.

Table 1. Experiments (in seconds)

	FF			RR		
	min	med	max	min	med	max
16N+16P+4CN	0.15	0.14	0.14	0.14	0.12	0.12
32N+32P+8CN	0.41	0.34	0.36	0.38	0.37	0.38
64N+64P+16CN	1.29	0.95	0.97	0.94	0.91	0.91
96N+96P+16CN	2.26	1.85	1.84	1.67	1.60	1.65
128N+128P+32CN	120.31	3.20	3.25	2.72	2.70	2.69
256N+256P+64CN	t.o.	10.44	10.26	8.50	8.17	8.30
`regular`						
16N+16P+4CN	0.25	0.21	0.21	0.21	0.20	0.21
32N+32P+8CN	0.58	0.48	0.49	0.48	0.46	0.47
64N+64P+16CN	1.76	1.29	1.23	1.27	1.17	1.18
96N+96P+16CN	3.03	2.34	2.25	2.20	1.96	1.96
128N+128P+32CN	120.50	3.76	3.57	3.65	3.13	3.20
256N+256P+64CN	t.o.	11.15	11.06	10.76	9.10	9.11

6. Conclusion and Future Work

In this paper, we have presented a real nurse rostering solution for an uncommon case of shift system, largely used in Chile. The study has been focused on six mid-size Chilean health care centers. We have presented two models by using state-of-the-art CP techniques, tools, and global constraints. The first model is mainly composed of logical relations, while the second is supported by the use of regular constraints. Although such models have been based on six real cases, they can easily be adapted to any "fourth shift"-based hospital, by mainly modifying the specific preferences. Both models have been implemented and solved in the Ecl^{i}ps^e solver allowing a fast and correct nurse assignment. The solution introduced here is ongoing work, and it can clearly be extended by considering bigger clinic centers. The combination of CP and SAT technology [26] or the integration of autonomous search [11, 18, 25, 10, 12, 10, 9, 8] will be interesting research directions to pursue as well.

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