# Combining VNS and soft global constraints for solving NRPs

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Due to their complexity and importance in real world modern hospitals, Nurse Rostering Problems (NRPs) have been extensively studied in both OR and AI for more than 40 years [1, 2]. Soft global constraints (SGC) proposed by [8, 9, 10] take advantage from the semantics of the constraint and from the semantics of its violation to efficiently perform filtering. NRPs can be modeled in a concise and elegant way using SGC [7]. In this paper, we show that NRPs can also be solved efficiently with solutions quality and computing times close to those obtained using ad'hoc methods.

## 1 Soft Global Constraints

Over-constrained problems are generally modeled as Constraint Optimization Problems (COP). A cost is associated to each constraint in order to quantify its violation. A global objective related to the whole set of costs is usually defined (e.g. to minimize the total sum of costs). Global constraints are often key elements in successfully modeling and solving real-life problems due to their efficient filtering. But, for over-constrained problems, such filtering can only be performed in very particular cases. To each SGC $c$ are associated a violation measure $\mu_c$ and a cost variable $Z_c$ that measures the violation of $c$. So the COP is transformed into a CSP where all constraints are hard and the cost variable $Z = \sum_c Z_c$ will be minimized. If the domain of a cost variable is reduced during the search, filtering will be performed on domains of other cost variables. Soft versions of well known global constraints such as `allDifferent`, `gcc` and `regular` have been proposed in [8, 9, 10]. First, they enable to model in a concise and elegant way over-constrained problems like NRPs [7]. Moreover, they provide efficient filtering as well as for (usual) global constraints.

## 2 Combining VNS and SGC filtering

VNS/LDS+CP [6] is a generic local search method based on Variable Neighborhood Decomposition Search [4]. Neighborhoods are obtained by unfixing a part of the current solution according to a neighborhood heuristic. Then the exploration of the search space related to the unfixed part of the current solution is performed by a partial tree search (Limited Discrepancy Search, [5]) with constraint propagation. Variable ordering for LDS selects the variable having the lowest ratio domain cardinality/degree. Value ordering selects the value which leads to the lowest increase of the violation cost. Constraint propagation is performed using SGC filtering. We considered three neighborhood heuristics : `rand` (which randomly selects nurse plannings), `maxV` (which selects the nurse plannings having the highest violation cost), and `dilution` : half of the nurse plannings are selected using `maxV`, and the other ones using `rand` in order to alternate between *intensification* phases using `maxV`. by considering nurse plannings with high violation cost, and *diversification* phases.

## 3 Experimental Results

The ASAP site (`http://www.cs.nott.ac.uk/~tec/NRP/`) records a large and various set of NRPs instances as well as the methods used to solve them. We performed experimentations over

| Instances | $n \times d$ | $s$ | opt. | Ad'hoc Approaches | | | VNS/LDS+CP | |
|---|---|---|---|---|---|---|---|---|
| | | | | **Algo.** | **Quality** | **Time (s)** | **Quality** | **Time (s)** |
| Ozkarahan | 14×7 | 3 | 0* | LP | - | - | **0** | 1 |
| Millar | 8×14 | 3 | 0* | Network | 2550 | *500* | **0** | 1 |
| | | | | TS+B&B | **0** | 1 | | |
| Musa | 11×14 | 2 | 175* | - | 199 | *28* | **175** | 11 |
| LLR | 26×7 | 4 | 301* | TS+CP | 366 | 16 | **312** | 275 |
| BCV-5.4.1 | 4×28 | 5 | 48* | Hybrid TS | **48** | 5 | **48** | 1 |
| | | | | VDS | **48** | 128 | | |
| Azaiez | 13×28 | 3 | 0* | LP | **0** | 150 | **0** | 43 |
| Valouxis | 16×28 | 4 | 20* | VDS | 60 | 32450 | **20** | 9128 |
| GPOST_A | 8×28 | 3 | 5* | IP [3] | **5** | 1285 | 8 | 474 |
| GPOST_B | 8×28 | 3 | 3* | 2-Phases | **3** | 14 | **3** | 367 |
| | | | | IP [3] | **3** | 441 | | |
| Ikegami 3Shift-DATA1 | 25×30 | 4 | 2* | TS+B&B | 6 | 111060 | 63 | 671 |
| ORTEC01 | 16×31 | 5 | 270* | IP+VNS | 541 | 3000 | 341 | 6046 |
| | | | | HO+VNS | 684 | 8600 | | |
| | | | | IP [3] | **270** | 120 | | |

TAB. 1 – Best results for ad'hoc methods vs best results for VNS/LDS+CP.

selected instances which are representative of the diversity and the size of NRPs (see Table 1 where $n$ is the number of nurses, $d$ the planning duration and $s$ the number of shifts). For each instance, **we always compare with the best ad'hoc method** for solving it. For all instances, except the first two ones where the processor is unknown, CPU times are normalised. Reported CPU times for our method always include the computing time for obtaining the initial solution. Despite its genericity and flexibility, our method has obtained (for more results, see [7]) :

- Solutions of better quality and better CPU times for `Millar`, `Musa`, `LLR`, `BCV` and `Valouxis`.
- Very promising results on instances as `GPOST_A`, `GPOST_B`, and `ORTEC_01`. The excellent CPU times obtained on these instances by [3] greatly take advantage of the structure of the problem by deriving new pattern rules to allocate particular shifts.

For very large instances as `ORTEC` or `Montreal` performances of our method could be greatly improved by using neighborhood heuristics especially designed for NRPs, and by reducing the lack of communication between SGC by extending arc consistency for soft binary constraints.

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