# Hybrid Variable Neighborhood Approaches to Exam Timetabling

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## 1. Introduction

A very important factor for the success of a local search is the neighborhood employed during the search. Variable Neighborhood Search (VNS) algorithms [5] employ more than one neighborhood and change the employment of these neighborhoods during the search. It provides a very effective way of escaping from local optima and is both versatile and successful compared to other local search techniques when applied to a range of different problem domains [5]. The aim of our research is to investigate the VNS methodology and their hybridizations with Genetic Algorithms for the university exam timetabling problem.

The exam timetabling problem consists of assigning a given set of exams to a number of timeslots subject to a set of constraints. These include avoiding the schedule of exams with common students to the same time, and minimizing the students taking exams scheduled too close to each other [2,3,8]. Metaheuristics represent the state-of-the-art in the last 10 years [7].

The most commonly used neighborhood in timetabling research is the single move neighborhood that reallocates single exams to new feasible timeslots. In this work we analyzed variants of neighborhood structures in VNS and demonstrated that a biased VNS is able to provide high quality performance across a number of timetabling problem instances. Furthermore this VNS approach when hybridized with a Genetic Algorithm that intelligently selects its neighborhoods is very successful compared with the state-of-the-art approaches. Indeed, the method produces some of the best known results in the literature in terms of solution quality on the standard benchmark problems.

## 2. The VNS and the GA-VNS Approach

Our initial tests include the development of VNS employing a set of 9 neighborhoods including single move, swap, move 2-5 exams randomly, move a whole timeslot, swap two timeslots, etc, with and without the Kempe chain move. A Kempe chain move neighborhood involves swapping a subset of exams that clash with each other in two distinct timeslots, and thus a chain of exams are moved between timeslots. It can represent much flexibility in the search, and has shown to be very successful when employed within a Simulated Annealing for exam timetabling [6].

We carried out a number of experiments on variants of VNS including Descent-ascent, Best Improvement, Variable Neighborhood Descent [5] and a Biased VNS employing the above mentioned 9 neighborhoods. The Biased VNS, which is based on a standard Variable Neighborhood Descent provided the best performance across the set of benchmark instances (see next section). At each step, an exam is chosen from a set of exams causing the highest penalty in the timetable rather than completely randomly from the exam set. This exam is then used to define a move using the Kempe chain neighborhood. That is, those exams that clash with this selected exam are swapped between the two timeslots involved.

Based on the Biased VNS, a Genetic Algorithm was then developed for neighborhood selection in VNS (GA-VNS). The aim is to investigate the use of search algorithms to investigate, at the high level, the employment of different neighborhoods within efficient VNS approaches. GA is shown to be very effective to evolve subsets of neighborhoods employed in efficient VNS approaches. As far as we are aware, this is an entirely new approach in both VNS and GA research on timetabling problems. Based on the original 9 neighborhoods used, a number of extra neighborhoods are introduced to allow an extensive study on different neighborhoods in VNS. These include making random 1-4 Kempe chain moves and Kempe chain moves with the exams causing the highest costs in the timetable, making in total 23 neighborhoods in the VNS. Of course more neighborhoods could be introduced based on these widely studied neighborhoods. This work is strongly related to the recent work on hyper-heuristics where high level heuristics are employed to choose low level heuristics that are used to work on solutions [1].

The chromosome in the GA represents the set of neighborhoods to be used within. The ordering of neighborhoods is unimportant since VNS cycles through all neighborhoods. Duplicates of neighborhoods within the chromosome are removed when the chromosome is translated to the actual set of neighborhoods to be used within VNS. Note that a chromosome in which all elements are the same would represent just that single neighborhood supplied to the VNS. A roulette wheel selection is used and 70 percent of the chromosomes are selected for the standard one-point crossover. The mutation operator changes an element (gene) of a chromosome to a random neighborhood with a given probability which provide the random element of the evolution.

## 3. Experiments

The benchmark exam timetabling problems firstly introduced in [4] have been tested. Over the years, two versions of the datasets have circulated using the same name. We have renamed the datasets and discussed the issue in more detail in [7]. The new naming conventions presented in [7] are used here. For more details see http://www.cs.nott.ac.uk/~rxq/data.htm.

Table 1 gives the best results found by the GA-VNS and VNS variations, and the best known solutions reported in the literature. We can see that the GA-VNS approach performs very well compared against the best approaches in the literature, reporting the best solutions for 6 out of 11 problems.

Table 1. Best results of GA-VNS, Biased VNS and in the literature for benchmark exam timetabling problems

| Data Set | Best Reported | Biased VNS | Best GA-VNS | Neighborhood Subset |
|---|---|---|---|---|
| car91 I | **4.6** | 4.9 | **4.6** | 16 |
| car92 I | 4.0 | 4.1 | **3.9** | 19 |
| ear83 I | **29.3** | 33.1 | 32.8 | 12 |
| hec92 I | **9.2** | 10.3 | 10.0 | 16 |
| kfu93 I | 13.5 | 13.2 | **13.0** | 15 |
| lse91 I | **9.6** | 10.4 | 10.0 | 20 |
| sta83 I | 157.3 | **156.9** | **156.9** | 23 |
| tre92 I | 8.0 | 8.3 | **7.9** | 13 |
| uta92 I | **3.2** | 3.3 | **3.2** | 15 |
| ute92 I | **24.4** | 24.9 | 24.8 | 18 |
| you83 I | **36.2** | 36.3 | 34.9 | 13 |

The number of neighborhoods which are searched by the GA in VNS that produce the best solutions is also given in Table 1. They represent different sub-sets of the 23 neighborhoods studied, and demonstrate the requirement of further in-deep investigations. Due to the modular neighborhood structure of VNS, the technique can be easily adapted and applied to exam timetabling problems. Further work will also fully investigate the application of VNS to problems with a wider range of side constraints without taking away from the generality of the method.

## References

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