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A bi-criteria hybrid Genetic Algorithm with robustness objective for the course timetabling problem

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ABSTRACT

Traditional methods of generating timetables may yield high-quality solutions, but they may not yield robust solutions that may easily be adapted to changing inputs. Incorporating late changes by making minimum modifications on the final timetable is an important need in many practical applications of timetabling. In this study, we focus on a subset of course timetabling problems, the curriculum-based timetabling problem. We first define a robustness measure for the problem, and then try to find a set of good solutions in terms of both penalty and robustness values. We model the problem as a bi-criteria optimization problem and solve it by a hybrid Multi-objective Genetic Algorithm, which makes use of Hill Climbing and Simulated Annealing algorithms in addition to the standard Genetic Algorithm approach. The algorithm is tested on the well known ITC-2007 instances and shown to identify high quality Pareto fronts.

1. Introduction

The course timetabling problem is one of the most widely studied problems in educational timetabling. As different institutions have different requirements and rules, numerous classes of timetabling problems can be found in the literature (Kingston, 2013; Pillay, 2014; Schaerf, 1999). A widely accepted timetabling classification made by Schaerf (1999) classifies timetabling problems into three main classes, namely school timetabling (also known as the class/teacher model), course timetabling and examination timetabling. Course timetabling (also known as university course timetabling) is further divided into two sub categories, post-enrollment-based and curriculum-based course timetabling.

The timetabling problem introduced by the Second International Timetabling Competition (ITC-2007) is now considered standard, and it contains many characteristics that are common to most variants of the problem. ITC-2007 is divided into three tracks, namely *examination timetabling, post-enrollment-based course timetabling* and *curriculum-based course timetabling* (CB-CTP). The datasets provided for each track include a number of instances with differing size and difficulty levels. In this study, we focus on the CB-CTP track (Di Gaspero et al., 2007), and use the dataset which is comprised of 21 instances as our test bed. The objective of the problem is to minimize the penalty which is defined as a function of the violation of the constraints in the problem. However, we approach it as a multi-objective optimization problem by considering another objective, namely the robustness. In many practical applications of timetabling, the availability of the resources may change, and as a result, the current timetable may no longer be valid. In such situations, late changes should be incorporated in the current timetable but by making minimal modification. In this research we assume the change request will be in the form of a request by an instructor to change one of his/her lectures' time assignment. A timetable is said to be *robust* if its modification does not result in a significantly lower-quality timetable in terms of the penalty function.

In multi-objective optimization problems, objectives under consideration conflict with each other, and optimizing a particular solution with respect to a single objective may yield poor solutions with respect to the other objectives. Thus, a reasonable approach to a multi-objective problem is to find a set of Pareto-optimal solutions, rather than a single solution. These solutions are optimal in the wider sense that no other solution in the search space is superior to them when all objectives are considered. They constitute the so-called Pareto-optimal set or Pareto-optimal front. In a two-objective problem, an objective of a solution in the Pareto-optimal front can only be improved by degrading the other objective. The studies in the area of multi-objective optimization aim to identify the Pareto optimal-front or, if this cannot be done, to generate good approximations of it.

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In this study, we model the CB-CTP of ITC-2007 as a bi-criteria optimization problem where one objective is the penalty function and the other is a robustness metric. Then, we solve it by a hybrid Multi-Objective Genetic Algorithm (MOGA), which makes use of Hill Climbing (HC) and Simulated Annealing (SA) algorithms in addition to the standard Genetic Algorithm (GA) approach with the aim of providing a good approximation to the Pareto-optimal front. To the best of our knowledge, this is the first study in the field of university course timetabling where robustness is considered as an objective. Experimental results show that the approach enables us to obtain very good Pareto fronts.

2. Literature review

Evolutionary approaches have been the primary tools to solve real-world multi-objective problems in the last decade. A thorough discussion of the various aspects of EAs can be found in the following books (Bäck, 1996; Golberg, 1989; Holland, 1975). Multi-objective EAs differ primarily from traditional EAs by using specialized fitness functions and introducing methods to promote solution diversity. There are a number of different EAs developed and implemented for different types of multi-objective optimization problems. The study of Fonseca and Fleming (1993) is among the first studies in this field. Widely cited MOGAs are NSGA (Srinivas and Deb, 1994), SPEA (Zitzler, 1999) and NSGA-II (Deb et al., 2002). A survey of GA-based multi-objective optimization techniques can be found in Coello (2000), and a tutorial describing multi-objective GAs is provided in Konak et al. (2006).

Meta-heuristic approaches have been extensively used to solve timetabling problems, perhaps due to the fact that these problems can vary greatly from one institution to another, and that metaheuristics are, by definition, types of higher level general-purpose algorithms that can be used with a wide range of different problem types. GA (Genetic Algorithm), SA (Simulated Annealing) (Kirkpatrick, 1984) and Tabu Search (TS) (Glover, 1989; 1990) are among the most popular meta-heuristics that have attracted the most attention of researchers and that have been successfully applied to a wider variety of optimization problems. A survey of meta-heuristic-based techniques for timetabling problems can be found in Lewis (2008). The benchmark datasets of the ITC-2007 provide a great opportunity for the researchers to compare the performance of their algorithms with others. Some examples of successful implementations of meta-heuristics for this dataset can be found in Lü and Hao (2010), Abdullah and Turabieh (2012) and Bellio et al. (2012). Interestingly, all of these make use of some kind of a hybrid approach, combining two types of meta-heuristics. Lü and Hao (2010) solves the CB-CTP with a hybrid TS approach. Abdullah and Turabieh (2012) uses a Tabu-based memetic algorithm that hybridises a GA with a TS algorithm for the same problem. Bellio et al. (2012) solves the CB-CTP with a hybrid local search algorithm based on a combination of SA and dynamic TS.

In all of the cases mentioned above, minimization of weighted sum of constraint violations is used as the only objective function. There are a few studies that approach the timetabling problems as multi-objective optimization problems. Carrasco and Pato (2001) use a bi-objective GA to solve school timetabling problem for minimizing violation of soft constraints from two competitive perspective of teachers and classes. Wong et al. (2004) presents a hybrid multi-objective evolutionary algorithm (MOEA) for a capacitated exam proximity problem. The timetable has to offer students maximum free time between exams while keeping the exam period as short as possible. Another multi-objective approach to the same problem is presented by Cheong et al. (2009) again using a MOEA but with a variable-length chromosome representation. However, they do not consider the assignment of exams to rooms, and they focus on the allocation of exams to periods. The exam timetabling problem is treated as a multi-objective optimization problem that involves minimization of the two objectives, which are number of clashes and the number of periods used. Datta et al. (2007) present a multi-objective GA to solve two real university course timetabling problems. The two conflicting soft constraints are taken as the two objective functions. These are (i) minimizing the average number of weekly free time-slots between two classes of a student, and (ii) minimizing the average number of weekly consecutive classes of a teacher. Recently, Mühlenthaler and Wanka (2016) have presented a study in which they consider the *fairness* objective in addition to the *penalty* objective, where fairness is defined as the fair distribution of the penalty assigned to the timetables among different curricula.

The earliest extensive research on scheduling under uncertainty has been done on machine and project scheduling under uncertainty. A recent review of the work done in this area is Ouelhadj and Petrovic (2009). In this literature, the evaluation of robustness is done along two dimensions. On the one hand, when a new schedule is created in response to a disruption the objective function value of the new schedule created should not be significantly worse than the initial one; this is referred to as *quality robustness*. On the other hand, some characteristic(s) of the schedule itself (e.g. start times of operations, assignments of courses to time slots) should not change significantly; this is known as *solution robustness* (Herroelen and Leus, 2004). The general approach of first creating an initial schedule and then reacting to disruption(s) by creating a new schedule is known as proactive–reactive scheduling. A recent example of the work done on reacting to a disruption in university course timetabling is Phillips et al. (2014), where the authors provide a general integer programming-based approach for the minimal perturbation problem in university course timetabling, where minimal perturbation objective is equivalent to the solution robustness objective defined above.

The work presented here is within the proactive–reactive scheduling framework, focusing on the proactive scheduling aspect of this framework. The disruption is a professor requesting a different time slot, and reaction to the disruption takes place in the form of re-assigning one or two lectures to a different time slot. As discussed in Section 3, although our measure of robustness targets quality robustness, solution robustness concern is addressed by limiting the change in the timetable when reacting to the disruption.

Our approach is conceptually similar to those of Jensen (2003) and Akkan et al. (2016). In both of these studies, the idea behind the neighborhood–based robustness measurement is that when an event triggers the need to reschedule and a set of schedules close to the proactive–schedule have good objective function values, one of these solutions in the neighborhood can be chosen to work around this event. The main concept of this approach has certain similarities to *recoverable robustness* developed by Liebchen et al. (2009, p. 3), which they describe as “looking for solutions to an optimization problem which in a limited set of scenarios can be made feasible, or *recovered*, by a limited effort.” Limited effort is “formalized as a class of admissible recovery algorithms” (p. 3). These recovery algorithms are subject to limitations on run time and distance of the new solution from the planned one. We limit the set of scenarios by allowing one professor to request a new time slot and our recovery algorithm assigns one or two lectures to a new time slot.

3. Problem definition

The CB-CTP of ITC-2007 is widely studied, because it applies to many Italian and international universities, although it is slightly