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Discrete Optimization

A honey-bee mating optimization algorithm for educational timetabling problems

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ABSTRACT

In this work, we propose a variant of the honey-bee mating optimization algorithm for solving educational timetabling problems. The honey-bee algorithm is a nature inspired algorithm which simulates the process of real honey-bees mating. The performance of the proposed algorithm is tested over two benchmark problems; exam (Carter's un-capacitated datasets) and course (Socha datasets) timetabling problems. We chose these two datasets as they have been widely studied in the literature and we would also like to evaluate our algorithm across two different, yet related, domains. Results demonstrate that the performance of the honey-bee mating optimization algorithm is comparable with the results of other approaches in the scientific literature. Indeed, the proposed approach obtains best results compared with other approaches on some instances, indicating that the honey-bee mating optimization algorithm is a promising approach in solving educational timetabling problems.

1. Introduction

Educational timetabling problems can be defined as the problem of assigning a number of events (exams/courses) to a given number of timeslots and rooms while satisfying a set of constraints (Qu et al., 2009; Lewis, 2008). These constraints are usually classified into two types. Hard constraints must be satisfied in order to provide a feasible solution, whereas, soft constraints can be violated (but we try to satisfy them as far as possible). The quality of a timetable is measured based on how well the soft constraints have been satisfied.

In recent years, there has been increased research interest into swarm-based approaches and they have been found to be effective in dealing with several NP-hard problems (Yang, 2008). Yang (2008) argued that the main reason for choosing swarm-based approaches is due to their ease of implementation and their flexibility (Baykasoùlu et al., 2007). A number of nature inspired algorithms have been proposed including genetic algorithms, ant colony algorithms, simulated annealing and honey-bee mating algorithms. The honey-bee mating algorithm is a relatively new approach which attempts to model the natural behavior of mating in real honey bees in order to solve combinatorial optimization problems.

Although honey-bee mating algorithms have been widely applied to solve optimization and NP-hard problems (Baykasoùlu et al., 2007), as far as we are aware, there has been no work undertaken to address educational timetabling problems by using a honey-bee mating algorithm. The strengths of honey-bee algorithms are their ability to simultaneously explore (probabilistically guided by the queen's transition in the space) and exploit (by employing a local search at each iteration) the problem search space. The queen (current best solution) is the dominate solution and stores different drone's genotypes in her mating pool. She can use some parts of these genotypes to create new broods, by combining some parts of the queen genotypes with some parts of the drone's genotype. Since the queen is the fittest individual it is hoped that this will evolve superior solutions.

Motivated by the above, this work investigates variants of honey-bee algorithms for solving educational (exam and course) timetabling problems and evaluates the algorithm against other approaches that have been presented in the scientific literature. The proposed variants attempt to avoid premature convergence by maintaining population diversity. These features distinguish honey-bee algorithms from other population based algorithms that have been utilised on university timetabling problems (for example, Burke et al., 1996; Socha and Samples, 2003; Pillay and Banzhaf, 2010).

The proposed method is tested against two benchmark datasets (the Carter un-capacitated dataset for exam timetabling and the Socha course timetabling dataset) and compared with the original honey-bee algorithm and other meta-heuristic methods. Results demonstrate that this nature inspired intelligent technique can be used to obtain high quality solutions for both exam and course timetabling problems.

The rest of the paper is organized as follows. Section 2 reviews population based algorithms for educational timetabling problems.

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The original honey-bee algorithm is presented in Section 3. Our proposed approach is presented in Section 4, followed by our results in Section 5. Finally, concluding remarks are presented in Section 6.

2. Problem descriptions

In this work, the performance of the proposed algorithm is demonstrated over two benchmark problems, which are exam (Carter's un-capacitated datasets) and course (Socha datasets) timetabling problems.

2.1. Exam timetabling problems

Exam timetabling problems can be defined as the allocation of a number of exams to a given number of time periods subject to the following set of hard and soft constraints (Carter et al., 1996; Qu et al., 2009):

- Hard constraint: exams of common students (conflicting exams) cannot be scheduled at the same time. A feasible timetable is one in which all exams have been assigned to feasible timeslots without violating the hard constraints.
- Soft constraint: conflicting exams should be spread as far apart as possible to allow sufficient revision time between exams for students.

The quality of a timetable is given by the minimization of the soft constraint violations. The proximity cost is used to calculate the penalty cost (Eq. (1)) (see Carter et al., 1996; Qu et al., 2009) as follows:

- S is the number of students in the problem.
- m is the number of exams in the problem.
- e is a set of exams.
- t represent the set of timeslots.

$$C = \sum_{k=1}^{m-1} \sum_{l=k+1}^{m} (w_i \times s_{kl})/S, \quad i \in \{0,1,2,3,4\}, \tag{1}$$

where

- s_{kl} is the number of students taking both exams e_k and e_l, if $i = |t_k - t_l| < 5$;
- $w_i = 2^{|4-i|}$ is the cost of scheduling two conflicted exams e_k and e_l (which have common enrolled students) with i timeslots apart, if $i = |t_k - t_l| < 5$, i.e. $w_0 = 16$, $w_1 = 8$, $w_2 = 4$, $w_3 = 4$ and $w_4 = 1$; t_k and t_l as the timeslot of exam e_k and e_l, respectively.

2.2. Course timetabling problem

University course timetabling problems can be defined as assigning a given number of courses to a given number of timeslots and rooms subject to a set of hard and soft constraints (Socha and Samples, 2003). In this work, we have used the same model presented in Socha and Samples (2003), represented as follows:

- A set of courses c_i ($i = 0,\ldots,C$).
- t_n represent the set of timeslots ($n = 1,\ldots,45$).
- A set of R rooms r_j ($j = 0,\ldots,R$).
- A set of F room features.
- A set of M students.

The course timetabling problem consists of assigning every course c_i to a timeslot t_n and room r_j so that the following hard constraints are satisfied:

- No student can be assigned to more than one course at the same time.
- The room should satisfy the features required by the course.
- The number of students attending the course should be less than or equal to the capacity of the room.
- No more than one course is allowed at a timeslot in each room.

The objective is to satisfy all hard constraints and to minimize the number of students involved in the violation of soft constraints. The soft constraints are equally penalized (penalty cost = 1 for each violation per student). The soft constraints are:

- A student should not have a course scheduled in the last timeslot of the day.
- A student should not have more than two consecutive courses.
- A student should not have a single course on a day.

3. Related work in education timetabling

Over the last two decades, meta-heuristic approaches have been successfully applied to educational timetabling problems. For example, graph based heuristics (Burke et al., 2007; Sabar et al., 2009b), tabu search (Di Gaspero and Schaerf, 2001), large neighbourhood search (Abdullah and Burke, 2006), great deluge algorithms (Landa-Silva and Obit, 2008), hybrid algorithms (Sabar et al., 2009a), and population based algorithms including memetic algorithms (Burke et al., 1996), ant colony (Socha and Samples, 2003) and genetic algorithms (Pillay and Banzhaf, 2010) have all been utilized. The honey-bee mating optimization (HBMO) algorithm belongs to the population-based algorithms. In this paper, we review the population based algorithms that have been applied to university timetabling problems. Interested readers are referred to recent surveys in this area (Qu et al., 2009; Lewis, 2008; McCollum et al., 2010; Burke and Petrovic, 2002) for more comprehensive coverage of other methodologies.

3.1. Population based algorithms for exam timetabling

Population based algorithms, such as genetic algorithms and ant colony algorithms, have been utilized to solve exam timetabling problems. Cote and Sabourin (2005) proposed a bi-objective evolutionary algorithm to minimize the timetable length and to space out conflicting exams as much as possible. The recombination operators were replaced by two local searches (tabu search and variable neighbourhood descent) to deal with hard and soft constraint violations. The methods obtained competitive results on a number of benchmark problems. However, replacing the crossover and mutation operators by two local searches led to an increased number of parameters that needed to be tuned, which is one of the main disadvantages of many meta-heuristic approaches.

Eley (2007) applied two ant algorithms to simultaneously construct and improve exam timetables. The first algorithm, MMAS-ET, is based on the MAX–MIN Ant System that was used by Socha and Samples (2003) on course timetabling problems. The second algorithm ANTCOL-ET is a modified version of ANTCOL (originally used by Costa and Hertz (1997) to solve graph colouring problems). Both ant algorithms were hybridized with a hill climber and tested on the Carter benchmark datasets. Results showed that the simple ant system ANTCOL-ET outperformed the more complex MMAS-ET. Indeed, the performance of ant systems can be considerably improved by adjusting the search parameters such as the evaporation rate, the pheromone deposit interval and the number of cycles. However, in the construction stage (exploration), the ants are trying to generate a feasible timetable from scratch by using previous knowledge (pheromone). Therefore, the algorithm may struggle to