A Reinforcement Learning – Great-Deluge Hyper-heuristic for Examination Timetabling

Ender Ozcan
University of Nottingham, United Kingdom
Mustafa Mısır
Yeditepe University, Turkey
Gabriela Ochoa
University of Nottingham, United Kingdom
Edmund K. Burke
University of Nottingham, United Kingdom

ABSTRACT

Hyper-heuristics are identified as the methodologies that search the space generated by a finite set of low level heuristics for solving difficult problems. One of the iterative hyper-heuristic frameworks requires a single candidate solution and multiple perturbative low level heuristics. An initially generated complete solution goes through two successive processes; heuristic selection and move acceptance until a set of termination criteria is satisfied. A goal of the hyper-heuristic research is to create automated techniques that are applicable to wide range of problems with different characteristics. Some previous studies show that different combinations of heuristic selection and move acceptance as hyper-heuristic components might yield different performances. This study investigates whether learning heuristic selection can improve the performance of a great deluge based hyper-heuristic using an examination timetabling problem as a case study.

Keywords: hyper-heuristics, reinforcement learning, great deluge, meta-heuristics, Exam timetabling

INTRODUCTION

Meta-heuristics have been widely and successfully applied to many different problems. However, significant development effort is often needed to produce fine tuned techniques for the particular problem or even instance at hand. A more recent research trend in search and optimisation, *hyper-heuristics* (Burke et al., 2003a; Ross, 2005; Chakhlevitch et al., 2008; Ozcan et al., 2008; Burke et al. 2009a, 2009b), aims at producing more general problem solving techniques, which can potentially be applied to different problems or instances with little development effort. A hyper-heuristic approach is able to intelligently choose an appropriate low-level heuristic, from a given repository of heuristics, to be applied at any given time. Thus, in hyper-heuristics, we are interested in adaptively finding solution methods, rather than directly producing a solution for the particular problem at hand.

Several hyper-heuristics approaches have been proposed in the literature, which can be categorised into approaches based on *perturbative* low-level heuristics, and those based on

constructive low-level heuristics. The latter type of hyper-heuristics builds a solution incrementally, starting with a blank solution, and using constructive heuristics to gradually build a complete solution. They have been successfully applied to several combinatorial optimisation problems such as: bin-packing (Ross et al., 2003), timetabling (Terashima-Marin et al., 1999; Asmuni et al., 2005; Burke et al., 2007, Qu et al., 2008a), production scheduling (Vazquez-Rodriguez et al., 2007), and cutting stock (Terashima-Marin et al., 2005). On the other hand, approaches based on perturbative heuristics, find a reasonable initial solution by some straightforward means (either randomly or using a simple constructive heuristic) and then use heuristics, such as shift and swap to perturb solution components with the aim of finding improved solutions. In other words, they start from a complete solution and then search or select among a set of neighbourhoods for better solutions. Perturbative (improvement) hyper-heuristics have been applied to real world problems, such as, personnel scheduling (Cowling et al., 2001; Burke et al., 2003b), timetabling (Burke et al., 2003b), and vehicle routing problems (Pisinger et al., 2007). In a perturbative hyper-heuristic framework, search is mostly performed using a single candidate solution. Such hyper-heuristics, iteratively, attempt to improve a given solution throughout two consecutive phases: *heuristic selection* and *move acceptance* as illustrated in Figure 1. A candidate solution (S_t) at a given time (t) is modified into a new solution (or solutions) using a selected heuristic (or heuristics). Then, a move acceptance method is employed to decide whether to accept or reject a resultant solution. This process is repeated until a predefined stopping condition is met. Only problem independent information flow is allowed between the problem domain and hyper-heuristic layers. A perturbative hyper-heuristic can be denoted as *heuristic selection − move acceptance* based on its components.

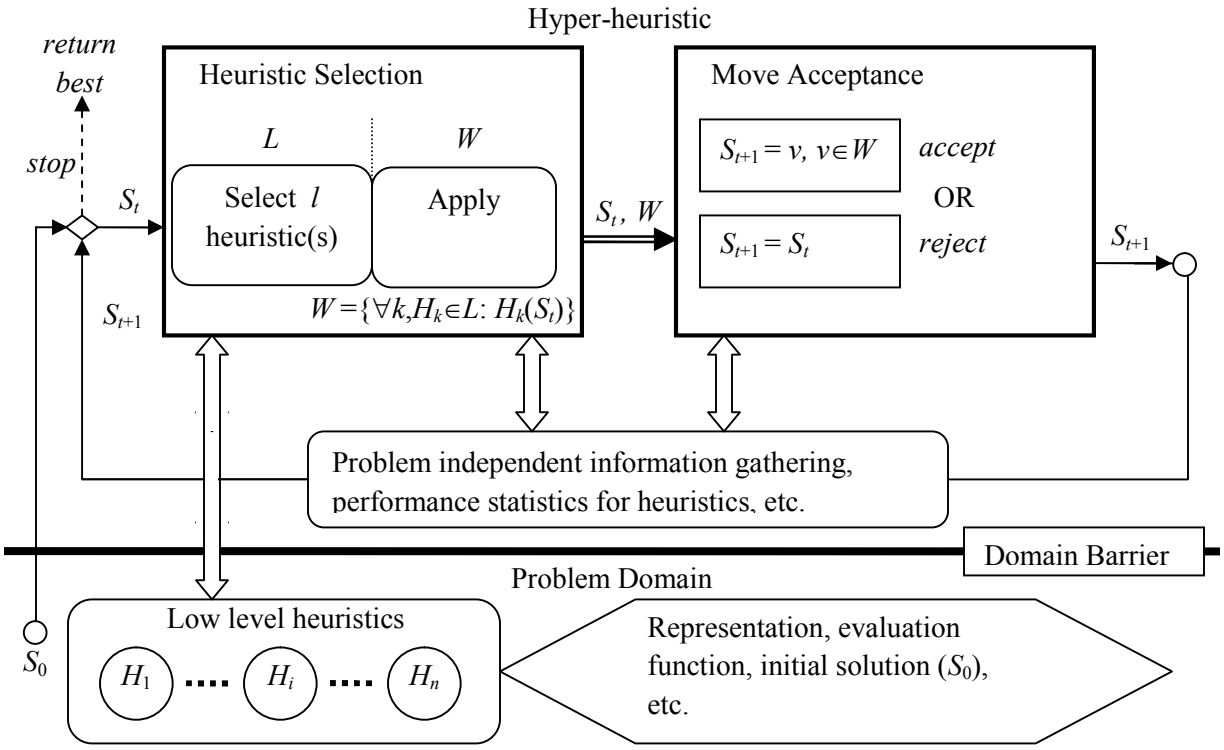


Figure 1. A hyper-heuristic framework based on a single point search

Great deluge is a well-known threshold acceptance criterion (Dueck, 1993). Kendall et al. (2004) employed random choice of low level heuristics (simple random) and great deluge for the first time as hyper-heuristic components for solving the channel assignment problem. Bilgin et al. (2006) experimented with thirty five different hyper-heuristics for solving an examination timetabling. The simple random−great deluge hyper-heuristic ranked the second, yet delivered a similar performance to the best approach; namely, choice function – simulated annealing hyper-heuristic. Obviously, simple random receives no feedback at all during the search to improve upon the heuristic selection process. Hence, in this study, g*reat-deluge* is preferred as the move acceptance component within a perturbative hyper-heuristic framework to investigate the effect of learning heuristic selection on the performance of a perturbative hyper-heuristic for solving the same examination timetabling problem as formulated in Bilgin et al. (2006). The learning mechanisms, inspired by the work in Nareyek (2003), are based on weight adaptation.

BACKGROUND

Hyper-heuristics and Learning

Although hyper-heuristic as a term has been introduced recently (Cowling et al., 2001a), the origins of the idea dates back to early 1960s (Fisher et al., 1961). A hyper-heuristic operates at a high level managing or generating low level heuristics which operate on the problem domain. Meta-heuristics have been commonly used as hyper-heuristics. A hyper-heuristic can conduct a single point or multi-point search. Population based meta-heuristics which perform multi-point search, such as learning classifier systems (Ross et al., 2002; Marín-Blázquez et al., 2005; Tereshima-Marin et al., 2007), evolutionary algorithms (Cowling et al., 2002c; Cowling et al., 2002d; Han et al., 2003a; Han et al., 2003b; Ross et al., 2003, Pillay et al., 2007), genetic programming (Burke et al., 2006; Keller et al., 2007a, Keller et al., 2007b; Burke et al., 2009a), ant colony optimisation (Burke et al., 2005b; Cuesta-Canada et al., 2005; Chen et al., 2007) have been applied to a variety of combinatorial optimisation problems as hyper-heuristics. Distributed computing methods can also be used to perform multi-point search (Rattadilok et al., 2004; Rattadilok et al., 2005; Ouelhadj et al., 2008). Ozcan et al. (2008) presented different hyper-heuristic frameworks showing that a matching performance to memetic algorithms can be achieved. In this study, perturbative hyper-heuristics using the framework as in Figure 1 based a single point search are in focus. The primary components of such hyper-heuristics are heuristic selection and move acceptance.

A major feature of a hyper-heuristic is its applicability to different problem instances having different characteristics as well as different problem domains. In this quest, machine learning techniques are vital for hyper-heuristics to make the right choices during the heuristic selection process. Existing learning hyper-heuristics incorporate *reinforcement learning* (Kaelbling et al., 1996; Sutton et al., 1998). A reinforcement learning system interacts with the environment and changes its state via a selected action in such a way to increase some notion of long term reward. Hence, a learning hyper-heuristic maintains a utility value obtained through predetermined reward and punishment schemes for each low level heuristic. A heuristic is selected based on the utility values of low level heuristics in hand at each step. Remembering and forgetting are the core ingredients of learning. Remembering can be achieved through the rewarding and punishment schemes. Forgetting can be achieved through the use of lower and upper bounds on the utility values. Some reinforcement learning methods use weighted average of learnt utility values. A dynamic weighting scheme can be employed favouring the outcome of the most recent

actions or choices. Reward and punishment schemes are allowed to use different adaptation rates in case of an improving and worsening move, respectively. For example, utility value of a selected heuristic can be increased at a constant rate linearly whenever there is an improvement after it is employed, otherwise the utility value can be decreased at a different rate, or even the utility value can be kept constant. Initialisation of the utility values, lower and upper bounds for them along with a memory adjustment scheme (weighting) are the rest of the constituents for a reinforcement learning based hyper-heuristic.

Some previously studied heuristic selection methods are summarised in Table 1. Simple random, random gradient, random permutation gradient, greedy and choice function heuristic selection methods are presented in Cowling et al. (2001a). All these approaches can be considered learning heuristic selection methods, except simple random. In (Cowling et al., 2001b), a parameter-free choice function was presented. As a problem domain, sales summit scheduling was used in both studies. Later, the choice function based hyper-heuristics were applied to nurse rostering (Cowling et al., 2002a) and project presentation scheduling (Cowling et al., 2002b). Cowling & Chakhlevitch (2003) investigated peckish heuristic selection strategies that eliminated the selection and application of all low level heuristics as in greedy heuristic selection.

Nareyek (2003) investigated reinforcement learning using different reward/penalty schemes and heuristic selection strategies on orc quest problem and logistics domain. Additive/subtractive adaptation rates combined with heuristic selection using the maximal utility generated better results as opposed to a fair random choice (softmax, roulette wheel). All heuristics were assigned to a utility value of 0, initially and raw utility values were maintained. Upper and lower bounds were defined for the utility values. In (Burke et al., 2003b), reinforcement learning was combined with tabu search in a hyper-heuristic and applied to timetabling problems. The aim of this modification was to prevent the selection of some heuristics for a while by inserting them into a variable-length tabu list. A non-tabu heuristic with the highest utility value was chosen at each step.

Table 1. Description of a set of heuristic selection methods used within perturbative hyper-heuristics.

Name	**Description**
Simple Random	Choose a low level heuristic randomly
Random Descent	Choose a low level heuristic randomly and employ the same heuristic as long as the candidate solution in hand is improved
Random Permutation Descent	Generate a random permutation of low level heuristics and form a cyclic list. Starting from the first heuristic, employ it repeatedly until a worsening move is hit, then go to the next heuristic in the list.
Greedy	Apply all low level heuristics to the same candidate solution separately and choose the heuristic that generates the best change in the objective value
Peckish	Apply a subset of all low level heuristics to the same and choose the heuristic that generates the best change in the objective value

Choice Function	Dynamically score each heuristic weighing their individual performance, combined performance with previously invoked heuristic and the time passed since the last call to the heuristic at a given step then a heuristic is chosen based on these scores.
Reinforcement Learning	Each heuristic carries a utility value and heuristic selection is performed based on these values. This value gets updated at each step based on the success of the chosen heuristic. An improving move is rewarded, while a worsening move is punished using a preselected adaptation rate.
Tabu Search	This method employs the same strategy as Reinforcement Learning and uses a tabu list to keep track of the heuristics causing worsening moves. A heuristic is selected which is not in the tabu list.

Some studies concentrate on move acceptance in hyper-heuristics rather than the heuristic selection methods, as accepting a move turns out to be an extremely important decision. In Cowling et al. (2001), heuristic selection methods are combined with either all moves accepted or only improving moves accepted strategy. On the other hand, Ayob & Kendall (2003) proposed three different Monte Carlo move acceptance strategies based on the objective value change due to the move, time (units), number of consecutive non-improving moves. Simple random was used as a heuristic selection within the hyper-heuristic for solving the component placement problem. The best move acceptance turned out to be *exponential Monte Carlo with counter*. One of the well known move acceptance is *simulated annealing* (SA) (Kirkpatrick, 1983). The improving moves or the moves that generate an equal quality solution are accepted, while a worsening move is not rejected immediately. Acceptance of a given candidate solution is based on a probabilistic framework that depends on the objective value change and a temperature that decreases in time (cooling). The difference between exponential Monte Carlo with counter and the simulated annealing is that the latter one uses this *cooling schedule* while the former does not. Bai & Kendall (2003) investigated the performance of simple random – simulated annealing hyper-heuristic on a shelf space allocation problem. Anagnostopoulos et al. (2006) applied a similar hyper-heuristic to a set of travelling tournament problem instances embedding a reheating scheme into the simulated annealing move acceptance. In (Bai et al., 2007), a reinforcement learning scheme is combined with simulated annealing with reheating as a hyper-heuristic and applied to three different problem domains: nurse rostering, course timetabling and 1D bin packing.

In (Dueck, 1993), two move acceptance strategies, namely *great deluge* (GD) and *record-to-record travel* that accept worsening moves based on a dynamic threshold value were presented. Kendall & Mohamad (2004) utilised a simple random – great deluge hyper-heuristic to solve a mobile telecommunication network problem. Great deluge uses a threshold (τ_t) that decreases in time linearly to determine an acceptance range for the solution qualities as presented in Equation (1), where *maxIter* is the maximum number of steps (or total time), t is the number of steps passed, ΔR is an expected range for the maximum fitness change between the initial fitness and f_{opt} which is the final objective value (e.g., lower bound).

$$\tau_t = f_{opt} + \Delta R\left(1 - \frac{t}{maxIter}\right) \quad (1)$$

In case of an improving move, it is accepted, while a worsening move is accepted as well only if the objective value of the resultant candidate solution at step *t* is less than the computed threshold. Kendall & Mohamad (2004) used a step based threshold formula with a maximum number of iterations as a termination criterion aiming a quadratic running time complexity for the overall algorithm.

Bilgin et al. (2007) employed different heuristic selection and move acceptance mechanisms and used their combinations as hyper-heuristics. The results showed that simple random – great deluge hyper-heuristic was the second best after choice function – simulated annealing considering the average performance of all hyper-heuristics over a set of examination timetabling problems. Consequently, a hyper-heuristic without learning delivered a comparable performance to another one with a learning mechanism. Therefore, in this study, reinforcement learning is preferred to be combined with great deluge to observe the effect of learning heuristic selection on the overall performance of the hyper-heuristic for solving the same problem. All the runs during the experiments in (Bilgin et al., 2007) were restricted to 600 seconds; hence, the threshold is computed based on the CPU time within the great deluge move acceptance strategy. If a heuristic takes less time, then the threshold value will be lower as compared to the one that takes longer time. This hyper-heuristic differs from the one that Kendall & Hussin (2005) have investigated, as their hyper-heuristic embeds a tabu list approach to keep the chosen heuristic from getting selected again for a number of steps (tabu duration) into reinforcement learning as a heuristic selection. Moreover, the low level heuristics contained a mixture of thirteen different constructive and perturbative low level heuristics.

Ozcan et al. (2009) combined different heuristic selection methods with late acceptance strategy, a new method that is initially presented as a local search for solving examination timetabling problem. Late acceptance requires a single parameter and it is a memory based approach. A trial solution is compared with a previously visited solution at a fixed distance apart from the current step in contrast to the conventional approaches that usually compare the trial solution with a current one. The trial solution is accepted, if there is an improvement over this previously visited solution. The results showed that reinforcement learning, reinforcement learning with tabu list or choice function heuristic selection methods did not improve the performance of the hyper-heuristic if late acceptance is used. Choosing a heuristic randomly at each step performed the best. More on hyper-heuristics can be found in Cowling et al. (2002b), Burke et al. (2003a), Ross (2005), Ozcan et al. (2008), Burke et al. (2009), Chakhlevitch & Cowling (2008).

Examination Timetabling Problem

Examination timetabling is a hard to solve real world problem addressed mainly by educational institutions, such as universities. The goal is finding the best assignment of available timeslots and possibly other resources, such as rooms for each examination subject to some constraints. There are two types of constraints: *hard* and *soft constraints*. Hard constraints must not be violated to achieve a *feasible* solution. For example, a student cannot take any pair of his/her examinations at the same time; hence, his/her examinations must not clash. On the other hand, soft constraints reflect preferences and such violations are allowed. For example, a number of

timeslots might be preferred in between the examinations of a student scheduled to the same day; still, a student having a consecutive examination might be acceptable. The main goal is to minimise the number of soft constraint violations while maintaining a feasible solution (or solutions). Researchers have been studying various aspects of examination timetabling problems since the early 1960s (Cole, 1964; Broder, 1964). Examination timetabling problems are NP-complete (Even, 1976). Since the search space of candidate solutions grow exponentially with respect to the number examinations to be scheduled, many different non-traditional approaches (e.g., meta-heuristics) have been investigated for solving a variety of examination timetabling problems. Table 2 and 3 provide some illustrative examples of these approaches.

Table 2. Different approaches to examination timetabling

Approach	**Reference(s)**
Decomposition and/or construction heuristics	Carter et al., (1996); Burke & Newall (1999); Qu & Burke, (2007, 2008a); Pillay et al. (2008)
Simulated annealing	Thompson & Dowsland (1996, 1998); Merlot et al. (2002); Burke et al., (2004)
Genetic algorithms and constraint satisfaction	Marin (1998)
Grouping genetic algorithm	Erben (2001)
Iterative greedy algorithm	Caramia et al. (2001)
Tabu search	Di Gaspero & Schaerf (2001); Burke et al. (2005a)
Multiobjective evolutionary algorithm	Paquete & Fonseca (2001); Cheong et al. (2007)
Greedy randomised adaptive search procedure	Casey & Thompson (2003)
Adaptive heuristic ordering strategies	Burke & Newall, (2004)
Very large neighbourhood search	Abdullah et al. (2004, 2007)
Fuzzy reasoning	Petrovic et al. (2005); Asmuni et al. (2005, 2007)
Variable neighbourhood search	Qu & Burke (2005)
Ant colony optimisation	Dowsland & Thompson (2005); Eley (2006)
Hybrid heuristics	Azimi (2005) ; Ersoy et al. (2007)
Neural network	Corr et al. (2006)
Case based reasoning based investigations	Petrovic et al. (2003); Yang & Petrovic (2005); Petrovic et al. (2007)
Alternating stochastic-deterministic local search	Caramia & Dell'Olmo (2007)
Hyper-heuristics	Kendall & Hussin (2005); Burke et al. (2007); Pillay & Banzhaf (2007); Qu et al. (2008a)

Most of the examination timetabling problems are studied from a practical point of view, as they arise due to the practical needs within institutions. Since different institutions have different requirements, there is a variety of examination timetabling problems in literature (Table 3; see Qu et al., 2009). Carter et al., (1996) introduced one of the widely used examination timetabling data sets made up of 13 real world problems, called as the *Toronto benchmarks*. 3 of them were obtained from Canadian high schools while the rest were from different universities around the world. It is of interest to know the best approach in the research community. Schaerf & Di Gaspero (2006) pointed out the importance of reproducibility and comparability of the results.

Toronto benchmarks enable researchers to compare their studies to the others. Yet, most of the comparisons are based on the best results achieved.

Competitions, such as, ITC2007 (http://www.cs.qub.ac.uk/itc2007/), are very functional in determining the state of the art for different problems including examination timetabling, as the approaches use the same platform to compete. Top five approaches are described as follows, respectively. The winner of the competition for the examination timetabling track was a three-stage approach developed by Müller (2008). Initially, a complete feasible solution is constructed, and then this solution is improved using a hill climbing approach. Finally, great deluge with a re-rising level scheme is employed. The second best approach designed by Gogos (2008) was also based on three-stages. After a high quality feasible solution is constructed, simulated annealing followed by mathematical programming is employed for improving the solution quality. Atsuta et al. (2007) used a general purpose constraint satisfaction problem solver which combined iterated local search and tabu search. De Smet (2008) embedded local search techniques into an open-source business rule management system, referred to as drools solver. Pillay (2007) employed an approach based on cell biology which mimicked cell behaviour. Under such an analogy, a variety of heuristics, such as swapping, violation directed rescheduling is employed to improve a constructed solution. A commercial point of view on the real world issues in course and examination timetabling was put forward by McCollum (2006). McCollum et al. (2009) attempted to unify examination timetabling problems under a different model considering these issues and other real world requirements. An excellent survey on examination timetabling is provided by Qu et al. (2009). Please refer to this survey for details on approaches, classifications, data sets and more.

Table 3. Some examination timetabling problems from different universities and the initial approaches proposed to solve them

Institution	**Reference**	**Approach**
University of Nottingham	Burke et al. (1995)	Memetic algorithm
Middle East Technical University	Ergul (1996)	Genetic algorithm
École de Technologie Supérieure	Wong et al. (2002)	Genetic algorithm
University of Melbourne	Merlot et al. (2002)	A multi-phase hybrid algorithm
University of Technology MARA	Kendall & Hussin (2005)	Hyper-heuristic
Yeditepe University	Ozcan et al. (2005)	Memetic algorithm

Ozcan et al. (2005) introduced the examination timetabling problem at Yeditepe University. In this initial study, different memetic algorithms that hybridises genetic algorithms and local search were described. A type of violation directed hill climbing was also investigated as a part of the memetic algorithm which turned out to be the best choice. This hill climbing approach was designed based on (Alkan & Ozcan, 2003; Corne et al., 1994; Ross et al., 1994). Later, Bilgin et al. (2007) modified the previous data set with new properties and generated a variant of Toronto benchmarks that fits into the problem formulation. In this work, the examination timetabling problem in (Bilgin et al. 2007) is used as a case study to investigate learning in a great deluge based hyper-heuristic.

SOLVING AN EXAMINATION TIMETABLING PROBLEM USING HYPER-HEURISTICS

Examination Timetabling Problem at Yeditepe University

The examination timetabling problem at Yeditepe University requires a search for finding the best timeslots for a given set of examinations under four hard constraints and a soft constraint. The hard constraints are as follows:

- Scheduled examination restriction: Each examination must be assigned to a timeslot only for once.
- Unscheduled examination restriction: All the examinations must be scheduled.
- Examination clash restriction (C_1): A student cannot enter into more than one examination at a given time.
- Seating capacity restriction (C_2): The number of students seated for all exams at a timeslot cannot be more than a given capacity.

The soft constraint is as follows:

- Examination spread preference (C_3): A student should have at least a single timeslot in between his/her examinations in the same day.

Let E represent the set of examinations $E=\{e_1,\ldots, e_j,\ldots,e_n\}$ and S denotes the ordered list of timeslots to be assigned to the examinations $S=\{t_1,\ldots, t_k,\ldots,t_p\}$. An array $A=\{a_1,\ldots, a_j,\ldots,a_n\}$ is used as a direct representation of a candidate solution, where each entry $a_j=t_k$, $t_k \in S$, indicating that e_j is assigned to a timeslot t_k in S. Hence, the scheduled and unscheduled examination restrictions are resolved by using this direct and complete representation that encodes a timeslot for each given examination. The quality of a given timetable (TT) with respect to a set of students and the courses that they enrolled (SR) is determined by calculating the weighted average of constraint violations.

$$quality(TT) = \frac{-1}{1+\sum_{\forall i} violations(C_i, TT, SR)\, w_i} \qquad (1)$$

where $i=\{1,2,3\}$ and *violations* measures the violations due to a constraint C_i in TT considering SR. The quality of the best solution for any given problem is -1, as there will be no constraint violations.

The Reinforcement Learning – Great Deluge Hyper-heuristic

Reinforcement Learning (RL) is a general term for a set of widely used approaches that provide a way to learn how to behave when an action comes or "*how to map situations to actions*" (Sutton & Barto, 1998) through *trail-and-error* interactions (Kaelbling et al., 1996). A perturbative hyper-heuristic combining reinforcement learning heuristic selection and great deluge move acceptance is implemented as shown in Figure 2. As suggested in Nareyek (2003), additive adaptation rate that increments the utility value of the low level heuristic is used in case of an improvement as a reward at step 14. This value is tested against three different negative

adaptation rates, namely subtractive, divisional and root, denoted as RL_1, RL_2 and RL_3, respectively for the punishment of a heuristic causing a worsening move at step 17:

$$RL_1 : u_i = u_i - 1 \quad (2)$$

$$RL_2 : u_i = u_i / 2 \quad (3)$$

$$RL_3 : u_i = \sqrt{u_i} \quad (4)$$

RL–GD ALGORITHM

Input – n: number of heuristics, u: array holding utility value for each heuristic, *totalTime*

1. // initialisation
2. Generate a random complete solution $S_{current}$;
3. Initialise utility values;
4. $f_{current} = f_0 = quality(S_{current})$;
5. $startTime = t = time()$; $level = f_{current}$
6. // main loop executes until total running time allowed is exceeded
7. **while** ($t < totalTime$) **{**
8. // heuristic selection
9. $i = selectHeuristic(u)$; // select a heuristic using the utility values
10. $S_{temp} = applyHeuristic(i)$;
11. $f_{temp} = quality(S_{temp})$;
12. $t = time() - startTime$;
13. // move acceptance
14. **if** ($f_{temp} < f_{current}$) **then {**
15. $u_i = reward(u_i)$; // improving move
16. $S_{current} = S_{temp}$;
17. **} else {**
18. $u_i = punish(u_i)$; // worsening move
19. **if** ($f_{temp} < qualityLB + (f_0 - qualityLB)(1 - t/totalTime)$) **then**
20. $S_{current} = S_{temp}$; // accept the move else reject the move
21. **}**
22. **}**

Figure 2. Pseudocode of the Reinforcement Learning – Great Deluge hyper-heuristic

Memory length is implemented not only in terms of adaptation rates, but also using a lower and an upper bound on the utility values. We experimented with four different ranges in $[0, number\_of\_heuristics \times (5i)]$, $i=\{1,2,3,4\}$. It is assumed that these bounds are checked during the steps 14 and 17. Optimistic initial utility values are utilised and all utilities are set to $\lfloor 0.75 \times upper\ bound \rfloor$ at step 3 to support exploration. As the environment might change dynamically, bounds on the utility values are essential in order to encourage exploration in further steps. Reinforcement learning is based on the idea that heuristics getting large rewards should be more likely to be selected again, while heuristics getting small rewards should be less likely to be selected again. The reinforcement scheme used returns the same reward for all

heuristic choices. Hence, using maximal utility value to select a heuristic is a reasonable choice. Moreover, selecting the heuristic with this strategy that will be denoted as *max* is reported in (Nareyek, 2003) to be the best choice for step 9. If there are multiple low level heuristics under consideration, since their utility values are the same, then a random choice is made. Another approach to decide whether a given total reward is small or large can be achieved by comparing that value to a relative *reference reward*, such as the average of all utility values. Additional to the maximal utility, another heuristic selection scheme that chooses a low level heuristic randomly from the ones that are over (and equal to) the average, denoted as *overAvr* is implemented. The lower bound (*qualityLB*) is set to -1 at step 19 considering the evaluation function (Equation 1) during the experiments.

In this study, we employed four low level heuristics (Bilgin et al., 2007). Three of them H_1, H_2 and H_3 are associated to three constraints C_1, C_2 and C_3, respectively. They probe constraint based neighbourhoods using a tournament aiming to resolve violations of a corresponding constraint only. Each low level heuristic operates as follows:

1. H_1 ($H(x)$): This heuristic chooses a number of examinations randomly that violate $x=C_1$ and this number is referred to as *toursize*1. Then, the examination causing the largest number of violations is selected. This examination is reassigned to a timeslot from a randomly selected timeslots (*toursize*2) which generates the least number of $x=C_1$ violations.
2. H_2: Using tournament strategy, a number of timeslots (*toursize*3) with capacity constraint violations is selected. Examinations in the timeslot that has the largest number of violations are marked for further processing. Examination with the largest number of enrolled students is rescheduled. Then this examination is reassigned to a timeslot from a randomly selected timeslots (*toursize*4) which generates the least amount of C_2 violations.
3. H_3: This heuristic employs the same strategy as described in $H(x)$ with $x=C_3$.
4. H_4: This heuristic makes a pass over all the examinations and reschedules the examination under consideration with a probability of 1/*number_of_examinations*.

EXPERIMENTS

The experiments are performed on Pentium IV 3 GHz LINUX (Fedora Core 8) PCs with 2 Gb memory. Each hyper-heuristic is tested on each instance for 50 trials and each trial is terminated after 600 CPU seconds.

Experimental Data

Reinforcement Learning – Great Deluge hyper-heuristics are tested on Toronto benchmarks and Yeditepe University. The number of exams determines the size of search space to be explored, but the difficulty of a given problem might change with respect to some other characteristics, such as the number of students or conflict density (ratio of the number of examination pairs that should not clash to the total number of examination pairs) that might implicitly or explicitly restrict the search space containing feasible solutions. Such properties for each experimental data are provided in Table 4.

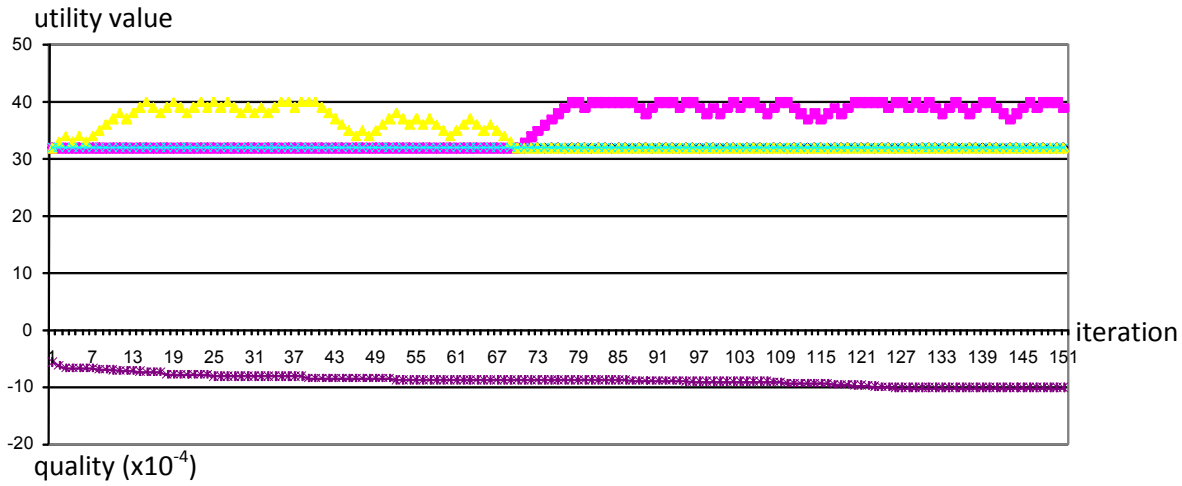
Table 4. Properties of the modified Toronto and Yeditepe benchmark problem instances

Data Set	Instance	Exams	Students	Enrolment	Conflict Density	Days	Capacity
Toronto	car91 I	682	16925	56877	0.13	17	1550
	car92 I	543	18419	55522	0.14	12	2000
	ear83 I	190	1125	8109	0.27	8	350
	hecs92 I	81	2823	10632	0.42	6	650
	kfu93	461	5349	25118	0.06	7	1955
	lse91	381	2726	10918	0.06	6	635
	pur93 I	2419	30029	120681	0.03	10	5000
	rye92	486	11483	45051	0.07	8	2055
	sta83 I	139	611	5751	0.14	4	3024
	tre92	261	4360	14901	0.18	10	655
	uta92 I	622	21266	58979	0.13	12	2800
	ute92	184	2749	11793	0.08	3	1240
	yor83 I	181	941	6034	0.29	7	300
Yeditepe	yue20011	140	559	3488	0.14	6	450
	yue20012	158	591	3706	0.14	6	450
	yue20013	30	234	447	0.19	2	150
	yue20021	168	826	5757	0.16	7	550
	yue20022	187	896	5860	0.16	7	550
	yue20023	40	420	790	0.19	2	150
	yue20031	177	1125	6716	0.15	6	550
	yue20032	210	1185	6837	0.14	6	550

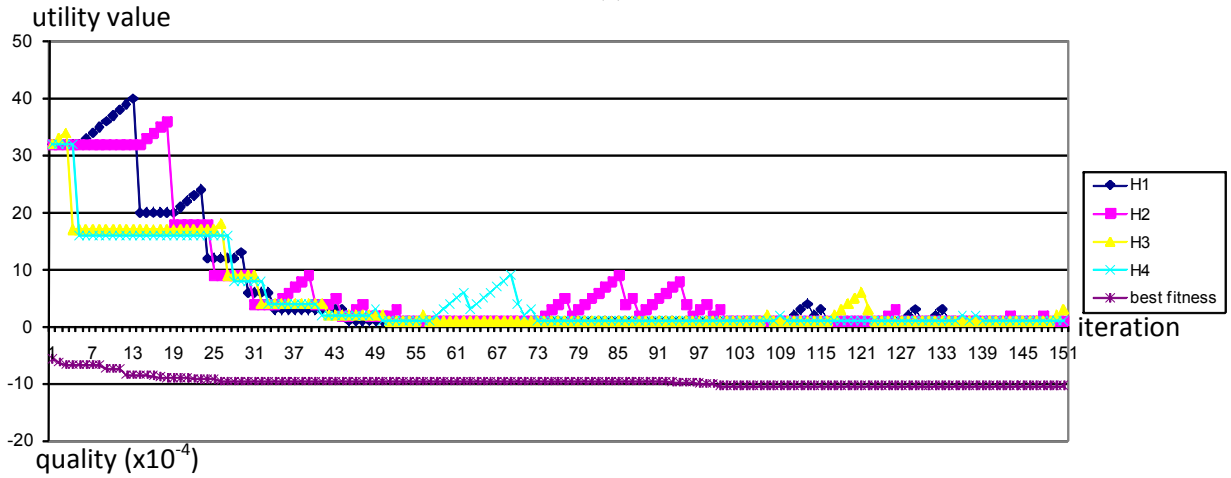
Results

Initial experiments are performed for parameter tuning. Unless mentioned otherwise, utility value upper bound is fixed as 40 and *max* is used as the utility based heuristic selection strategy within the reinforcement learning hyper-heuristics. A sample run is performed for sta83 I using a reinforcement learning – great deluge hyper-heuristic. Figure 3 illustrates the change in utility values for each low level heuristic and improvement based on different negative adaptation rates for this run. If a low level heuristic worsens the solution after a number of successive improving moves, the best heuristic still gets a chance to operate on the candidate solution. The frequency of that chance is determined by the negative adaptation rate. For example, H_3 gets selected more frequently when the adaptation rate is subtractive(/divisional) rate as compared to divisional(/root) rate before the optimistic utility values of all heuristics reduces toward the lower bound (see Figure 3). The more severe (high) this rate is, the more exploration of different heuristics is favoured. All the low level heuristics get invoked within tens of steps while using divisional and root adaptation rates (Figure 3. (b) and (c)), whereas only two heuristics get invoked while using subtractive adaptation rate (Figure 3. (a)). The results show that all low level heuristics are valuable in improving a candidate solution. It seems that the quality of a

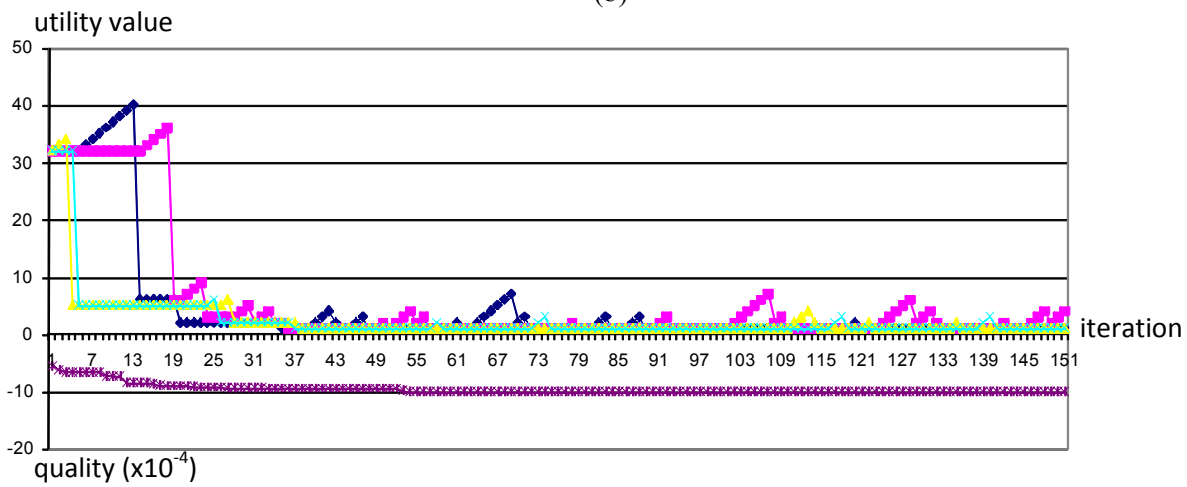
solution is improved slowly whenever a slow negative adaptation rate is used. Naturally, there is still the chance of getting stuck at a local optimum in the long run.



(a)



(b)



(c)

Figure 3. Plot of utility value for each low level heuristic and quality versus iteration on sta83 I using reinforcement learning – great deluge hyper-heuristic based on (a) subtractive, (b) divisional and (c) root negative adaptation rates with *max*, *utility upper bound*=40, respectively.
In order to observe the effect of memory length via different combinations of negative adaptation {subtractive, divisional, root} and upper bound for the utility values {20, 40, 60, 80}, a set of experiments have been performed on the Toronto problem instances. As a total twelve different choices are executed for each data and each choice is ranked from 1 (best) to 12 (worst) using the results from the runs. The average rank of a choice over all data and the related standard deviation are provided in Figure 4. Determining the best adaptation rate which is also vital to adjust the memory length seems to be a key issue in fully utilising a reinforcement learning scheme within a hyper-heuristic. Different adaptation rates might yield different performances. The results show that the RL_1 heuristic selection method with a utility upper bound of 40 delivers the best average performance when combined with the great deluge method as a hyper-heuristic. Yet, this performance variation is not statistically better than the rest.

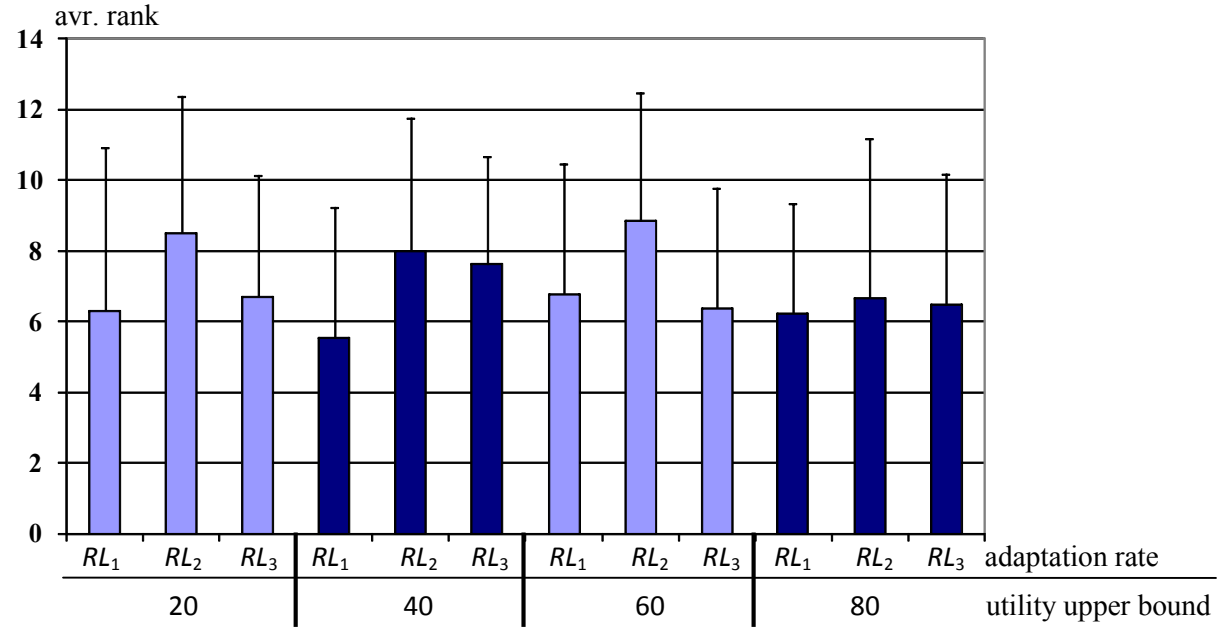


Figure 4. Average rank of each adaptation rate and utility upper bound pair over all Toronto benchmark.

Using the best configuration from the previous set of experiments, another one is performed over Toronto problem instances to compare the average performances of utility based heuristic selection schemes; *max* and *overMax*. Figure 5 summarises the experimental results. Maximal utility selection performs slightly better than *overMax* with an average rank of 1.42 for the problem instances {car91 I, car92 I, kfu93, lse91, pur93 I, rye92, ute92}. There is a tie for sta83 I. Still, the performance difference between *max* and *overMax* is not statistically significant. As, in general, *overMax* shows success in solving problem instances with relatively high conflict densities, there might be still potential for a future use of this approach.

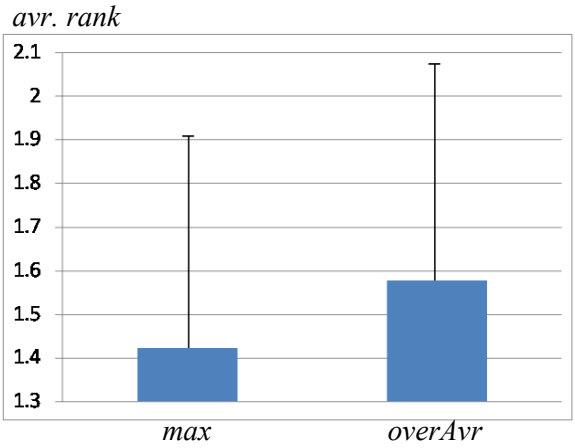


Figure 5. Comparison of utility value based heuristic selection schemes over Toronto benchmark based on their average ranks.

Reinforcement learning heuristic selection method, that is referred to as RL_1 utilises additive reward, subtractive punishment schemes with a utility upper bound of 40 and *max*. RL_1 is combined with great deluge and tested against simple random – great deluge hyper-heuristic during the final set of experiments. The results are provided in Table 5. Percentage improvement in the table uses the approach whichever generates a better result (average best of fifty trials) as the baseline for comparison. The simple random – great deluge hyper-heuristic generates better average performance for eight problem instances. It is especially successful in solving Yeditepe problems instances which are relatively smaller with low conflict densities as compared to Toronto instances. Yet, RL_1 improves the performance of simple random hyper-heuristic with the great deluge move acceptance on eleven problem instances (out of twenty one problem instances), and for two problem instances there is a tie.

Table 5. Comparison of reinforcement learning and simple random heuristic selection within a hyper-heuristic using great deluge acceptance move method. "≥" and "≈" indicate "is better than" and "delivers a similar performance", respectively. Percentage improvement uses the average best quality obtained in fifty runs for the better approach as the baseline.

Instance	Exams	Conflict Density	Comparison	%-improv.
car91 I	682	0.13	RL_1–GD ≥ SR–GD	1.70
car92 I	543	0.14	RL_1–GD ≥ SR–GD	1.68
ear83 I	190	0.27	RL_1–GD ≥ SR–GD	2.02
hecs92 I	81	0.42	**SR–GD ≥ RL_1–GD**	**11.85**
kfu93	461	0.06	RL_1–GD ≥ SR–GD	2.09
lse91	381	0.06	RL_1–GD ≥ SR–GD	2.47
pur93 I	2419	0.03	**SR–GD ≥ RL_1–GD**	**0.32**
rye92	486	0.07	RL_1–GD ≥ SR–GD	3.43
sta83 I	139	0.14	RL_1–GD ≥ SR–GD	0.06

tre92	261	0.18	**SR–GD ≥ RL_1–GD**	**5.05**
uta92 I	622	0.13	**SR–GD ≥ RL_1–GD**	**0.23**
ute92	184	0.08	RL_1–GD ≥ SR–GD	0.28
yor83 I	181	0.29	RL_1–GD ≥ SR–GD	1.13
yue20011	140	0.14	RL_1–GD ≈ SR–GD	0.00
yue20012	158	0.14	RL_1–GD ≥ SR–GD	0.53
yue20013	30	0.19	RL_1–GD ≈ SR–GD	0.00
yue20021	168	0.16	**SR–GD ≥ RL_1–GD**	**1.49**
yue20022	187	0.16	**SR–GD ≥ RL_1–GD**	**0.83**
yue20023	40	0.19	**SR–GD ≥ RL_1–GD**	**0.71**
yue20031	177	0.15	RL_1–GD ≥ SR–GD	5.26
yue20032	210	0.14	**SR–GD ≥ RL_1–GD**	**0.88**

Finally, RL_1 – great deluge hyper-heuristic is compared to two previous studies. Bilgin et al. (2007) showed that the choice function – simulated annealing hyper-heuristic out of thirty five approaches performs the best for examination timetabling. In a recent study, Ozcan et al. (2009) introduced a new move acceptance strategy that can be used in hyper-heuristics. The experiments resulted with the success of a simple random – late acceptance hyper-heuristic, performing even better than the choice function – simulated annealing. Both of these approaches are compared to the RL_1 – great deluge hyper-heuristic in Table 6.

Table 6. Comparison of RL_1 – great deluge hyper-heuristic to the previous studies; (1) choice function – simulated annealing hyper-heuristic (Bilgin et al., 2007), (2) simple random – late acceptance hyper-heuristic (Ozcan et al., 2009). Each approach is ranked from 1 (best) to 3 (worst) for each Toronto problem instance.

Instance	***RL_1*–GD**	**(1) CF–SA**	**(2) SR–LAS**
car91 I	2	3	1
car92 I	1	3	2
ear83 I	1	2	3
hecs92 I	1	3	2
kfu93	1	3	2
lse91	2	3	1
pur93 I	2	3	1
rye92	2	3	1
sta83 I	1	3	2
tre92	1	3	2
uta92 I	2	3	1
ute92	3	1	2
yor83 I	2	3	1
avr.	1.62	2.77	1.62

A hyper-heuristic learns how to make *good* moves through both the heuristic selection and move acceptance. If a move is rejected, in a way the selected heuristic is annulled. Hence, if a hyper-heuristic uses a simple random heuristic selection, it does not imply that there is no learning within that hyper-heuristic. Late acceptance strategy uses a fixed length memory to hold the quality of some previously visited solutions. Simple random heuristic selection diversifies the search, while the late acceptance strategy intensifies the search process by approving the better moves based on its memory. This course of action can be considered as learning. Reinforcement learning not only improves on simple random heuristic selection when combined with great deluge but also generates better results as compared to another learning hyper-heuristic; choice function – simulated annealing. Moreover, its performance is comparable to that of the simple random – late acceptance hyper-heuristic as well.

CONCLUSION

Hyper-heuristics offer a variety of general search methodologies for solving combinatorial optimisation problems. They can handle problems not only with different characteristics from a given problem domain, but also from different problem domains. A hyper-heuristic itself is a heuristic that drives the search process at a high level by controlling a set of low level heuristics. These low level heuristics can be perturbative or constructive. In this study, hyper-heuristics that control perturbative low level heuristics are explored. An examination timetabling problem encountered at Yeditepe University every semester is used as a case study to investigate reinforcement learning as a heuristic selection with different components combined with great deluge move acceptance within a single point search framework.

A learning hyper-heuristic can follow the best moves within a given period of time based on its memory. Still, there is no guarantee that the decisions made during the search process will lead it towards the global optimum. Bai et al. (2007) observed that the memory length is vital in learning and the use of a learning mechanism with *short* term memory combined with a simulated annealing move acceptance generated the best result in their experiments over a set of course timetabling problems. They used weighted adaptation and tested various *learning rates* that adjust the influence of rewards compiled at different stages of search. In this study, other factors of memory length that affect the learning process, such as adaptation rate, lower and upper bounds on the utility values are identified and tested using relatively short memory lengths. Furthermore, two different heuristic selection strategies based on the utility values are assessed. The reinforcement learning – great deluge hyper-heuristic with the components {lower bound=0, upper bound=40, heuristic selection strategy=*max*, positive adaptation rate =*additive*, negative adaptation rate=*subtractive*} improves the performance of simple random – great deluge hyper-heuristic for solving an examination timetabling problem. Still, the main issue remains regarding the memory length. It is not trivial to define a fixed short term memory or even a dynamic strategy that modifies the memory length during the search process for a given problem instance.

REFERENCES

Abdullah, S., Ahmadi, S., Burke, E. K., & Dror, M. (2004). Applying Ahuja-Orlin's large neighbourhood for constructing examination eimetabling solution. In E. K. Burke and M. Trick (Ed.), *the 5th International Conference on the Practice and Theory of Automated Timetabling (PATAT'04)*, (pp. 413-419).

Abdullah, S., Ahmadi, S., Burke, E. K., & Dror, M. (2007). Investigating Ahuja-Orlins large neighbourhood search for examination timetabling. *OR Spectrum, 29*(2), (pp. 351-372).

Alkan, A., & Ozcan, E. (2003). Memetic algorithms for timetabling, *Proceedings of 2003 IEEE Congress on Evolutionary Computation*, (pp. 1796-1802).

Alkan, A., & Ozcan, E. (2003). Memetic algorithms for timetabling, In *Proceedings of the IEEE Congress on Evolutionary Computation (CEC'03)*, (pp. 1796-1802).

Anagnostopoulos, A., Michel, L., Hentenryck, P. V., & Vergados, Y. (2006). A simulated annealing approach to the traveling tournament problem. *Journal of Scheduling, 9*, (pp. 177-193), Kluwer Academic Publishers.

Asmuni, H., Burke, E. K., Garibaldi, J. M., & McCollum, B. (2007). A novel fuzzy approach to evaluate the quality of examination timetabling. In *Proceedings of the 6th International Conference on the Practice and Theory of Automated Timetabling (PATAT'06), LNCS, 3867*, (pp. 327-346), Springer.

Atsuta, M., Nonobe, K., & Ibaraki, T. (2007). ITC2007 Track 1: An Approach using general CSP solver. http://www.cs.qub.ac.uk/itc2007/.

Ayob, M., & Kendall, G. (2003). A monte carlo hyper-Heuristic to optimise component placement sequencing for multi head placement machine. In *Proceedings of the International Conference on Intelligent Technologies (InTech'03)* (pp. 132-141).

Azimi, Z. N. (2005). Hybrid heuristics for examination timetabling problem. *Applied Mathematics and Computation 163*(2):705-733.

Bai, R., Blazewicz, J., Burke, E., Kendall, G., & McCollum, B. (2007). *A simulated annealing hyper-heuristic methodology for flexible decision support*. Technical Report, Univeristy of Nottingham.

Bai, R., Burke, E. K., Kendall, G. & McCollum, B. (2007) Memory length in hyper-heuristics: an empirical study. In *Proceeding of 2007 IEEE Symposium on Computational Intelligence in Scheduling (CISched2007)*, (pp.173-178).

Bai, R., & Kendall, G. (2003). An investigation of automated planograms using a simulated annealing based hyper-heuristics. In Ibaraki, T.; Meta-heuristics: Progress as Real Problem Solvers, Nonobe, K. & Yagiura, M. (Ed.), selected papers from *the 5th Metaheuristics International Conference (MIC'03)* (pp. 87-108), Springer.

Bilgin, B., Ozcan, E., & Korkmaz, E. E. (2007). An experimental study on hyper-heuristics and exam scheduling. In *Proceedings of the 6th International Conference on the Practice and Theory of Automated Timetabling (PATAT'06), LNCS 3867*, (pp. 394-412), Springer.

Broder, S. (1964). Final examination scheduling. *Communications of the ACM 7*(8), 494-498.

Burke, E. K., Bykov, Y., Newall, J. P., & Petrovic, S. (2004). A time-predefined local search approach to exam timetabling problems. *IIE Transactions on Operations Engineering, 36*(6), 509-528.

Burke, E. K., Dror, M., Petrovic, S., & Qu, R. (2005a). Hybrid graph heuristics within a hyper-heuristic approach to exam timetabling problems. In B.L. Golden, S. Raghavan and E. A. Wasil

(Ed.), *The Next Wave in Computing, Optimization, and Decision Technologies, Conference Volume of the 9th informs Computing Society Conference*, (pp. 79–91), Springer.

Burke, E., Hyde, M., & Kendall, G. (2006). Evolving bin packing heuristics with genetic programming. In Runarsson, T.; H-G.B.; Burke, E.; Merelo-Guervos, J.; Whitley, L. & Yao, X. (Ed.), *Proceedings of the 9th Parallel Problem Solving from Nature (PPSN'06), 4193*, (pp. 860-869), Springer-Verlag.

Burke, E., Hyde, M., & Kendall, G., Ochoa, G., Ozcan, E., & Woodward, J. R. (2009a). Exploring hyper-heuristic methodologies with genetic programming. In C. Mumford & L. Jain (Ed.), *Computational Intelligence: Collaboration, Fusion and Emergence*, to appear.

Burke, E., Hyde, M., & Kendall, G., Ochoa, G., Ozcan, E., & Rong, Q. (2009b). *Survey of hyper-heuristics*. Technical Report, Univeristy of Nottingham.

Burke, E., Kendall, G., Newall, J., Hart, E., Ross, P., & Schulenburg, S. (2003a). Hyper-heuristics: an emerging direction in modern search technology. In Glover and Kochenberger (Ed.), *Handbook of Metaheuristics, 57,* (pp. 457-474), Kluwer International Publishing.

Burke, E., Kendall, G., Silva, D., O'Brien, R., & Soubeiga, E. (2005b). An ant algorithm hyperheuristic for the project presentation scheduling problem. In *Proceedings of the IEEE Congress on Evolutionary Computation (CEC'05), 3*, (pp. 2263-2270).

Burke, E., Kendall, G., & Soubeiga, E. (2003b). A tabu-search hyper-heuristic for timetabling and rostering. *Journal of Heuristics, 9*, 451-470, Kluwer Academic Publishers.

Burke, E. K., McCollum, B., Meisels, A., Petrovic, S., & Qu, R. (2007) A graph-based hyper-heuristic for educational timetabling problems. *European Journal of Operational Research 176*(1),177-192.

Burke, E. K., & Newall, J. P. (2004). Solving examination timetabling problems through adaption of heuristic orderings: models and algorithms for planning and scheduling problems. *Annals of Operations Research, 129*, 107–134.

Burke, E. K., & Newall, J. P. (1999). A multi-stage evolutionary algorithm for the timetable problem. *IEEE Transactions on Evolutionary Computation, 3*(1), 63-74.

Burke, E. K., Newall, J. P., & Weare, R. F. (1995). A memetic algorithm for university exam timetabling. In *Proceedings of the 1st International Conference on the Practice and Theory of Automated Timetabling (PATAT'95),* (pp. 241-250).

Caramia, M., DellOlmo, P., & Italiano, G. F. (2001). New algorithms for examination timetabling. In S. Naher & D. Wagner (Ed.), *Algorithm Engineering 4th International Workshop (WAE'00), LNCS, 1982*, (pp. 230-241), Springer.

Caramia, M., & Dell'Olmo, P. (2007). Coupling stochastic and deterministic local search in examination timetabling. *Operations Research*, *55*(2).

Carter, M. W., Laporte, G., & Lee, S. (1996). Examination timetabling: algorithmic strategies and applications. *Journal of the Operational Research Society, 47*(3), 373-383.

Casey, S., & Thompson, J. (2003). GRASPing the examination scheduling problem. In E. K. Burke & P. De Causmaecker (Ed.)*, Practice and Theory of Automated Timetabling: Selected Papers from the 4th International Conference*. *LNCS, 2740*, (pp. 232-244), Springer.

Chakhlevitch, K., & Cowling, P. I. (2008). Hyperheuristics: recent developments. *Adaptive and Multilevel Metaheuristics*, (pp. 3-29).

Chen, P.-C., Kendall, G., & Berghe, G. V. (2007). An ant based hyper-heuristic for the travelling tournament problem. *Proceedings of IEEE Symposium of Computational Intelligence in Scheduling (CISched'07)*, (pp. 19-26).

Cheong, C. Y., Tan, K. C., & Veeravalli, B. (2007). Solving the exam timetabling problem via a multi-objective evolutionary algorithm – a more general approach. In *Proceedings of the IEEE Symposium on Computational Intelligence in Scheduling (CI-Sched'07)*, (pp. 165-172).

Cole, A. J. (1964). The preparation of examination timetables using a small-store computer. *Computer Journal, 7*, (pp. 117-121).

Corne, D., Ross, P., & Fang, H. L. (1994). Fast practical evolutionary timetabling. *AISB Workshop on Evolutionary Computing*, (pp. 250-263).

Corr,, P.H., McCollum, B., McGreevy, M. A. J., McMullan, P. (2006). A new neural network based construction heuristic for the examination timetabling problem. T. P. Runarsson et al. (eds.), *PPSN IX*, *LNCS* 4193, (pp. 392-401).

Cowling, P., Kendall, G., & Han., L. (2002d). An adaptive length chromosome hyperheuristic genetic algorithm for a trainer scheduling problem. *Proceedings of the 4th Asia-Pacific Conference on Simulated Evolution And Learning (SEAL'02),* (pp. 267-271), November 18-22, Orchid Country Club, Singapore.

Cowling, P., Kendall, G., & Han, L. (2002c). An investigation of a hyperheuristic genetic algorithm applied to a trainer scheduling problem. In *Proceedings of the IEEE Congress on Evolutionary Computation (CEC'02),* (pp. 1185-1190).

Cowling P., Kendall, G., & Hussin N. M. (2002). A survey and case study of practical examination timetabling problems. In *Proceedings of the 4th International Conference on the Practice and Theory of Automated Timetabling (PATAT'02)*, (pp. 258-261).

Cowling, P., Kendall, G., & Soubeiga, E. (2001a). A hyperheuristic approach to scheduling a sales summit. In *Proceedings of the 3rd International Conference on Practice and Theory of Automated Timetabling (PATAT'00)*, (pp. 176-190), Springer-Verlag.

Cowling, P., Kendall, G., & Soubeiga, E. (2001b). A parameter-free hyperheuristic for scheduling a sales summit. In *Proceedings of 4th Metaheuristics International Conference (MIC'01)*, (pp. 127-131).

Cowling, P., Kendall, G., & Soubeiga, E. (2002a). Hyperheuristics: a robust optimisation method applied to nurse scheduling. In *Proceedings of the 7th International Conference on Parallel Problem Solving from Nature (PPSN'02)*, (pp. 851-860), Springer-Verlag.

Cowling, P., Kendall, G., & Soubeiga, E. (2002b). Hyperheuristics: a tool for rapid prototyping in scheduling and optimisation. In *Proceedings of the Applications of Evolutionary Computing on EvoWorkshops,* (pp. 1-10), Springer-Verlag.

Cowling, P., & Chakhlevitch, K. (2003). Hyperheuristics for managing a large collection of low level heuristics to schedule personnel. In *Proceedings of the IEEE Congress on Evolutionary Computation (CEC'03)*, (pp. 1214-1221), IEEE Computer Society Press, Canberra, Australia.

Cuesta-Canada, A., Garrido, L., & Terashima-Marin, H. (2005). Building hyper-heuristics through ant colony optimization for the 2d bin packing problem. *Proceedings of the 9th International Conference on Knowledge-Based Intelligent Information and Engineering Systems (KES'05), LNCS, 3684*, (pp. 654–660).

De Smet, G. (2008). ITC2007 - Examination track, *Practice and Theory of Automated Timetabling (PATAT'08)*, Montreal, 19-22, August 2008.

Di Gaspero, L., & Schaerf, A. (2001). Tabu search techniques for examination timetabling. In Burke E.K. and Erben, W. (Ed.), selected papers from *the 3rd International Conference on the Practice and Theory of Automated Timetabling (PATAT'00), LNCS, 2079*. (pp. 104-117).

Dowsland, K., & Thompson, J. (2005). Ant colony optimization for the examination scheduling problem. *Journal of the Operational Research Society*, *56*(4), (pp. 426-438).

Dueck, G. (1993). New optimization heuristics: the great deluge algorithm and the record-to-record travel. *Journal of Computational Physics*, *104*, (pp. 86-92), Academic Press Professional, Inc.

Eley, M. (2006). Ant algorithms for the exam timetabling problem. In *Proceedings of the 5th International Conference on the Practice and Theory of Automated Timetabling (PATAT'04)*, (pp. 364-382).

Erben, W. (2001). A grouping genetic algorithm for graph colouring and exam timetabling. In Burke, E. K. and Erben, W., (Ed.)*, the 3rd International Conference on the Practice and Theory of Automated Timetabling (PATAT'00), LNCS, 2079*, (pp. 132-156), Springer, Berlin.

Ergul, A. (1996). GA-based examination scheduling experience at Middle East Technical University. *Practice and Theory of Automated Timetabling, Springer, LNCS, vol 1153*, (pp. 212-226).

Ersoy, E, Ozcan, E., & Uyar, S. (2007). Memetic algorithms and hyperhill-climbers. In *Proceedings of the 3rd Multidisciplinary International Scheduling Conference: Theory and Applications (MISTA'07)*, (pp. 156-166).

Even S, Itai A, Shamir A (1976) On the complexity of timetable and multicommodity Flow problems. *SIAM Journal on Computing* 5(4):691-703.

Fisher H, Thompson GL (1961) Probabilistic learning combinations of local job-shop scheduling rules. In: *Factory Scheduling Conference*, Carnegie Institue of Technology.

Gogos, C., Alefragis, P., & Housos, E. (2008). A multi-staged algorithmic process for the solution of the examination timetabling problem. In *Proceedings of the 7th International Conference on Practice and Theory of Automated Timetabling (PATAT'08)*, Montreal.

Han, L., & Kendall, G. (2003a). An investigation of a tabu assisted hyper-heuristic genetic algorithm. *Proceedings of the IEEE Congress on Evolutionary Computation (CEC'03), 3*, (pp. 2230-2237).

Han, L., & Kendall, G. (2003b). Guided operators for a hyper-heuristic genetic algorithm. In T. D. Gedeon and L.C.C. Fung, (Ed.), *Proceedings of AI-2003: Advances in Artificial Intelligence. The 16th Australian Conference on Artificial Intelligence (AI'03)*, *2903*, (pp. 807-820).

Kaelbling, L. P., Littman, M., & Moore, A. (1996). Reinforcement learning: a survey. *Journal of Artificial Intelligence Research, 4*, (pp. 237-285).

Keller, R. E., & Poli, R. (2007a). Cost-benefit investigation of a genetic-programming hyper-heuristic. In *Proceedings of the 8th International Conference on Artificial Evolution (EA'07)*, Tours, France, (pp. 13-24).

Keller, R. E., Poli, R. (2007b). Linear genetic programming of parsimonious metaheuristics. In: *Proceedings of the IEEE Congress on Evolutionary Computation (CEC'07)*, Singapore, (pp. 4508-4515).

Keller, R. E., & Poli, R. (2007b). Linear genetic programming of parsimonious metaheuristics. In *Proceedings of the IEEE Congress on Evolutionary Computation (CEC'07)*, Singapore, (pp. 4508-4515).

Kendall, G., & Hussin, N. M. (2005). Tabu search hyper-heuristic approach to the examination timetabling problem at university of technology MARA. In E. K. Burke and M. Trick (Ed.), *Proceedings of the 5th International Conference on the Practice and Theory of Automated Timetabling (PATAT'04)*, *LNCS, 3616*, (pp. 270-293), Springer.

Kendall, G., & Mohamad, M. (2004). Channel assignment in cellular communication using a great deluge hyper-heuristic. In *Proceedings of the 12th IEEE International Conference on Network (ICON'04),* (pp. 769-773).

Kirkpatrick, S., Gelatt, C., & Vecchi, M. (1983). Optimization by simulated annealing. *Science, 220*, (pp. 671-680).

Marin, H. T. (1998). *Combinations of GAs and CSP strategies for solving examination timetabling problems*. Ph.D. Thesis, Instituto Tecnologico y de Estudios Superiores de Monterrey.

Marín-Blázquez, J., & Schulenburg, S. (2005). A hyper-heuristic framework with XCS: learning to create novel problem-solving algorithms constructed from simpler algorithmic ingredients. In Kovacs, T.; Llorà, X.; Takadama, K.; Lanzi, P.; Stolzmann, W. & Wilson, S. (Ed.), the *8th International Workshop on Learning Classifier Systems (IWLCS'05), 4399*, (pp. 193-218), Springer.

Mccollum, B. (2006). University timetabling: Bridging the gap between research and practice. In: *Proc. of the 5th International Conference on the Practice and Theory of Automated Timetabling*, (pp. 15-35), Springer.

McCollum, B, McMullan, P, Burke, E. K., Parkes, A. J., & Qu, R. (2009). A new model for automated examination timetabling, *Annals of OR*, to appear.

Merlot, L. T. G., Boland, N., Hughes, B. D., & Stuckey, P. J. (2002). A hybrid algorithm for the examination timetabling problem. In: E.K. Burke and P. De Causmaecker (Ed.), *the 4th International Conference on the Practice and Theory of Automated Timetabling (PATAT'02), LNCS, 1153*, (pp. 207-231).

Müller, T. (2008). ITC2007 Solver description: a hybrid approach. *Practice and Theory of Automated Timetabling (PATAT'08)*, Montreal, 19-22, August 2008.

Nareyek, A. (2003). Choosing search heuristics by non-stationary reinforcement learning. *Metaheuristics: Computer Decision-Making*, 523-544, Kluwer Academic Publishers.

Ouelhadj, D., & Petrovic, S. (2008). A Cooperative Distributed Hyper-heuristic Framework for Ouelhadj, D., & Petrovic, S. (2008). A cooperative distributed hyper-heuristic framework for scheduling. In *Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics (SMC'08),* (pp. 2560-2565).

Ozcan, E., Bilgin, B., & Korkmaz, E. (2008). A comprehensive analysis of hyper-heuristics. *Intelligent Data Analysis*, *12*, 3-23, IOS Press.

Ozcan, E., & Ersoy, E. (2005). Final exam scheduler – FES. *Proceedings of the IEEE Congress on Evolutionary Computation (CEC'05), 2*, (pp. 1356-1363).

Ozcan, E., Bykov, Y., Birben, M., Burke, K. E. (2009). Examination timetabling using late acceptance hyper-heuristics. In *Proceedings of Genetic and Evolutionary Computation Conference (GECCO'09)*.

Paquete, L. F., & Fonseca, C. M. (2001). A study of examination timetabling with multiobjective evolutionary algorithms. In *Proceedings of the 4th Metaheuristics International Conference (MIC'01)*, (pp. 149-154).

Petrovic, S., Patel, V., & Yang, Y. (2005). Examination timetabling with fuzzy constraints. In Burke, E. K. and M. Trick, (Ed.), *the 5th International Conference on the Practice and Theory of Automated Timetabling (PATAT'05), LNCS, 3616*, (pp. 313-333), Springer-Verlag.

Petrovic, S., Yang, Y., & Dror, M. (2003). Case-based initialisation for examination time-tabling. In *Proceedings of 1st Multidisciplinary International Conference on Scheduling: Theory and Applications (MISTA'03)*, (pp. 137–154).

Petrovic, S., Yang, Y., & Dror, M. (2007). Case-based selection of initialisation heuristics for metaheuristic examination timetabling. *Expert Systems with Applications: An International Journal, 33*(3), (pp. 772-785).

Pillay, A. (2007). Developmental Approach to the Examination timetabling Problem. http://www.cs.qub.ac.uk/itc2007/.

Pillay, N., &, Banzhaf, W. (2007). A genetic programming approach to the generation of hyper-heuristics for the uncapacitated examination timetabling problem. In Neves J, Santos MF, Machado J (Ed.), *Progress in Artificial Intelligence, 13th Portuguese Conference on Artificial Intelligence*, *LNCS*, *4874*, (pp. 223–234), Springer.

Pillay, N., Banzhaf, W. (2008). A study of heuristic combinations for hyper-heuristic systems for the uncapacitated examination timetabling problem. *European Journal of Operational Research* (2008), doi:10.1016/j.ejor.2008.07.023.

Qu, R., Burke, E. K., Mccollum, B., Merlot, L. T., and Lee, S. Y (2009). A survey of search methodologies and automated system development for examination timetabling. *Journal of Scheduling, 12*(1), (pp. 55-89).

Qu, R., & Burke, E. K. (2005). Hybrid variable neighbourhood hyper-heuristics for exam timetabling problems. In *Proceedings of the 6th Metaheuristic International Conference (MIC'05)*, (pp. 22-26).

Qu, R., & Burke, E. K. (2007). Adaptive decomposition and construction for examination timetabling problems.In *Proceedings of the 3rd Multidisciplinary International Scheduling Conference: Theory and Applications (MISTA'07)*, (pp. 418-425).

Qu, R., Burke, E. K., & McCollum, B. (2008a). Adaptive automated construction of hybrid heuristics for exam timetabling and graph colouring problems. *European Journal of Operational Research, 198*(2), 392-404.

Qu, R., Burke, E. K., McCollum, B., Merlot, L., & Lee, S. (2008b). A survey of search methodologies and automated system development for examination timetabling. *Journal of Scheduling, DOI: 10.1007/s10951-008-0077-5*.

Rattadilok, P., Gaw, A., & Kwan, R. (2004). *A Distributed Hyper-heuristic for Scheduling*. Technical Report, University of Leeds, School of Computing.

Rattadilok, P., Gaw, A., & Kwan, R. (2005). Distributed choice function hyper-heuristics for timetabling and scheduling. *Proceedings of the 5th International Conference on the Practice and Theory of Automated Timetabling (PATAT'2004)*, (pp. 51-67), Springer-Verlag.

Ross, P. (2005). Hyper-heuristics. In: Burke, E.K., Kendall, G. (eds), *Search Methodologies: Introductory Tutorials in Optimization and Decision Support Techniques*, chap 17, (pp. 529-556), Springer.

Ross, P., Corne, D., & Fang, H. L. (1994). Improving evolutionary timetabling with delta evaluation and directed mutation. *Proceedings of the International Conference on Evolutionary Computation. The Third Conference on Parallel Problem Solving from Nature*, (pp. 556-565), Springer-Verlag.

Ross, P., Hart, E., Marin-Blazquez, J., & Schulenberg, S. (2003). Learning a procedure that can solve hard bin-packing problems: a new GA-based approach to hyperheuristics. *Proceedings of Genetic and Evolutionary Computation Conference (GECCO'2003)*, (pp. 1295-1306).

Ross, P., Schulenburg, S., Marn-Blázquez, J., & Hart, (2002). Hyper-heuristics: learning to combine simple heuristics in bin-packing problems. In *Proceedings of the Genetic and Evolutionary Computation Conference (GECCO'02)*, (pp. 942-948), Morgan Kaufmann Publishers.

Schaerf, A., & Di Gaspero, L. (2006). Measurability and reproducibility in timetabling research: State-of-the-art and discussion (invited paper). In E. K. Burke & H. Rudova (Ed.), *the 6th International. Conference on the Practice and Theory of Automated Timetabling (PATAT'06)*, (pp. 53-62).

Sutton, R. S., & Barto, A. G. (1998). *Reinforcement learning: an introduction*. The MIT Press.

Tereshima-Marin, H. T., Zarate, C. J. F., Ross, P., & Valenzuela-Rendon, M. (2007). Comparing two models to generate hyper-heuristics for the 2d-regular bin-packing problem. In *Proceedings of the 9th Annual Conference on Genetic and Evolutionary Computation (GECCO'07)*, (pp. 2182-2189).

Terashima-Marin, H., Ross, P., & Valenzuela-Rendon, M. (1999). Evolution of constraint satisfaction strategies in examination timetabling. In *Proceedings of the Genetic and Evolutionary Computation Conference* (GECCO'99), (pp 635-642).

Terashima-Marin, H., Moran-Saavedra, A., & Ross, P. (2005). Forming hyper-heuristics with GAs when solving 2D-regular cutting stock problems. In *Proceedings of the 2005 IEEE Congress on Evolutionary Computation*, *2*, (pp. 1104-1110), IEEE Press.

Thompson, J. M., & Dowsland, K. A. (1996). Variants of simulated annealing for the examination timetabling problem. *Annals of Operations Research, 63*, 105–128.

Thompson, J. M., & Dowsland, K. A. (1998). A robust simulated annealing based examination timetabling system. *Computers & Operations Research, 25*, 637-648.

Vazquez-Rodriguez, J.A., Petrovic, S. & Salhi, A. (2007). A combined meta-heuristic with hyper-heuristic approach to the scheduling of the hybrid flow shop with sequence dependent setup times and uniform machines. In P. Baptiste, G. Kendall, A. Munier-Kordon & F. Sourd (Ed.), *the 3rd Multi-disciplinary International Scheduling Conference: Theory and Applications (MISTA'07)*, (pp. 506-513), Paris, France.

Wong, T., Cote, P., & Gely, P. (2002). Final exam timetabling: a practical approach. In *Proceedings of the IEEE Canadian Conference on Electrical and Computer Engineering, 2*, (pp 726-731).

Yang, Y., & Petrovic, S. (2005). A Novel similarity measure for heuristic selection in examination timetabling. In E. K. Burke & M. Trick (Ed.), *Practice and Theory of Automated Timetabling: Selected Papers from the 5th International Conference, LNCS, 3616*, (pp. 377-396), Springer.