A Shuffled Complex Evolution Based Algorithm for Examination Timetabling

Benchmarks and a New Problem Focusing Two Epochs

Nuno Leite[1,3,*], Fernando Melício[3] and Agostinho C. Rosa[2,3]

[1]*Instituto Superior de Engenharia de Lisboa/ADEETC, Polytechnic Institute of Lisbon, Rua Conselheiro Emídio Navarro, n.° 1, 1959-007, Lisboa, Portugal*

[2]*Department of Bioengineering/Instituto Superior Técnico, Universidade de Lisboa, Av. Rovisco Pais, n.° 1, 1049-001 Lisboa, Portugal*

[3]*Institute for Systems and Robotics/LaSEEB, Instituto Superior Técnico, Universidade de Lisboa, Av. Rovisco Pais, n.° 1, TN 6.21, 1049-001, Lisboa, Portugal*

Keywords: Examination Timetabling, Shuffled Complex Evolution Algorithm, Memetic Computing, Great Deluge Algorithm, Toronto Benchmarks, Two-Epoch Examination Timetabling.

Abstract: In this work we present a memetic algorithm for solving examination timetabling problems. Two problems are analysed and solved. The first one is the well-studied single-epoch problem. The second problem studied is an extension of the standard problem where two examination epochs are considered, with different durations. The proposed memetic algorithm inherits the population structure of the Shuffled Complex Evolution algorithm, where the population is organized into sets called *complexes*. These complexes are evolved independently and then shuffled in order to generate the next generation complexes. In order to explore new solutions, a crossover between two complex's solutions is done. Then, a random solution selected from the top best solutions is improved, by applying a local search step where the Great Deluge algorithm is employed. Experimental evaluation was carried out on the public uncapacitated Toronto benchmarks (single epoch) and on the ISEL-DEETC department examination benchmark (two epochs). Experimental results show that the proposed algorithm is efficient and competitive on the Toronto benchmarks with other algorithms from the literature. Relating the ISEL-DEETC benchmark, the algorithm attains a lower cost when compared with the manual solution.

1 INTRODUCTION

The Examination Timetabling Problem (ETTP) is a combinatorial optimisation problem which objective is to allocate course exams to a set of limited time slots, while respecting some *hard constraints*, such as respect maximum room capacity, guarantee room exclusiveness for given exams, guarantee that no students will sit two or more exams at the same time slot, guarantee exam ordering (e.g. larger exams must be scheduled at the beginning of the timetable), among others (McCollum et al., 2012). The ETTP is a multi-objective problem in nature as several objectives (reflecting the various interested parties, e.g., students, institution, teachers) are considered (Burke et al., 2008). However, due to complexity reasons, the ETTP has been dealt as a single-objective problem. A second type of constraints, named *soft constraints*, are also considered but there is no obligation to observe them. The optimisation goal is usually the minimisation of the soft constraints violations.

The ETTP, as other problems (e.g. Course timetabling) belong to the general class of timetabling problems which include *Transportation* and *Sports* timetabling, *Nurse scheduling*, among others. In terms of complexity, University timetabling problems belong to the NP-complete class of problems (Qu et al., 2009). In the past 30 years, several heuristic solution methods have been proposed to solve the ETTP. The *meta-heuristics* form the most successful methods applied to ETTP. These are mainly divided into two classes (Talbi, 2009): single-solution based meta-heuristics and population-based meta-heuristics. Single-solution meta-heuristics include algorithms such as simulated annealing, tabu search,

*This work was supported by the FCT – *Fundação para a Ciência e a Tecnologia* Project PEst-OE/EEI/LA0009/2013 and by the FCT grant Ref. No. SFRH/PROTEC/67953/2010.

Leite N., Melício F. and Rosa A..
A Shuffled Complex Evolution Based Algorithm for Examination Timetabling - Benchmarks and a New Problem Focusing Two Epochs.
DOI: 10.5220/0005164801120124
In *Proceedings of the International Conference on Evolutionary Computation Theory and Applications* (ECTA-2014), pages 112-124
ISBN: 978-989-758-052-9

and variable neighbourhood search. Population-based meta-heuristics include genetic algorithms, ant colony optimisation, particle swarm optimisation and memetic algorithms. Particle swarm optimisation integrates the larger branch named Swarm Intelligence (Kamil et al., 1987). In Swarm Intelligence the behaviour of self-organised systems (e.g., frog swarm in a swamp, fish swarm, honeybee mating) is simulated. For a recent survey of approaches applied to the ETTP see (Qu et al., 2009). Population-based approaches, especially hybrid methods that employ single-solution meta-heuristics in an exploitation phase, form the most successful methods. These hybrid methods are named Memetic Algorithms (Neri et al., 2012), and integrate the larger branch known as Memetic Computing. In the literature, several population-based methods were proposed for solving the ETTP: ant colony (Dowsland and Thompson, 2005), particle swarm optimisation (Chu et al., 2006), fish swarm optimisation algorithm (Turabieh and Abdullah, 2011a; Turabieh and Abdullah, 2011b), and honeybee mating optimisation (Sabar et al., 2009).

In previous research undertaken (Leite et al., 2013), the ETTP was approached by an adaptation of the Shuffled Frog-Leaping Algorithm (SFLA) (Eusuff et al., 2006). The SFLA is, by its turn, based on the Shuffled Complex Evolution (SCE) approach (Duan et al., 1993). Both are evolutionary algorithms (EA) containing structured populations and an efficient exploitation phase (local search). They were successfully applied to Global optimisation problems.

An important feature that must be observed when designing an EA-based approach is the diversity management (Neri, 2012), as a poor population diversity leads the algorithm to stagnate prematurely. Another emergent approach that uses a structured population is the Cellular Genetic Algorithm (cGA) (Alba and Dorronsoro, 2008), which promotes a smooth actualization of solutions through the population, therefore maintaining the diversity.

In this work, we propose a memetic algorithm for solving combinatorial optimisation problems. In the presented work, we show its application to the ETTP. The method, coined SCEA – Shuffled Complex Evolution Algorithm, inherits features from the SCE and SFLA approaches, namely the population is organized into sub-populations called *complexes* (*memeplexes* in SFLA). Population diversity is maintained in the SCEA using both a crossover operator and a special solution update mechanism. The method is hybridised with the single-solution method Great Deluge Algorithm (GDA) (Dueck, 1993). The GDA is a simulated annealing variant which comprises a deterministic acceptance function of neighbouring solutions.

Table 1: Hard and Soft constraints for the uncapacitated ETTP considered in this work. The H_2 constraint appears in the two-epoch formulation.

Constraint and Type	Explanation
H_1 (Hard)	There cannot exist students sitting for more than one exam simultaneously.
H_2 (Hard)	A minimum distance between the two exams of a course must be observed.
S_1 (Soft)	The exams should be spread out evenly through the timetable.

There exist several public benchmarks available for algorithm testing and comparison purposes. The most used are the *Toronto*, and the *International Timetabling Competition 2007* (ITC 2007) benchmarks (Qu et al., 2009). The SCEA is applied to the *uncapacitated Toronto benchmarks* (Carter et al., 1996), comprising 13 ETTP real instances (single examination epoch), and also to the uncapacitated ETTP instance of the Electrical, Telecommunications and Computer Department at the Lisbon Polytechnic Institute (ISEL-DEETC), which comprises two examination epochs.

The paper is organized as follows. Section 2 presents the ETTP formulations of the considered ETTP instances. In Section 3 we describe the proposed memetic algorithm for solving the ETTP. Section 4 presents simulation results and analysis on the algorithm performance. Finally, conclusions and future work are presented in Section 5.

2 EXAMINATION TIMETABLING PROBLEMS

In this section we describe in more detail the two ETTP problems analysed in this work. The first problem is the well-studied single-epoch problem, where a single examination epoch with fixed number of time slots is considered. The second problem is a new problem emerged from practice, where two examination epochs are considered, with different number of time slots allotted for each epoch.

Table 1 describe the hard and soft constraints of the ETTP instances analysed in this work.

2.1 The Single-epoch Problem

The single-epoch problem standard formulation was adapted from (Abdullah et al., 2009) and (Burke et al., 2004)), and is presented next. The following terms were defined:

- E_i, is the set of N examinations ($i = 1,\ldots,N$);
- T, is the number of time slots;
- $C = (c_{ij})_{N\times N}$ (*Conflict matrix*), is a symmetric matrix of size N where each element, denoted by c_{ij} $(i,j \in \{1,\ldots,N\})$, represents the number of students attending exams i and j;
- M, is the total number of students;
- t_k $(1 \le t_k \le T)$ denotes the assigned time slot for exam k $(k \in \{1,\ldots,N\})$.

The optimisation objective is the minimisation of the sum of proximity costs given by:

$$\text{minimise} \quad f_c = \frac{1}{M} \cdot \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} c_{ij} \cdot prox(i,j) \tag{1}$$

where

$$prox(i,j) = \begin{cases} 2^{5-|t_i-t_j|} & if \;\; 1 \le |t_i - t_j| \le 5 \\ 0 & otherwise \end{cases}, \tag{2}$$

subject to

$$\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} c_{ij} \cdot \lambda(t_i,t_j) = 0 \quad \text{and} \tag{3}$$

$$\lambda(t_i,t_j) = \begin{cases} 1 & if \; t_i = t_j \\ 0 & otherwise \end{cases}.$$

Equation (2) measures the proximity cost of exams i and j which is greater than zero for exams that are five or less time slots apart. Equation (3) represents the hard constraint H_1. Equation (1) represents the soft constraint S_1.

2.1.1 Toronto Datasets

As previously mentioned in Section 1, for the single-epoch problem, we use in our simulations the Uncapacitated Toronto benchmarks, Version I (Table 2).

2.2 The Two-epoch Problem

The two-epoch problem is an extension of the standard problem where two examination epochs of different dimensions are considered instead of just a single epoch. A snapshot of timetables having two epochs is given in Tables 8 and 9.

A new hard constraint (constraint H_2 in Table 1) is specified in the two-epoch problem for guaranteeing a minimum number of time slots between the two examinations of the same course, in order to give the necessary study time, exam correction and proofing. In the two-epoch problem formulation, the following terms were added to the single-epoch problem formulation:

Table 2: Specifications of the uncapacitated Toronto benchmarks (version I).

Data set	Students	Exams	Conflict density	Time slots
car91	16925	682	0.13	35
car92	18419	543	0.14	32
ear83	1125	190	0.27	24
hec92	2823	81	0.42	18
kfu93	5349	461	0.06	20
lse91	2726	381	0.06	18
pur93	30032	2419	0.03	42
rye92	11483	486	0.07	23
sta83	611	139	0.14	13
tre92	4360	261	0.18	23
uta92	21266	622	0.13	35
ute92	2749	184	0.08	10
yor83	941	181	0.29	21

- T and L, are, respectively, the number of time slots of the first epoch and the total number of time slots (sum of the first and second epochs's time slots). The number of time slots of the second epoch is then $L - T$;
- $C_{relax} = (c_{relax_{ij}})_{N\times N}$ (*Relaxed conflict matrix*), is a relaxed version of the conflict matrix C. This matrix is used in the generation of the second examination epoch. Further details are given below.
- u_k $(T+1 \le u_k \le L)$ denotes the assigned time slot for exam k $(k \in \{1,\ldots,N\})$ in the second examination epoch.

The hard constraint H_2 is specified by:

$$u_k - t_k \ge L_{min}, \tag{4}$$

where L_{min} is the minimum time slot distance between the first and second epoch exams of a given course.

The devised algorithm for solving the two-epoch problem executes the following steps:

1. Treat the two epochs as two distinct single-epoch problems. Solve the second epoch problem by considering the standard single-epoch formulation presented in Section 2.1, but using the relaxed conflict matrix, C_{relax};
2. Then, solve the first epoch problem using the standard formulation as depicted in Section 2.1 with the added constraint H_2, that is, by adding Eq. (4).
3. At the end of the optimisation step, we join the two timetables forming the two-epoch timetable that respects both H_1 and H_2 constraints. The cost of the two-epoch timetables is the sum of the costs of the individual timetables.

Table 3: Characteristics of the DEETC dataset.

Parameter	Value	
Number of exams		80
Number of students		1238
Number of enrolments		4548
Conflict matrix density	1st epoch	0.32
	2nd epoch	0.31
Number of time slots	1st epoch	18
	2nd epoch	12

Some final details are now given. In the ISEL-DEETC dataset, the second epoch is more constrained than the first epoch, having less time slots (18 and 12 time slots, respectively, for the first and second epochs). In order to be possible to generate feasible initial solutions for the second epoch, some entries (with very few students enrolled) were set to zero, resulting in a relaxed conflict matrix. However, this pre-processing is problem dependent and for that reason not obligatory. The algorithm starts by generating the second examination epoch followed by the generation of the first examination epoch (with the added constraint H_2), but this order is not strict. We could have started by the inverse order. However, this latter experiment was not carried out in this work.

In order to optimise the first epoch while respecting the hard constraint H_2, we have to apply modified versions of the initialisation procedure, the crossover and the neighbourhood operators. These modified versions work with feasible timetables that satisfy both hard constraints, H_1 and H_2. As a final detail, we mention that while we optimised the timetables using the proximity cost specified in Eq. (2), which measures conflicts in a neighbourhood of five time slots, in our collected results we use the measure published in (Leite et al., 2012), which only considers conflicts from two consecutive time slots, and do not consider conflicts on Saturdays. We use this later measure here in order to be able to compare results with the method published in (Leite et al., 2012).

2.2.1 ISEL-DEETC Dataset

The problem instance considered in this work is the DEETC timetable of the winter semester of the 2009/2010 academic year. This benchmark data is detailed in (Leite et al., 2012). The DEETC timetable comprises five programs: three B.Sc. programs (named LEETC, LEIC and LERCM) and two M.Sc. programs (named MEIC and MEET). B.Sc. and M.Sc. programs have six and four semesters duration, respectively. The DEETC dataset characteristics are listed in Table 3.

3 SHUFFLED COMPLEX EVOLUTION ALGORITHM FOR EXAMINATION TIMETABLING

In this section we describe the SCEA algorithm for solving the ETTP. The SCEA is based on ideas from the SCE (Duan et al., 1993) and the SFLA (Eusuff et al., 2006) approaches. In the SCE, the population is organized into *complexes* whereas in the SFLA it is organized into *memeplexes*. In the text, we use these two terms interchangeably.

In the SCE and SFLA approaches, global search is managed as a process of natural evolution. The sample points form a population that is partitioned into distinct groups called complexes (memeplexes). Each of these evolve independently, by searching the space into different directions. After completing a certain number of generations, the complexes are combined, and new complexes are formed through the process of shuffling. These procedures enhance survivability by a sharing of information about the search space, constructed independently by each complex (Duan et al., 1993).

The SCEA main steps are illustrated in Figure 1, whereas the SCEA local search step is depicted in Figure 2. The main loop of SCEA is identical to the SCE and SFLA main loop, where complexes are formed by creating random initial solutions that span the search space. Here, instead of points, the solutions correspond to complete and feasible timetables.

The local search step (Figure 2) was fully redesigned from the SCE and SFLA methods, in order to operate with ETTP solutions. Like SFLA, we maintain the best and worst solutions of the memeplex, denoted respectively as P_b and P_w, and elitism is achieved by maintaining the best global solution, denoted as P_g. The local search step starts by selecting, randomly, and according with crossover probability cp, two parent solutions, P_1 and P_2, for recombination in order to produce a new offspring. P_1 must be different from the complex's best solution. The solution P_1 is recombined with solution P_2 (see the crossover operation depicted in Figure 3) and the resulting offspring replaces the parent P_1. After this, the complex is sorted in order of increasing objective function value. The crossover operator was adapted from the crossover operator of (Abdullah et al., 2010; Sabar et al., 2009).

After the crossover, a solution in the complex is selected for improvement according to an improve probability, ip. The solution is improved by employing the local search meta-heuristic GDA (*Great Del-*

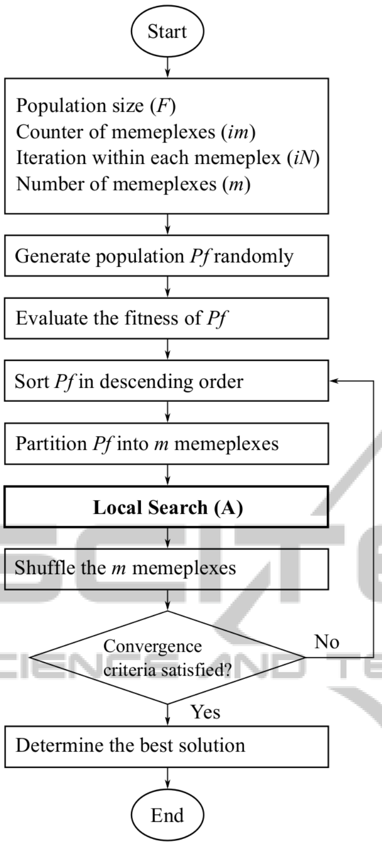


Figure 1: SCEA main steps.

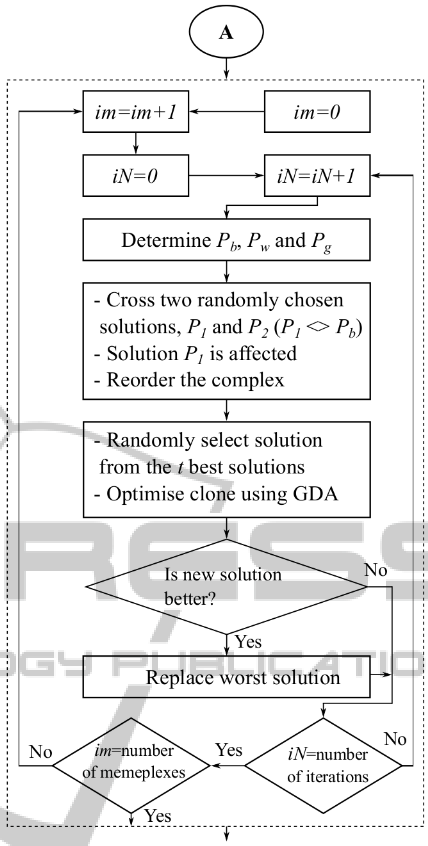


Figure 2: SCEA Local search step.

uge Algorithm) (Dueck, 1993). The template of GDA is presented in Algorithm 3.1. The GDA mimics the exploration made by a climber trying to reach the top of a mountain while is raining incessantly. This scenario leads to the name of the algorithm: great deluge. As the rain never stops, the water level gradually increases until it reaches the climber. The goal of the climber is finding the way to the top (maximisation problem) before is reached by the water level. It can go up or down from that is always above the water level.

The selection of the solution to improve is made on the group of the top t best solutions. The exploitation using GDA is done on a clone of the original solution, selected from this group. If the optimised solution is better than the original, then it will replace the complex's worst solution. This updating step in conjunction with the crossover operator guarantees a reasonable diversity, in an implicit fashion.

The GDA was integrated in the SCEA in the following fashion. We use as the initial solution s_0 the chosen solution to improve. The level $LEVEL$ is set to the fitness value of this initial solution s_0. The search stops when the water level is equal to the solution fitness.

Algorithm 3.1: Template of the Great Deluge Algorithm.

Input:

- s_0 /* Initial solution */
- Initial water level $LEVEL$
- Rain speed UP /* $UP > 0$ */

$s = s_0$; /* Generation of the initial solution */
repeat
  Generate a random neighbour s';
  If $f(s') < LEVEL$ Then $s = s'$ /* Accept
  the neighbour solution */
  $LEVEL = LEVEL - UP$; /* update the water
  level */
until Stopping criteria satisfied
Output: Best solution found.

Initial Solution Construction

The construction of the initial feasible solutions is done by a heuristic algorithm which uses the Saturation Degree graph colouring heuristic (Carter et al.,

t_1	e_2	e_{14}	e_{10}	e_3	e_{16}
t_2	e_1	e_{11}	e_4		
t_3	e_9	e_{20}	e_5	e_{18}	
t_4	e_6	e_{13}	e_7		
t_5	e_8	e_{12}	e_{15}	e_{17}	e_{19}

(a) Solution P_1

t_1	e_{15}	e_{20}			
t_2	e_9	e_2	e_{12}	e_{10}	e_7
t_3	e_6	e_1	e_{17}	e_{13}	
t_4	e_5	e_{18}	e_4	e_{16}	
t_5	e_8	e_{14}	e_{11}	e_3	e_{19}

(b) Solution P_2

t_1	e_2	~~e_{14}~~	e_{10}	~~e_3~~	e_{16}			
t_2	e_1	e_{11}	e_4	~~e_8~~	e_{14}	~~e_{11}~~	e_3	e_{19}
t_3	e_9	e_{20}	e_5	e_{18}				
t_4	e_6	e_{13}	e_7					
t_5	e_8	e_{12}	e_{15}	e_{17}	~~e_{19}~~			

(c) New solution P_1

Figure 3: Crossover between P_1 and P_2. The resulting solution P_1 in (c) is the result of combining the solution P_1 (a) with other solution P_2 (b). The operator inserts into P_1, at a random time slot (shown dark shaded in (a) and (c)), exams chosen from a random time slot from solution P_2 (shown dark shaded in (b)). When inserting these exams (shown light gray in (c)), some could be infeasible or already existing in that time slot (respectively, the case of e_8 and e_{11} in (c)). These exams are not inserted. The duplicated exams in the other time slots are removed.

1996).

GDA's Neighbourhood
In the local search with GDA we used the Kempe chain neighbourhood (Demeester et al., 2012).

Two-epoch Feasibility
In order to be able to execute the SCEA on the two-epoch problem, we have to implement a different version of the initialisation procedure, and the crossover and neighbourhood operators, that could manage the hard constraint H_2 mentioned in Section 2. This different version is executed in the first epoch generation, while the original version is executed in the second epoch generation.

4 EXPERIMENTS AND COMPARISONS

4.1 Problem Instances and Experimental Settings

The performance of the SCEA was evaluated using the Toronto datasets (see Table 2). All these 13 instances can be downloaded from ftp://ftp.mie.utoronto.ca/pub/carter/testprob. We also solved the two-epoch ISEL-DEETC instance (Table 3). For the ISEL-DEETC, there's a manual solution available (for the five timetables corresponding to the five engineering programs) from the ISEL academic services. The algorithm is programmed in the C++ language. The implemented code uses the ParadisEO framework (Talbi, 2009). The hardware and software specifications are: Intel Core i7-2630QM, CPU @ 2.00 GHz $\times$ 8, with 8 GB RAM; OS: Ubuntu 14.04, 64 bit; Compiler used: GCC v. 4.8.2.

The parameters of SCEA are: Population size $F = 24$, Memeplex count $m = 3$, Memeplex size $n = 8$ (no sub-memeplexes were defined), and Number of time loops (convergence criterion) $L = 100000000$. The number of best solutions to consider for selection on a complex is given by $t = n/4 = 2$. The Great Deluge parameter, UP, was set to: $UP = 1e-7$. The crossover and improvement probabilities, respectively, cp and ip, were set equal to 0.2 and 1.0. The parameter values were chosen empirically. To obtain our simulation results, the SCEA was run five times on each instance with different random seeds. The running time of the algorithm was limited to 24 hours to all datasets except for the `pur93`. For this larger dataset, the running time was limited to 48 hours.

4.2 Comparative Results and Discussion

Tables 4 and 5 show the best results of the SCEA on the Toronto datasets as well as a selection of the best results available in the literature. The listed methods include only results validated by (Qu et al., 2009) (dated until 2008). In the last two rows of each table, the *TP* and *TP (11)* indicate, respectively, the total penalty for the 13 instances and the total penalty except the `pur93` and `rye92` instances. Tables 6 and 7 compare SCEA with the top six best algorithms. For the SCEA we present the lowest penalty value f_{min}, the average penalty value f_{ave}, and the standard deviation σ over five independent runs. For the reference algorithms we present the best and average (where available) results and the number of runs. Figure 4 illustrate the SCEA evolution on the `yor83` dataset.

The authors analysed in Tables 6 and 7 mention computation times that are within several minutes – 1 hour, to several hours (12 hours maximum).

The best results obtained by SCEA are competitive with the ones produced by state-of-the-art algorithms. It attains a new lower bound on the `yor83` dataset. We also observe that the SCEA obtains the lowest sum of average cost on the *TP* and *TP (11)*

Table 4: Simulation results of SCEA and comparison with selection of best algorithms from literature. Values in bold represent the best results reported. "–" indicates that the corresponding instance is not tested or a feasible solution cannot be obtained.

Dataset	(Carter et al., 1996)	(Burke and Newall, 2002)	(Merlot et al., 2003)	(Burke and Newall, 2004)	(Burke et al., 2004)	(Kendall and Hussin, 2005)
car91	7.10	4.65	5.10	5.00	4.80	5.37
car92	6.20	4.10	4.30	4.30	4.20	4.67
ear83	36.40	37.05	35.10	36.20	35.40	40.18
hec92	10.80	11.54	10.60	11.60	10.80	11.86
kfu93	14.00	13.90	13.50	15.00	13.70	15.84
lse91	10.50	10.82	10.50	11.00	10.40	–
pur93	**3.90**	–	–	–	4.80	–
rye92	**7.30**	–	8.40	–	8.90	–
sta83	161.50	168.73	157.30	161.90	159.10	157.38
tre92	9.60	8.35	8.40	8.40	8.30	8.39
uta92	3.50	3.20	3.50	3.40	3.40	–
ute92	25.80	25.83	25.10	27.40	25.70	27.60
yor83	41.70	37.28	37.40	40.80	36.70	–
TP (11)	327.10	325.45	310.80	325.00	312.50	–
TP	338.30	–	–	–	326.20	–

Dataset	(Yang and Petrovic, 2005)	(Burke and Bykov, 2006)	(Eley, 2006)	(Burke and Bykov, 2008)	(Abdullah et al., 2009)	(Sabar et al., 2009)
car91	4.50	4.42	5.20	4.58	4.42	4.79
car92	3.93	**3.74**	4.30	3.81	3.76	3.90
ear83	33.71	32.76	36.80	32.65	**32.12**	34.69
hec92	10.83	10.15	11.10	10.06	**9.73**	10.66
kfu93	13.82	12.96	14.50	12.81	**12.62**	13.00
lse91	10.35	**9.83**	11.30	9.86	10.03	10.00
pur93	–	–	–	4.53	–	–
rye92	8.53	–	9.80	7.93	–	10.97
sta83	158.35	157.03	157.30	157.03	156.94	157.04
tre92	7.92	7.75	8.60	7.72	7.86	7.87
uta92	3.14	3.06	3.50	3.16	**2.99**	3.10
ute92	25.39	24.82	26.40	24.79	24.90	25.94
yor83	36.35	34.84	39.40	34.78	34.95	36.18
TP (11)	308.29	301.36	318.40	301.25	**300.32**	307.17
TP	–	–	–	313.71	–	–

quantities, and the lowest sum of best costs on the *TP* quantity, for the Toronto datasets. This demonstrates that SCEA can optimise very different datasets with good efficiency. A negative aspect of SCEA is the time taken compared with other algorithms. The time taken is a reflex of the high diversity of the method mixed with the low decreasing rate *UP*. A low *UP* value is needed in order for the GDA to find the best exam movements. If the *UP* value is higher, the optimisation is faster but with worse results, because the initial, larger conflict, exams are scheduled into sub optimal time slots, and thus the remainder exams, as the water level decreases, could not be scheduled in the optimal fashion.

4.3 Two-epoch Problem

For the two-epoch problem, we run the SCEA with the same parameters. The L_{min} parameter was set to $L_{min} = 10$ (first and second epoch examinations of a given course are 10 time slots apart). Tables 8 and 9 illustrate, respectively, the manual and auto-

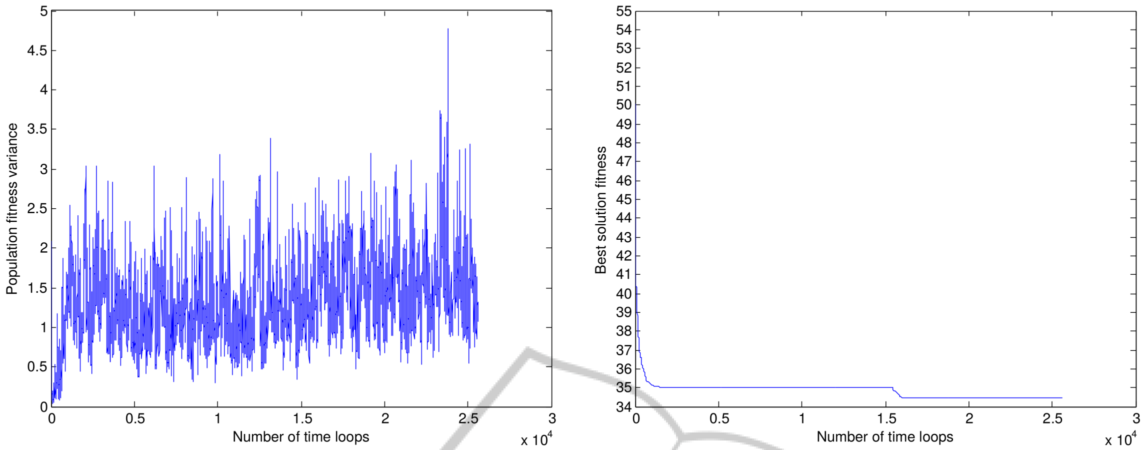
Table 5: Simulation results of SCEA and comparison with selection of best algorithms from literature (continued).

Dataset	(Burke et al., 2010)	(Abdullah et al., 2010)	(Turabieh and Abdullah, 2011a)	(Demeester et al., 2012)	(Abdullah and Alzaqebah, 2013)	(Alzaqebah and Abdullah, 2014)	**SCEA**
car91	4.90	**4.35**	4.81	4.52	4.76	4.62	4.41
car92	4.10	3.82	4.11	3.78	3.94	4.00	3.75
ear83	33.20	33.76	36.10	32.49	33.61	33.14	32.62
hec92	10.30	10.29	10.95	10.03	10.56	10.43	10.03
kfu93	13.20	12.86	13.21	12.90	13.44	13.59	12.88
lse91	10.40	10.23	10.20	10.04	10.87	10.75	9.85
pur93	–	–	–	5.67	–	–	4.10
rye92	–	–	–	8.05	8.81	9.17	7.98
sta83	**156.90**	**156.90**	159.74	157.03	157.09	157.06	157.03
tre92	8.30	8.21	8.00	**7.69**	7.94	8.00	7.75
uta92	3.30	3.22	3.32	3.13	3.27	3.27	3.08
ute92	24.90	25.41	26.17	**24.77**	25.36	25.16	24.78
yor83	36.30	36.35	36.23	34.64	35.74	35.58	**34.44**
TP (11)	305.80	305.40	312.84	301.02	306.58	305.60	300.62
TP	–	–	–	314.74	–	–	**312.70**

Table 6: Simulation results of SCEA and comparison with the best algorithms from literature. Values in bold represent the best results reported. "–" indicates that the corresponding instance is not tested or a feasible solution cannot be obtained.

Dataset	(Carter et al., 1996)	(Burke and Bykov, 2006)	(Abdullah et al., 2009) (five runs)		(Burke et al., 2010)
	f_{min}	f_{min}	f_{min}	f_{ave}	f_{min}
car91	7.10	4.42	4.42	4.81	4.90
car92	6.20	**3.74**	3.76	3.95	4.10
ear83	36.40	32.76	**32.12**	33.69	33.20
hec92	10.80	10.15	**9.73**	10.10	10.30
kfu93	14.00	12.96	**12.62**	**12.97**	13.20
lse91	10.50	**9.83**	10.03	10.34	10.40
pur93	**3.90**	–	–	–	–
rye92	**7.30**	–	–	–	–
sta83	161.50	157.03	156.94	157.30	**156.90**
tre92	9.60	7.75	7.86	8.20	8.30
uta92	3.50	3.06	**2.99**	3.32	3.30
ute92	25.80	24.82	24.90	25.41	24.90
yor83	41.70	34.84	34.95	36.27	36.30
TP (11)	327.10	301.36	**300.32**	306.36	305.80
TP	338.30	–	–	–	–

matic solutions for the most difficult timetable, the LEETC timetable. Table 10 shows the comparison of the manual solution timetables conflicts with two runs of SCEA. The SCEA could generate timetables with lower cost comparing with the manual solution. We note that SCEA optimise the merged timetable comprising the five timetables and not the individual timetables, so in some cases, some programs timetables have worse cost (e.g. Run1, 2nd epoch). The results produced in the first epoch, are comparable with the results published in (Leite et al., 2012).



(a) (b)

Figure 4: SCEA evolution on `yor83` dataset (a) Population fitness variance evolution along time; (b) Best solution fitness evolution along time.

Table 7: Simulation results of SCEA and comparison with the best algorithms from literature (continued).

Dataset	(Abdullah et al., 2010) (five runs)	(Demeester et al., 2012)(20 runs)		**SCEA**(five runs)		
	f_{min}	f_{min}	f_{ave}	f_{min}	f_{ave}	σ
car91	**4.35**	4.52	4.64	4.41	**4.45**	0.03
car92	3.82	3.78	3.86	3.75	**3.77**	0.01
ear83	33.76	32.49	**32.69**	32.62	**32.69**	0.07
hec92	10.29	10.03	**10.06**	10.03	**10.06**	0.03
kfu93	12.86	12.90	13.24	12.88	13.00	0.13
lse91	10.23	10.04	10.21	9.85	**9.93**	0.12
pur93	–	5.67	5.75	4.10	**4.17**	0.05
rye92	–	8.05	8.20	7.98	**8.06**	0.06
sta83	**156.90**	157.03	157.05	157.03	**157.03**	0.00
tre92	8.21	**7.69**	**7.79**	7.75	7.80	0.05
uta92	3.22	3.13	3.17	3.08	**3.15**	0.05
ute92	25.41	**24.77**	24.88	24.78	**24.81**	0.02
yor83	36.35	34.64	34.83	**34.44**	**34.73**	0.17
TP (11)	305.40	301.02	302.42	300.62	**301.42**	
TP	–	314.74	316.37	**312.70**	**313.65**	

5 CONCLUSIONS

We presented a memetic algorithm that combines features from the SCE and the GDA meta-heuristics. The experimental evaluation of the SCEA shows that it is competitive with state-of-the-art methods. In the set of the 13 instances of the Toronto benchmark data it attains the lowest cost on one dataset, and the lowest sum of best and average cost with a low standard deviation. The algorithm main disadvantage is the time taken on the larger instances.

Further studies should address the diversity management in order to accelerate the algorithm while maintaining a satisfactory diversity.

As future research, we intend to apply our solution method to the instances of the 1st Track (Examination Timetabling) of the 2nd International Timetabling Competition (ITC2007), which contain more hard and soft constraints.

Table 8: Manual solution for the LEETC examination timetable. The courses marked in bold face are shared with other programs. The number of clashes of this timetable is 287 and 647, respectively, for the first and second epochs.

Course	First epoch																		Second epoch											
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
	Mo	Tu	Wd	Tr	Fr	Sa	Mo	Tu	Wd	Tr	Fr	Sa	Mo	Tu	Wd	Tr	Fr	Sa	Mo	Tu	Wd	Tr	Fr	Sa	Mo	Tu	Wd	Tr	Fr	Sa
ALGA			x																		x									
Pg							x																x							
AM1												x																x		
FAE																	x													x
ACir														x											x					
POO								x																x						
AM2											x											x								
LSD																		x											x	
E1															x												x			
MAT					x															x										
PE													x													x				
ACp																	x													x
EA									x														x							
E2	x																		x											
SS						x															x									
RCp											x															x				
PICC/CPg															x													x		
PR			x																	x										
FT							x																	x						
SEAD1																		x											x	
ST														x													x			
RCom					x														x											
RI										x												x								
SE1													x													x				
AVE								x																x						
SCDig												x													x					
SOt																	x													x
PI												x											x							
SCDist															x														x	
EGP	x																			x										
OGE	x																			x										
SG	x																			x										

Table 9: Automatic solution for the LEETC examination timetable. The courses marked in bold face are shared with other programs. The number of clashes of this timetable is 218 and 632, respectively, for the first and second epochs. As can be observed, all first epoch examinations respect the minimum distance ($L_{min} = 10$) to the corresponding exam time slot in the second epoch.

Course	First epoch																		Second epoch											
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
	Mo	Tu	Wd	Tr	Fr	Sa	Mo	Tu	Wd	Tr	Fr	Sa	Mo	Tu	Wd	Tr	Fr	Sa	Mo	Tu	Wd	Tr	Fr	Sa	Mo	Tu	Wd	Tr	Fr	Sa
ALGA	x																		x											
Pg																		x												x
AM1										x																	x			
FAE														x										x						
ACir					x																x									
POO																	x												x	
AM2											x																	x		
LSD													x												x					
E1							x																x							
MAT			x																	x										
PE															x											x				
ACp												x												x						
EA									x																					x
E2						x																x								
SS		x																	x											
RCp								x																		x				
PICC/CPg				x																			x							
PR	x																			x										
FT																		x											x	
SEAD1														x											x					
ST																x												x		
RCom			x																			x								
RI							x														x									
SE1												x														x				
AVE																	x												x	
SCDig										x																	x			
SOt													x											x						
PI			x																											x
SCDist				x																			x							
EGP						x														x										
OGE						x														x										
SG						x														x										

Table 10: DEETC's program number of clashes for the manual and automatic two-epoch solutions.

Timetable	**Manual sol.**		**Automatic sol.**			
			Run 1		**Run 2**	
	1st ep.	2nd ep.	1st ep.	2nd ep.	1st ep.	2nd ep.
LEETC	287	647	218	632	261	550
LEIC	197	442	153	480	227	418
LERCM	114	208	83	249	123	195
MEIC	33	63	18	86	15	66
MEET	50	144	20	165	36	124
Combined	**549**	**1163**	**399**	**1129**	**511**	**1060**
Sum	**1712**		**1528**		**1571**	

REFERENCES

Abdullah, S. and Alzaqebah, M. (2013). A hybrid self-adaptive bees algorithm for examination timetabling problems. *Appl. Soft Comput.*, 13(8):3608–3620.

Abdullah, S., Turabieh, H., and McCollum, B. (2009). A hybridization of electromagnetic-like mechanism and great deluge for examination timetabling problems. In Blesa, M. J., Blum, C., Gaspero, L. D., Roli, A., Sampels, M., and Schaerf, A., editors, *Hybrid Metaheuristics*, volume 5818 of *Lecture Notes in Computer Science*, pages 60–72. Springer.

Abdullah, S., Turabieh, H., McCollum, B., and McMullan, P. (2010). A tabu-based memetic approach for examination timetabling problems. In Yu, J., Greco, S., Lingras, P., Wang, G., and Skowron, A., editors, *RSKT*, volume 6401 of *Lecture Notes in Computer Science*, pages 574–581. Springer.

Alba, E. and Dorronsoro, B. (2008). *Cellular Genetic Algorithms*. Springer Publishing Company, Incorporated, 1st edition.

Alzaqebah, M. and Abdullah, S. (2014). An adaptive artificial bee colony and late-acceptance hill-climbing algorithm for examination timetabling. *J. Scheduling*, 17(3):249–262.

Burke, E., Bykov, Y., Newall, J., and Petrovic, S. (2004). A time-predefined local search approach to exam timetabling problems. *IIE Transactions*, 36(6):509–528.

Burke, E., Eckersley, A., McCollum, B., Petrovic, S., and Qu, R. (2010). Hybrid variable neighbourhood approaches to university exam timetabling. *European Journal of Operational Research*, 206(1):46 – 53.

Burke, E. and Newall, J. (2004). Solving examination timetabling problems through adaption of heuristic orderings. *Annals of Operations Research*, 129(1-4):107–134.

Burke, E. K. and Bykov, Y. (2006). Solving Exam Timetabling Problems with the Flex-Deluge Algorithm. In *Proceedings of the Sixth International Conference on the Practice and Theory of Automated Timetabling*, pages 370–372. ISBN: 80-210-3726-1.

Burke, E. K. and Bykov, Y. (2008). A late acceptance strategy in Hill-Climbing for exam timetabling problems. In *PATAT '08 Proceedings of the 7th International Conference on the Practice and Theory of Automated Timetabling*.

Burke, E. K., McCollum, B., McMullan, P., and Parkes, A. J. (2008). Multi-objective aspects of the examination timetabling competition track. *Proceedings of PATAT 2008*.

Burke, E. K. and Newall, J. P. (2002). Enhancing timetable solutions with local search methods. In Burke, E. K. and Causmaecker, P. D., editors, *PATAT*, volume 2740 of *Lecture Notes in Computer Science*, pages 195–206. Springer.

Carter, M., Laporte, G., and Lee, S. Y. (1996). Examination Timetabling: Algorithmic Strategies and Applications. *Journal of the Operational Research Society*, 47(3):373–383.

Chu, S.-C., Chen, Y.-T., and Ho, J.-H. (2006). Timetable scheduling using particle swarm optimization. In *Proceedings of the First International Conference on Innovative Computing, Information and Control - Volume 3*, ICICIC '06, pages 324–327, Washington, DC, USA. IEEE Computer Society.

Demeester, P., Bilgin, B., Causmaecker, P. D., and Berghe, G. V. (2012). A hyperheuristic approach to examination timetabling problems: benchmarks and a new problem from practice. *J. Scheduling*, 15(1):83–103.

Dowsland, A. and Thompson, M. (2005). Ant colony optimization for the examination scheduling problem. *Journal of the Operational Research Society*, 56(4):426–438.

Duan, Q., Gupta, V., and Sorooshian, S. (1993). Shuffled complex evolution approach for effective and efficient global minimization. *Journal of Optimization Theory and Applications*, 76(3):501–521.

Dueck, G. (1993). New optimization heuristics: The great deluge algorithm and the record-to-record travel. *Journal of Computational Physics*, 104(1):86 – 92.

Eley, M. (2006). Ant algorithms for the exam timetabling problem. In *PATAT VI*, volume 3867 of *Lecture Notes in Computer Science*, pages 364–382. Springer.

Eusuff, M., Lansey, K., and Pasha, F. (2006). Shuffled frog-leaping algorithm: a memetic meta-heuristic for discrete optimization. *Engineering Optimization*, 38(2):129–154.

Kamil, A., Krebs, J., and Pulliam, H. (1987). *Foraging behavior*. Plenum Press.

Kendall, G. and Hussin, N. (2005). An investigation of a tabu-search-based hyper-heuristic for examination timetabling. In *Multidisciplinary Scheduling: Theory and Applications*, pages 309–328. Springer US.

Leite, N., Melício, F., and Rosa, A. (2013). Solving the examination timetabling problem with the shuffled frog-leaping algorithm. In *Proceedings of the 5th International Joint Conference on Computational Intelligence*, pages 175–180.

Leite, N., Neves, R. F., Horta, N., Melicio, F., and Rosa, A. C. (2012). Solving an Uncapacitated Exam Timetabling Problem Instance using a Hybrid NSGA-II. In *Proceedings of the 4th International Joint Conference on Computational Intelligence*, pages 106–115.

McCollum, B., McMullan, P., Parkes, A. J., Burke, E. K., and Qu, R. (2012). A New Model for Automated Examination Timetabling. *Annals of Operations Research*, 194:291–315.

Merlot, L., Boland, N., Hughes, B., and Stuckey, P. (2003). A hybrid algorithm for the examination timetabling problem. In *PATAT IV*, volume 2740 of *Lecture Notes in Computer Science*, pages 207–231. Springer.

Neri, F. (2012). Diversity management in memetic algorithms. In (Neri et al., 2012), pages 153–165.

Neri, F., Cotta, C., and Moscato, P., editors (2012). *Handbook of Memetic Algorithms*, volume 379 of *Studies in Computational Intelligence*. Springer.

Qu, R., Burke, E., McCollum, B., Merlot, L. T. G., and Lee, S. Y. (2009). A Survey of Search Methodologies and Automated System Development for Examination Timetabling. *Journal of Scheduling*, 12:55–89.

Sabar, N. R., Ayob, M., and Kendall, G. (2009). Solving examination timetabling problems using honey-bee mating optimization (etp-hbmo). In *Proceedings of the 4th Multidisciplinary International Scheduling Conference: Theory and Applications (MISTA 2009), 10-12 Aug 2009, Dublin, Ireland*, pages 399–408.

Talbi, E.-G. (2009). *Metaheuristics - From Design to Implementation*. Wiley.

Turabieh, H. and Abdullah, S. (2011a). A hybrid fish swarm optimisation algorithm for solving examination timetabling problems. In *LION*, number 6683 in Lecture Notes in Computer Science, pages 539–551. Springer.

Turabieh, H. and Abdullah, S. (2011b). An integrated hybrid approach to the examination timetabling problem. *Omega*, 39(6):598–607.

Yang, Y. and Petrovic, S. (2005). A novel similarity measure for heuristic selection in examination timetabling. In *PATAT V*, volume 3616 of *Lecture Notes in Computer Science*, pages 247–269. Springer.