Electromagnetism-like Mechanism with Force Decay Rate Great Deluge for the Course Timetabling Problem

Salwani Abdullah[1], Hamza Turabeih[1], Barry McCollum[2]

[1]Center for Artificial Intelligence Technology,
Universiti Kebangsaan Malaysia, 43600 Bangi, Selangor, Malaysia
{salwani, hamza}@ftsm.ukm.my
[2]Department of Computer Science, Queenös University Belfast, Belfast BT7 1NN United Kingdom
b.mccollum@qub.ac.uk

Abstract. Combinations of population-based approaches with local search have provided very good results for a variety of scheduling problems. This paper describes the development of a population-based algorithm called Electromagnetism-like mechanism with force decay rate great deluge algorithm for university course timetabling. This problem is concerned with the assignment of lectures to a specific numbers of timeslots and rooms. For a solution to be feasible, a number of hard constraints must be satisfied. A penalty value which represents the degree to which various soft constraints are satisfied is measured which reflects the quality of the solution. This approach is tested over established datasets and compared against state-of-the-art techniques from the literature. The results obtained confirm that the approach is able to produce solutions to the course timetabling problem which demonstrate some of the lowest penalty values in the literature on these benchmark problems.

Keywords: Electromagnetism-like mechanism, force decay rate great deluge, course timetabling.

1 Introduction

Course timetabling problems have long attracted the attention of the Operational Research and Artificial Intelligence communities. In addition, variations of the problem have been the subject of two competitions via the website at http://www.metaheuristics.org and McCollum *et al*. (2007). A wide variety of approaches for constructing course timetables have been described and discussed in the literature (McCollum, 2007). Carter (1986) divided these approaches into four broad categories: sequential methods, cluster methods, constraint-based methods and meta-heuristics. Petrovic and Burke (2004) added the following categories: multi criteria approaches, case based reasoning approaches and hyper-heuristics/self adaptive approaches. Socha *et al*. (2002) applied an ant based approach to the eleven datasets which are investigated here. Rossi-Doria *et al*. (2003) consider the same datasets and present a comparison of a number of metaheuristic methods. Burke *et al*.

(2003) introduced a tabu-based hyperheuristic and applied it to university course timetabling in addition to nurse rostering. Burke *et al*. (2007) employed tabu search within a graph based hyper-heuristic and applied it to both examination and course timetabling benchmark datasets with the aim was to raise the level of generality by operating on different problem domains. Abdullah *et al*. (2005) developed a variable neighbourhood search approach which used a fixed tabu list to penalise particular neighbourhood structures. Abdullah *et al*. (2007a) applied a randomized iterative improvement approach using a composite of eleven neighbourhood structures. Abdullah *et al*. (2007b) presented a hybrid approach combining a mutation operator with their previous randomized iterative improvement algorithm (Abdullah *et al.*, 2007a). McMullan (2007) applied the extended great deluge algorithm to the same datasets which were originally introduced by Socha *et al*. (2007). Landa-Silva and Obit (2008) introduced non-linear great deluge which generates non-linear decay rate for three different categories of datasets. The combination of genetic algorithm and local search has been employed by Abdullah and Turabeih (2008) and is able to produce promising results on the same test instances.

The paper is organized as follows: the next section introduces the university course timetable problem with a set of hard and soft constraints. In section 3 we represent the main concept on Electromagnetism-like mechanism. Section 4 introduces the force decay rate great deluge algorithm. The simulation results are represented in section 5, and finally conclusion and future work are represented in section 6.

2 Problem Description

The problem involves in assigning lecture events to timeslots and rooms subject to a variety of hard and soft constraints. Hard constraints represent an absolute requirement. A timetable which satisfies the hard constraints is known as a *feasible* solution. The problem description that is employed in this paper is adapted from the description presented in Socha *et al*. (2002) and was the same as the description used in the first international competition. The following hard and soft constraints are presented:

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

Soft constraints that are equally penalized are as follows:

- *A student has a course scheduled in the last timeslot of the day.*
- *A student has more than 2 consecutive courses.*
- *A student has a single course on a day.*

The problem has:

- A set of N courses, $e = \{e_1,$é $,e_N\}$
- 45 timeslots
- A set of R rooms

- A set of *F* room features
- A set of *M* students.

The objective is to satisfy the hard constraints and to minimise the violation of the soft constraints. In real-world situations, it is usually impossible to satisfy all soft constraints (McCollum, 2007), but minimising the violations of soft constraints represents an increase in the quality of the solution.

3 The Electromagnetism-like Mechanism

Electromagnetism-like Mechanism (EM) algorithm begins with a population of randomly generated feasible timetables. The method uses an attraction-repulsion mechanism to move a population of timetables towards optimality. The main idea of EM algorithm was introduced by Birbil and Fang (2003) and is based on two timetables experiencing forces of mutual attraction or repulsion depending on their individual penalty. The strength of the attraction/repulsion is directly proportional to the product of their charges and inversely proportional to the square of the distance between them. Each particle (timetable) represents a solution and the charge of each particle relates to its solution quality. The better solution quality of the particle, the higher charge the particle has. Moreover, the electrostatic force between two point charges is directly proportional to the magnitudes of each charge and inversely proportional to the square of the distance between the charges (Birbil and Fang, 2003, Birbil *et al.*, 2004). Maenhout and Vanhoucke (2007) presented a novel meta-heuristic technique based on Electromagnetic like mechanism to tackle nurse scheduling problem (NSP). Debels *et al*. (2006) applied EM algorithm to enhance the movement of a scatter search scheduling algorithm. EM also has been applied successfully by Debels and Vanhoucke (2006) for a project scheduling problem. In our problem, the fixed charge of timetable *i* is shown as follows:

$$q^{i} = \exp\left(-T \frac{f(x^{i}) - f(x^{best})}{\sum_{k=1}^{m} (f(x^{k}) - f(x^{best}))} \right)$$

where:

q^i:	the charge for timetable *i*
$f(x^i)$:	penalty of the timetable *i*
$f(x^k)$:	penalty of the timetable *k*
$f(x^{best})$:	penalty of the best timetable
m:	population size
T:	number of timeslots

The solution quality or charge of each individual timetable determines the magnitude of an attraction and repulsion effect in the population. A better solution encourages other particles to converge to attractive valleys while a bad solution discourages particles to move toward this region. These particles move along with the total force and so diversified solutions are generated. The following formulation is the total force of particle *i*.

$$F^i = \sum_{j \neq i}^{m} \left\{ \begin{array}{ll} (f(x^j) - f(x^i)) \dfrac{q^i q^j}{\left\| f(x^j) - f(x^i) \right\|^2} & if \;\; f(x^j) < f(x^i) \\ (f(x^i) - f(x^j)) \dfrac{q^i q^j}{\left\| f(x^j) - f(x^i) \right\|^2} & if \;\; f(x^j) \geq f(x^i) \end{array} \right\}, \forall i$$

The process of evaluating the total force for the course timetabling problem is illustrated in Fig. 1. As is shown resulting timetables 1, 2 and 3 have penalties 210, 170 and 165 respectively. Because timetable 1 is worse than timetable 3 while timetable 2 is better than timetable 3, timetable 1 represent a repulsion force which is F_{13} and timetable 2 encourages timetable 3 to move to the neighborhood region of timetable 2. Consequently, timetable 3 moves along with total force F.

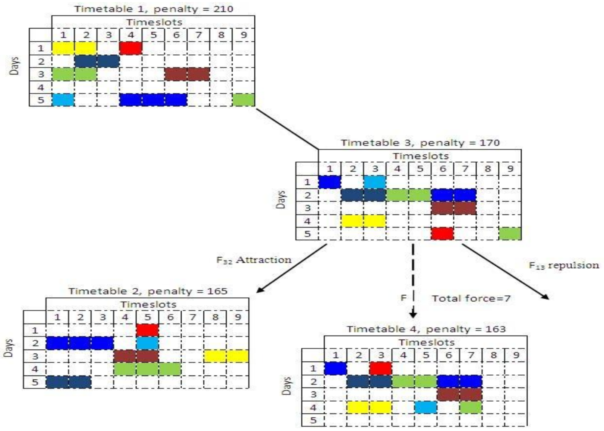
Timetable 1, penalty = 210
Timeslots
Days
Timetable 3, penalty = 170
Timeslots
Days
F_{32} Attraction
F_{13} repulsion
F
Total force=7
Timetable 2, penalty = 165
Timeslots
Days
Timetable 4, penalty = 163
Timeslots
Days

Fig 1. An example of attract-repulse effect on timetable 3

The fundamental procedures of EM include initialize, selection, calculating total force, moving timetable based on Great Deluge and evaluating the quality of the timetable. The generic pseudo-code for the EM is shown in Fig. 2. At every iteration, the total force, F, will be calculated and is used as a decay rate in the great deluge algorithm. The algorithm stops when the termination criterion is met. In this algorithm, the termination criterion is set as a number of iterations.

```
EM procedures()
  Initialization()
  do while (not termination-criterion)
     Calculate total force,F, for each timetable
     Apply force decay rate great deluge algorithm
     Evaluate timetables
  end do
```

Fig 2. Generic pseudo-code for the EM algorithm

4 Force Decay Rate Deluge Algorithm

The Great Deluge algorithm (GD) is a generic algorithm applied to optimization problems, which was introduced by Dueck (1993). It is a local search procedure that is far less dependent upon parameters than simulated annealing with regards to the implementation described here. It needs just two parameters: the amount of computational time that the user wishes to ñspendò and an estimate of the quality of solution that a user requires. Apart from accepting a move that improves the solution quality, the great deluge algorithm also accepts a worse solution if the quality of the solution is less than or equal to a determined level. In this work, the ñlevelò is initially set within the EM algorithm. The GD terminates when the achieved solution reaches the estimated quality. The pseudo code for our implementation of the force decay rate great deluge algorithm is adapted from Abdullah and Burke (2006) as presented in Fig. 3.

```
Set initial solution as Sol;
Calculate the initial penalty cost, f(Sol);
Set best solution, $Sol_{best}$ ← Sol;
Set EstimatedQuality of final solution,
    EstimatedQuality = f(Sol)- total force,F;
Set number of iterations, NumOfIte;
Set initial level: level ← f(Sol);
Set force decay rate
    $\beta$ = ((f(Sol)- EstimatedQuality)/(NumOfIte);
Set iteration ← 0;
do while (iteration < NumOfIte)
    Define neighbourhood of Sol by randomly assigning course to a
    valid timeslot to generate a new solution called Sol*;
    Calculate f(Sol*);
    if (f(Sol*) < f($Sol_{best}$))
          Sol ← Sol*;
          $Sol_{best}$ ← Sol*;
       else
          if (f(Sol*)≤ level)
             Sol ← Sol*;
    level = level - $\beta$;
    Increase iteration by 1;
end do;
```

Fig 3. The pseudo code for the force decay rate great deluge algorithm

5 Simulation Results

The proposed algorithm was programmed using Matlab and simulations were performed on the Intel Pentium 4 2.33 GHz computer and tested on a standard benchmark course timetabling problem originally proposed by the Meteheuristic Network. The parameters used in the EM algorithm are chosen after preliminary experiments. The number of generation and the population size are set to 100000 and

50, respectively, and are comparable similar with the papers in the literature Birbil and Fang (2003). Table 1 shows the comparison of our final results in terms of penalty cost compared to other recent published results in the literature. The best results are presented in bold. Our algorithm is capable to find feasible timetables for all eleven cases.

Table 1. Comparison of our results with other approaches in the literature

Dataset	Our method	M1	M2	M3	M4	M5	M6	M7
s1	**0**	2	**0**	6	**0**	**0**	**0**	3
s2	**0**	4	**0**	7	**0**	**0**	**0**	4
s3	**0**	2	**0**	3	**0**	**0**	**0**	6
s4	**0**	**0**	**0**	3	**0**	**0**	**0**	6
s5	**0**	4	**0**	4	**0**	**0**	**0**	**0**
m1	175	254	242	372	317	221	**80**	140
m2	197	258	161	419	313	147	**105**	130
m3	216	251	265	359	357	246	**139**	189
m4	149	321	181	348	247	165	**88**	112
m5	190	276	151	171	292	130	**88**	141
l	912	1026	-	1068	-	**529**	730	876

Note:
M1: Genetic algorithm and local search by Abdullah and Turabeih (2008)
M2: Randomised iterative improvement algorithm by Abdullah *et al*. (2007a)
M3: Graph hyper heuristic by Burke *et al*. (2007)
M4: Variable neighbourhood search with tabu by Abdullah *et al*. (2005)
M5: Hybrid evolutionary approach by Abdullah *et al*. (2007b)
M6: Extended great deluge by McMullan (2007)
M7: Non linear great deluge by Linda-Silva and Obit (2008)

It can be seen that the extended great deluge by McMullan (2007) has better results compared to others, followed by non-linear great deluge by Landa-Silva and Obit (2008). In general, our approach is able to obtain competitive results with other approaches in the literature. We extended our experiments by increasing the number of iterations with the objective to demonstrate that our algorithm is able to produce good results given extra processing time. We note that in real world situations, course timetabling is an off line problem, and the processing time is usually not critical (McCollum, 2007). The emphasis in this paper is on generating good quality solutions and the price to pay for this can be taken as being extended amount of computational time. Table 2 shows the comparison of our approach by prolonging the computational time with best known results in the literature. We use the same amount of iterations i.e. 200000 by Landa-Silva and Obit (2008) (note that the authors set a different number of iterations for different group of datasets) (2008) and McMullan (2007). Note that only medium and large datasets are considered in this extended experiment.

Table 2. Comparison with best known results

Dataset	Our method	Best known
m1	96	**80**
m2	**96**	105
m3	**135**	139
m4	**79**	88

m5	**87**	88
l	683	**529**

Again, the best results are presented in bold. Our approach is better than the best known results on four dataset. The extended experiments are able to improve the solutions between 25% to 54% compared to our previous results. This illustrates the effectiveness of our approach given extra processing time.

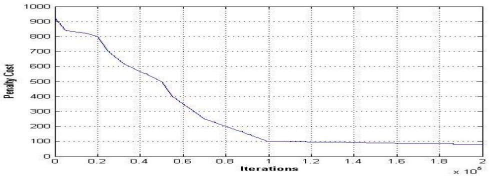

Fig 4. The result of the algorithm applied on *m4* dataset

Fig. 4 shows the behavior of the algorithm when applied to *m4* dataset. In all the figures above, the x-axis represents the number of iterations whilst the y-axis represents the penalty cost. The penalty cost can be quickly reduced at the beginning of the search where there is (possibly) a lot of room for improvement. It is believed that better solutions can be obtained in these experiments because of the ability of the algorithm in exploring different region of the solution space in which our algorithm works on 50 different solutions at every iteration. The figure also shows that by prolonging the search process, our approach is able to find a good solution. However, the longer the search times, the slower the improvement of the solutions are.

6 Conclusion and Future Work

In this paper, we employed Electromagnetism-like Mechanism (EM) with force decay rate great deluge for course timetabling problems. The proposed method is able to produce both feasible and good quality timetables that are of consistently high quality across all the benchmark problems. Our future work will tackle curriculum-based course timetabling problems and try to reduce the time taken while improving the quality of the solutions.

References

1. Abdullah, S., Burke, E.K.: A Multi-start large neighbourhood search approach with local search methods for examination timetabling. The International Conference on Automated Planning and Scheduling (ICAPS 2006), pp 334-337 (2006)
2. Abdullah, S., Turabieh, H.: Generating university course timetable using genetic algorithms and local search. The Third 2008 International Conference on Convergence and Hybrid Information Technology ICCIT, vol. I, pp 254-260 (2008)
3. Abdullah, S., Burke, E.K., McCollum, B.: An investigation of variable neighbourhood search for university course timetabling. The 2nd Multidisciplinary International Conference on Scheduling: Theory and Applications (MISTA), pp. 413ï 427 (2005)

4. Abdullah, S., Burke, E.K., McCollum, B.: Using a randomised iterative improvement algorithm with composite neighbourhood structures for university course timetabling. In Metaheuristics: Progress in complex systems optimization (Operations Research / Computer Science Interfaces Series), Chapter 8. Published by Springer, ISBN:978-0-387-71919-1 (2007a)
5. Abdullah, S., Burke, E.K., McCollum, B.: A hybrid evolutionary approach to the university course timetabling problem. IEEE Congres on Evolutionary Computation, ISBN: 1-4244-1340-0, pp 1764-1768 (2007b)
6. Birbil, S.I., Fang, S.C: An electromagnetism-like mechanism for global optimization. Journal of Global Optimization 25, pp 263ï 282 (2003)
7. Birbil, S.I., Fang, S.C., Sheu, R.L.: On the convergence of a population-based global optimization algorithm. Journal of Global Optimization 30, pp 301ï 318 (2004)
8. Burke, E.K., Kendall, G., Soubeiga, E.: A tabu-search hyper-heuristic for timetabling and rostering. Journal of Heuristics, 9(6), pp 451-470 (2003)
9. Burke, E.K., Meisels, A., Petrovic, S., Qu, R.: A graph-based hyper-heuristic for timetabling problems. European Journal of Operational Research 176, pp 177-192 (2007)
10. Carter, M.W.: A survey of practical applications of examination timetabling algorithms,ò Operations Research, vol. 34, pp. 193ï 202 (1986)
11. Debels, D., Vanhoucke, M.: An electromagnetism meta-heuristic for the resource-constrained project scheduling problem. LNCS, vol. 3871, Springer, pp 259ï 270 (2006)
12. Debels, D., De Reyck, B., Leus, R., Vanhoucke, M.: A hybrid scatter search/electromagnetism metaheuristic for project scheduling. Eur. J. Oper. Res. 169, 638ï 653 (2006)
13. Dueck, G.: New Optimization Heuristics. The great deluge algorithm and the record-to-record travel. Journal of Computational Physics 104, pp 86-92 (1993)
14. Landa-Silva, D., Obit, J.H.: Great deluge with non-linear decay rate for solving course timetabling problem. The fourth international IEEE conference on Intelligent Systems. Varna, Bulgaria (2008).
15. Maenhout, B., Vanhoucke, M.: An electromagnetic meta-heuristic for the nurse scheduling problem, Journal of Heuristics. Vol. 13, pp. 315-401 (2007)
16. McCollum, B.: A perspective on bridging the gap between theory and practice in university timetabling. LNCS 3867, Springer-Verlag, pp 3-23 (2007)
17. McCollum, B., Schaerf, A., Paechter, B., McMullan, P., Lewis, R., Parkes, A., Di Gaspero, L., Qu, R., Burke, E.K.: Setting the research agenda in automated timetabling: The second international timetabling competition, Accepted for publication to INFORMS Journal of Computing (2007)
18. McMullan, P.: An extended implementation of the great deluge algorithm for course timetabling, Computational Science ï ICCS, Part I, LNCS 4487, Springer-Verlag Berlin Heidelberg, pp 538ï 545 (2007)
19. Petrovic, S., Burke, E.K.: University timetabling. Handbook of Scheduling: Algorithms, Models and Performance Analysis, Chapter 45, (Editor: J. Leung), CRC, Press (2004)
20. Rossi-Doria, O., Samples, M., Birattari, M., Chiarandini, M., Dorigo, M., Gambardella, L.M., Knowles, J., Manfrin, M., Mastrolilli, M., Paechter, B., Paquete, L., Stützle, T.: A comparison of the performance of different meta-heuristics on the timetabling problem. The Practice and Theory of Automated Timetabling IV: Selected Papers from 4th International Conference on the Practice and Theory of Automated Timetabling (PATAT IV), Gent, Belgium. LNCS 2740, Springer-Verlag. (Editors: E.K. Burke and P. De Causmaecker), pp 329-354 (2003)
21. Socha, K., Knowles, J., Samples, M.: A max-min ant system for the university course timetabling problem. The Proceedings of the 3rd International Workshop on Ant Algorithms (ANTS 2002), LNCS 2463, Springer-Verlag, pp 1-13 (2002)