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Exploring Fruit Fly Evolutionary Algorithm in A University Examination Timetabling Environment

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In this paper, we explore a fruit fly evolutionary algorithm in solving a complex university examination timetabling problem where examinations need to be assigned to limited number of timeslots and rooms, subject to a set of student and lecturer related constraints. A new evolutionary algorithm namely the Fruit-Fly Optimization Algorithm (FOA) which is based on the behavior of finding food by the fruit fly is used as solution methodology. It is a method that is still limited in optimization and artificial intelligence area for finding global optimization. We use FOA for solving the problem and introduce new neighborhood structures related with median difficult exams to suit with the problem solving. Experimental results show that FOA with the introduced neighborhood structure can produce high quality solutions within examination timetabling problem. It is concluded that FOA with the introduced neighborhood structure is simple, yet effective in solving a complex examination timetabling problem.

Keywords: examination timetabling; fruit fly-evolutionary algorithm; neighborhood structure; population-based algorithm

I. INTRODUCTION

Complex university examination timetabling problem represents a real-world administrative activity faced by most of academic institutions. The complexity is mostly due to an increasing number of student enrolments, introduction of flexible course structures, a wider variety of courses being offered and preferences and restrictions which must be catered. Eventually, these situations have somehow affected the quality of the examination timetable especially, the spread of students within examination timetable and students' revision time. The examination timetabling problem is defined as the problem of assigning examinations into a limited number of timeslots so that there are no conflicts or clashes (Carter *et al.* 1994). It is known that this problem is an NP (non-deterministic polynomial time) hard (Schindl, 2005), which practically means that solving it in polynomial time is not possible. Hence, generating a timetable can be a very challenging task especially when involving complex problem.

In solving the examination timetabling problem, one should consider two types of constraints i.e. hard constraints and soft constraints. Hard constraint is a must to consider and if broken then the solution is considered infeasible. Soft constraint determines the quality of a solution and if broken it somehow does not affect the feasibility of a solution. Constraints involved in examination timetabling problem are related to examinations, timeslots and room preferences, weekend schedule and timeslot length (Kahar & Kendall, 2010).

Generally, the examination timetabling can be formulated as graph coloring problem. Some studies have used graph theory in solving examination timetabling problem (Qu *et al.* 2009; Abdul-Rahman *et al.* 2014a; Abdul-Rahman *et al.* 2014b; Abdul-Rahman *et al.* 2014c), where the examinations are assigned to timeslots based on sequential

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strategies related with difficulties of examination assignment.

In solving this problem, most of the researchers have focused metaheuristic approaches (Qu *et al.* 2009). The approaches can be categorized into local search-based and population-based approaches. Local search-based approaches begin with a single solution, while population-based approaches start with a population of solutions. Both types of approaches employ iterative searching techniques for improving solution quality by escaping from local minima. Tabu search (Kendall & Mohd Hussin, 2005), simulated annealing (Burke &Newall, 2004), great deluge algorithm (Kahar & Kendall, 2015) and variable neighborhood search (Abdul-Rahman *et al.* 2013) are categorized under local search-based. The variable neighborhood search is an approach which explore various neighborhood structures to escape from local optima. On the other hand, approaches such as evolutionary approach i.e. genetic algorithm (Pillay & Banzhaf, 2010) and swarm-based approach i.e. ant colony optimization (Dowsland & Thompson, 2005) and particle swarm optimization (Marie-Sainte, 2015) are approaches classified under population-based metaheuristics.

The evolutionary approach to timetabling problem is also a growing research area. Many approaches have been considered in solving the problem including its hybridization and new foundations. Currently, a new evolutionary algorithm namely the Fruit-Fly Optimization Algorithm (FOA) has been introduced (Pan, 2012). It is a method that is still limited in optimization and artificial intelligence area. There are several studies which employed FOA. Shi & Miao (2013) optimized the selection of parameters in Support Vector Regression (SVR) algorithm using FOA to fit and simulate experimental data of turbine's failures. Liu *et al.* (2012) proposed a modified FOA (MFOA) based on Particle Swarm Optimization (PSO) and Simulated Annealing (SA) for the Proportional - Integral - Derivative (PID) controller problem, while (Wang &Zou, 2012) applied FOA to identify the structural parameters in the ship maneuvering response models. A multi-swarm fruit fly optimization algorithm employing multi-swarm behavior to improve the original fruit fly optimization algorithm has been proposed by Yuan *et al.* (2014).

Studies also found that FOA is a robust optimization algorithm as compared to other optimization algorithms (Shi & Miao, 2013). FOA is said to be simple and good searching methodology (Liu *et al.* 2012). In addition, FOA has shown a better result in global optimization problem compared to other swarm-based metaheuristic algorithms (Pan, 2012). However, this approach is still far immature within the timetabling research environment. Motivated by this justification, this paper presents on exploring fruit-fly algorithm for solving a complex university examination timetabling problem. New neighborhood structures related with median difficult exams are introduced to suit with the problem solving. The FOA with new neighborhood structures is employed on a complex examination timetabling problem proposed by Pan (2012).

The rest of this paper is organized as follows: Section 2 discusses the FOA, neighborhood structures and graph coloring heuristics in solving the problem. Section 3 discusses on the experiment, problem descriptions and experimental results. Finally, the conclusion and future work are presented in Section 4.

II. FRUIT-FLY OPTIMIZATION ALGORITHM

The FOA is a comparatively new swarm-based approach, which was proposed by Pan (2012). It is an interactive evolutionary computation with the aim to obtain global optimization. This approach imitates the biological behavior of fruit-fly in finding food where this insect is good in sensing and perception, especially in osphresis and vision as compared to others. Due to its good osphresis and vision, fruit-fly can sensitively detect food location and company's flocking location and fly towards the food source.

The general procedure of FOA by Pan (2012) is presented in Figure 1. FOA starts with identifying random initial location of *initX_axis* and *initY_axis* of a fruit fly. Starting from the initial location, random direction is generated and the distance for each individual fly is calculated based on Euclidean distance. The distance to the origin is used to estimate first since the food location is unknown. Based on the distance, the smell concentration, S_i for each individual fly is calculated and replaced the value into smell concentration judgment function or fitness function. The individual flies are compared in terms of its fitness function. The best fitness function and it coordinates of x and y are kept for comparison. The steps are repeated until a stopping condition is met.

1. Random initial location of fruit fly swarm.

   initX_axis; initY_axis

2. Generate random direction and calculate distance for the food search using osphresis by an individual fruit fly.

   X_i = *X-axis* + *RandomValue*;

   Y_i = *Y-axis* + *RandomValue*;

3. Calculate the smell concentration judgment value (S_i) based on the distance of food location, $Dist_i$. Since the food location is unknown, then the distance to the origin is estimated first, where

   $$Dist_i = \sqrt{X_i^2 + Y_i^2}$$

   $$S_i = 1 / Dist_i$$

4. Substitute smell concentration judgment value (S) into smell concentration judgment function (or called Fitness function) so as to find the smell concentration ($Smell_i$) of the individual location of the fruit fly.

   $$Smell_i = Function(S_i)$$

Figure 1. General procedure of FOA (Pan, 2012)

FOA considers locations and distances of fruit flies in determining a better food source. In order to suit with the proposed problem, the general FOA is modified since examination timetabling problem does not require coordinates. In order to find for a better fitness function, a comparison with the current best fitness function with the new generated fruit flies or fitness function is obtained. This study introduced new neighborhood structures to generate new solution instead of random generation.

Figure 2 shows the proposed FOA for solving an examination timetabling problem. As a start, an initial solution of an examination timetabling problem, *InitSol* as a fruit fly is generated using graph coloring heuristics and its fitness function, $FittVal_{InitSol}$ is calculated. Based on the *InitSol*, types of neighborhood structure, N_i to be employed is identified and used the neighborhood to generate m number of solutions or a swarm of fruit fly. The fitness function value of each generated solution, $FittVal_i$ are calculated and compared. The best solution of all fruit flies which has the minimum *FittVal* is obtained and kept. Step 3 until 5 are repeated on the current best solution until it met a stopping condition. The best solution or the best fruit fly is kept for future references.

A. Graph Coloring Heuristics

Graph coloring heuristics is used to generate the examination orderings based on examinations' difficulty while assigning them into the timetable (Abdul-Rahman, 2014a; Abdul-Rahman, 2014c). Usually this difficulty is related with students' clashing, enrolment and number of available timeslots to be assigned.

1. Generate initial solution of examination timetabling problem, *InitSol* as a fruit fly using graph coloring heuristics.
2. Calculate the fitness function value, $FittVal_{InitSol}$ of initial solution of a fruit fly.
3. Generate m times random neighbours of *InitSol* based on types of chosen neighbourhood, N_i.
4. Calculate the fitness function value, $FittVal_i$ of m solutions of fruit flies generated in 3 to estimate the distances between $FittVal_{InitSol}$ of initial solution.
5. Compare the fitness function value of m solutions of fruit flies.
6. Keep the best solution of a fruit fly which has minimum *FittVal*

Figure 2. FOA procedure for solving an examination timetabling problem

In this study, we consider the largest degree heuristics to construct an initial solution. The largest degree heuristics order the examinations decreasingly based on the number of examinations in conflict whenever they are assigned in the same timeslot. This type of ordering makes it straightforward for implementing the neighborhood structure related with median examinations.

B. Neighborhood Structures

The choice of neighborhood structure affects the solution search for a better quality one. The purpose of testing different neighborhood structures is to investigate the effectiveness of a neighborhood structure to escape from a local optimum. Since different neighborhood structures incline to have a different local minimum, thus it is important to study on the effect of neighborhood structure.

Four neighborhood structures are considered in this study where before the implementation of the neighborhood structure, examinations are ordered based on their decreasing difficulty using graph coloring heuristics while maintaining its feasibility. The implemented neighborhood structures are as follows:

1. Single swap median exam (SSME) – Choose one median examination and move to a new random feasible timeslot.
2. Single swap random exam (SSRE) – Choose one examination at random and move to a new random feasible timeslot.
3. Single median random exam (SMRE) - Choose one median examination and swap with a new random feasible examination.
4. Single median median exam (SMME) - Choose one median examination and swap with a new random feasible examination within the median range.

In this study, neighborhood structures related with median difficulty examinations are introduced. Set of median examinations are considered for swapping because these examinations are classified as medium in terms of its difficulty. In order to obtain a set of median examinations, a median examination as the "middle" value of a data set is identified. A parameter value is set to obtain a set of median examinations. For example, if we set the parameter value as 5 then the number of median examinations is 11 including the middle examination (if the total number of examinations is odd). On the other hand, if the total number of examinations is even, with parameter value of 5, the total number of median examinations is 10. Figure 3 shows the illustration of neighborhood structure for single median random exam (SMRE). The parameter value is two and the total number of examinations is 10, then the median examinations are four. The shaded examinations are the median examinations. For the neighborhood structure of single median random exam, one random exam from a set of median exams and a random exam which is not from the median exams are chosen and swapped to generate new solution for the FOA.

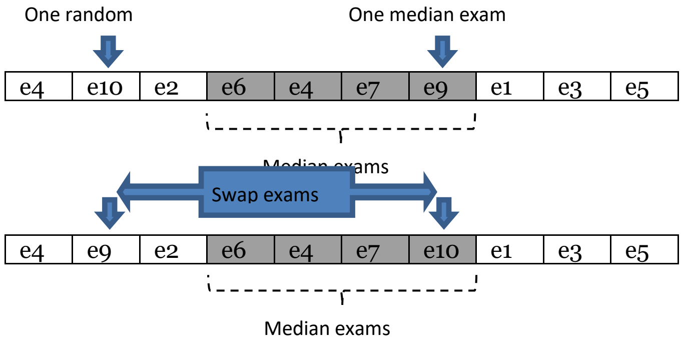

Figure 3. Illustration of neighborhood structure for single median random exam (SMRE)

III. EXPERIMENTS

The stopping conditions for the experiments were set as 100 iterations. Ten runs were obtained for each types of neighborhood orderings dataset where the population of initial solutions is obtained using a graph coloring heuristic. The swarm population size is set as ten. The parameter for the median examination is set as 5. The solution which has minimum fitness function value (in bold font) is considered as the best solution when compared with other neighborhood structures.

A. Problem Description

This study was conducted to solve an examination timetabling problem at the Universiti Utara Malaysia (UUM) by using FOA. The problem is considered as a complex problem since it involved many real-world constraints related with student and lecturer preferences (Abdul-Rahman, 2014b). The data set used in this study is a real examination data of undergraduate students for semester A131. The conflict density of the dataset is 0.04 showing that 4% of the students are in conflict whenever assigning them into the same timeslots. The dataset consists of 13,359 undergraduate students, 632 courses, 719 lecturers and 40 different venues for the examinations. Table 1 summaries the data. There are two examination slots available, providing a morning and afternoon session for each examination day.

Table 1. UUM Dataset of Semester A131

Exam	Students	Lecturers	Conflict Density	Timeslot	Room
632	13,359	719	0.04	38	40

The list of hard and soft constraints for the problem at UUM is presented as follows:

- H1: No student should sit more than one examination simultaneously
- H2: The total number of students assigned to a room(s) must be less than the total room capacity
- H3: Every examination must be scheduled in exactly one timeslot
- H4: Every examination assigned to a room should end at the same time
- H5: Every room must be assigned to at least one lecturer
- H6: Each lecturer is assigned to a timeslot and room according to their teaching group
- H7: Each lecturer cannot be assigned to more than one room in the same timeslot

The quality of the solution is measured based on the soft constraints, as follows:

- S1: Examinations should be spread as evenly as possible over the examination period for students to do revision
- S2: Examinations should be spread as evenly as possible over the examination period for lecturers' marking time
- S3: Large size examinations should be scheduled as early as possible
- S4: Minimizing splitting examinations into different rooms

B. Experimental Results

The experimental results are provided in Table 2 with different types of neighborhood structure for the ten runs. The table reports the best fitness function values obtained for the ten runs, given the maximum, minimum, average and standard deviation value for each neighborhood structure. The best result for each run is highlighted in bold font.

In Table 2, both SSRE and SMRE are equally performing well when compared with other types of neighborhood structures in terms of fitness function value where five best solutions each (in bold font) were obtained. In terms of standard deviation, SMRE shows the best with 0.03148 when compared with SSRE which obtained 0.9577. However, in terms of solution average, SSRE is better than SMRE.

The SSME and SMME performed not very well with very low standard deviation values. This is maybe due to these types of neighborhood structures can easily get trapped in a local optimum. Based on the results, it shows that neighborhood structure is one of the important criteria in FOA that needs to be carefully determined because it may affect the solution search, thus enabling for better solution quality. It is suggested that by increasing the number of iteration or any other parameters, it may increase the effectiveness of the FOA.

Table 2. The Results of FOA Using Different Neighborhood Structures

Run	SSME	SSRE	SMRE	SMME
1	132.9464	**132.7973**	132.8217	132.9301
2	132.9500	132.8097	**132.8032**	132.9445
3	132.9463	132.8911	**132.8566**	132.9279
4	132.9462	132.9357	**132.7719**	132.9277
5	132.9100	132.8292	**132.7850**	132.9407
6	132.9463	**132.7814**	132.8446	132.9279
7	132.9492	**132.7432**	132.7561	132.9279
8	132.9500	**129.8028**	132.7925	132.9279
9	132.9499	**132.7945**	132.8081	132.9277
10	132.9499	132.8544	**132.7845**	132.9279
min	132.9100	129.8028	132.7561	132.9277
max	132.9500	132.9357	132.8566	132.9445
average	132.9444	132.5239	132.8024	132.931
std. dev.	0.0122	0.9577	0.03148	0.0062

IV. CONCLUSION

In this paper, the investigation on FOA in solving a complex examination timetabling problem at UUM is presented. FOA is a swarm-based approach which based on the nature of fruit fly in finding food. Different neighborhood structures are tested on FOA to see the performance of FOA in solving a complex examination timetabling problem. In this study, neighborhood structures based on median difficulty examinations were introduced. The difficulty level is based on examinations clashing and the examinations were firstly ordered based on largest degree graph coloring heuristics. The results show that neighborhood structure in FOA is very important as it affects the solution search and final solution. It is concluded that this approach is simple and yet effective; hence it has potential for practical use. In future work, we intend studying the benchmark datasets of examination timetabling such as Toronto and Track of the 2nd International Timetabling Competition (Abdul-Rahman, 2014c) to further investigate the effectiveness of FOA in solving examination timetabling problem.

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VI. REFERENCES

Abdul-Rahman, S. Bargiela, A., Burke, E.K., McCollum, B. & Ozcan, E. (2014a). A constructive approach for examination timetabling based on adaptive decomposition and ordering. Annals of Operations Research, 218(1), pp. 3-21.

Abdul-Rahman, S., Sobri, N.S., Omar, M.F., Benjamin, A.M. & Ramli, R. (2014b). A graph coloring heuristic for solving examination timetabling problem at University Utara Malaysia. AIP Conference Proceedings of the International Conference on Quantitative Sciences and Its Applications (ICOQSIA2014), 1635(497), pp. 491-496.

Abdul-Rahman, S. Bargiela, A., Burke, E.K., McCollum, B. & Ozcan, E. (2014c). Linear combination of heuristic orderings in constructing examination timetable. European Journal of Operational Research; 232(2), pp. 287–297.

Abdul-Rahman, S. Bargiela, A., Burke, E.K., McCollum, B. & Ozcan, E. (2013). Investigation of multistage approaches to examination timetabling. Proceedings of the 6th Multidisciplinary International Scheduling Conference: Theory & Applications (MISTA2013), pp. 528-542.

Burke, E.K. & Newall, J.P. (2004). Solving examination timetabling problems through adaptation of heuristics orderings. Annals of Operations Research, 129, pp. 107-134.

Carter, M.W., Laporte, G. & Chinneck, J.W. (1994). A general examination scheduling system. Interfaces, 24, pp. 109-120.

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

Kahar, M.N.M. & Kendall, G. (2010). The examination timetabling problem at University Malaysia Pahang: Comparison of a constructive heuristic with an existing software solution. European Journal of Operational Research, 207, pp. 557-565.

Kahar, M.N.M. & Kendall, G. (2015). A great deluge algorithm for a real-world examination timetabling problem. Journal of the Operational Research Society, 66(1), pp. 116-133.

Kendall, G. & Mohd Hussin, N. (2005). Tabu search hyper-heuristic approach to the examination timetabling problem at university technology mara. In Burke, E. K. & Trick, M., editors, Practice and theory of automated timetabling V, pp. 199-217.

Liu, Y., Wang, X. & Li, Y. (2012). A modified fruit-fly optimization algorithm aided PID controller designing. Proceedings of the 10th World Congress on Intelligent Control and Automation (WCICA), pp. 233-238.

Marie-Sainte, S.L. (2015). A survey of particle swarm optimization techniques for solving university examination timetabling problem. Artificial Intelligence Review, 44(4), pp. 537–546.

Pan, W-T. (2012). A new fruit fly optimization algorithm: Taking the financial distress model as an example, Knowledge-Based System, 26(2), pp. 69-74.

Pillay, N. & Banzhaf, W. (2010). An informed genetic algorithm for the examination timetabling problem. Applied Soft Computing, 10(2), pp. 457-467.

Qu, R., Burke E.K. & McCollum, B. (2009). Adaptive automated construction of hybrid heuristics for exam timetabling and graph colouring problems. European Journal of Operational Research, 198(2), pp. 392-404.

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

Schindl, D. (2005). Some new heredity classes where graph coloring remains NP-hard. Discrete Mathematics, 295, pp. 197-202.

Shi, Z. & Miao, Y. (2013). Prediction research on the failure of steam turbine based on fruit fly optimization algorithm support vector regression, Advanced Materials Research, 614-615, pp. 409-413.

Wang, X-G. & Zou, Z-J. (2012). Identification of ship maneuvering response model based on fruit fly optimization algorithm. Journal of Dalian Maritime University, 38, pp. 1-4+8.

Yuan, X., Dai, X., Zhao, J.& He, Q. (2014). On a novel multi-swarm fruit fly optimization algorithm and its application. Applied Mathematics and Computation, 233, pp. 260-271.