An outclassing Multi-objective Hybrid Genetic-based Discrete PSO for Solving the PECT Problem

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Abstract: - The Post Enrolment based Course Timetabling (PECT) Problem belongs to, one of the classical problems, the timetabling problems, and it is a part of the most real-life problems that come with multiple constraints of nature. Such a problem is investigated together with both hard and soft constraints, and the solution is an optimal timetable satisfying both constraints as far as possible which reflects the quality of the solution. As a result, there are many approaches to solving the PECT Problem. However most approaches rely upon both the determination of parameters or understanding of domain knowledge. In this research, the Genetic-based Discrete Particle Swarm Optimization (PSO) has been developed with two different local search approaches: Local Search and Tabu Search to solve multi-objective functions and get good solutions by improving the performance of searching solution, which has few parameters to be tuned, and it can outperform all related algorithms from the published work.

Key-Words: - multi-objective optimization problem, hybrid algorithm, genetic-based discrete particle swarm optimization, local search, tabu search, post enrolment based course timetabling problem.

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1 Introduction

The Post Enrolment Based Course Timetabling Problem (PECTP) is a real-world problem, which is a problem that occurs continuously in all universities. However, the resources and constraints of each university are different from one university to another. It is an NP-complete problem, [1], which is well known that there is no available algorithm to solve with the degree of polynomial running time. Moreover, the PECTP is related to resource allocation such as events, features, and students into optimal rooms and timeslots that are scheduled using the completed enrolments of all students, classified as a combinatorial optimization problem, [2]. In this work, the representation of a solution with discrete variables was designed to suit the nature of the problem described above, and it also helps to quickly seek a feasible solution, resulting in a more effective solution. In addition to designing the representation of a solution, constraints are the main important factor to consider carefully, and they are classified into hard constraints and soft constraints. In case of violating hard constraints, the solution is infeasible. However, the soft constraints can be violated, and the quality of the solution is measured by the number of soft constraint violations. As a result, the soft constraints must be satisfied as much as possible, and it also directly affects the efficiency of the solution.

The meta-heuristic algorithms will be used as the main tool emphasized on nature-inspired algorithms in this research, and there are many popular meta-heuristic algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Local Search (LS), Tabu Search (TS), Simulated Annealing (SA) and Hybrid Approaches (HA). Particularly, Genetic-based Discrete Particle Swarm Optimization (GDPSO) was chosen as the main algorithm, and a single-objective algorithm to solve PECTP that hybridizes Genetic-based Discrete Particle Swarm Optimization with Local Search and Tabu Search (HGDPSOLTS) was proposed in [3], and it was able to solve the PECTP with a good performance. However, in the real world, PECTP is considered as multi-objective optimization problem rather than a single-objective optimization problem. For this reason, this research extends the HGDPSOLTS in [3] which used the model of single-objective function to solve the problem in the form of a multi-objective function to see its performance compared with [4] and the other methods from the literature by using 11 standard testing benchmark datasets from Metaheuristic

Network (MN). This will provide supporting evidence to answer the research question: Is multi-objective model solving better than single-objective model solving PECTP?

2 Multi-Objective PECTP

The model of PECTP used in this work was proposed in [5], and optimum rooms and time slots are assigned to each event based on the enrolment data of the students with an attempt of satisfying both hard and soft constraints.

The PECTP model consists of a set of n events $E = \{e_1, e_2, \ldots, e_n\}$, a set of 45 timeslots $T = \{t_1, t_2, \ldots, t_{45}\}$ (5 days of 9 hours on each day), a set of m rooms $R = \{r_1, r_2, \ldots, r_m\}$ with different size-seating capacity on each room (events can occur in fitting rooms), a set of k students $S = \{s_1, s_2, \ldots, s_k\}$ attending each event, and a set of l features $F = \{f_1, f_2, \ldots, f_l\}$ such as computer, and internet connection, providing by each room and requesting by each event. The timetable framework used in this work with x-axis representing rooms and y-axis representing time slots is shown in Figure 1.

timeslot 1	event 1		
timeslot 2		event 2	
.			
.			event n
.	event 3		
timeslot 45			
	room 1	...	**room m**

Fig. 1: The framework of assigning timeslots and rooms to events of PECTP

There are three hard constraints that a feasible solution cannot violate as follows.

- H1: Students can attend only one event at the same timeslot.
- H2: All attending students can fit in the room satisfying all required features of the event.
- H3: Each room is assigned only one event in any timeslot.

Concurrently, there are three soft constraints that a feasible solution should satisfy as much as possible:

- S1: The event with the last time slot of a day (timeslot 9, 18, 27, 36 or 45) should not be attended by students.
- S2: On the same day, students should not participate in more than two events of consecutive time slots.
- S3: In a day, students should not attend only one event.

The three soft constraints are respectively divided into three objective functions: $f_1(x), f_2(x)$ and $f_3(x)$, and they should be minimized as much as possible. Consequently, this leads to solving the PECTP in the form of a multi-objective function.

3 Proposed Hybrid Approach

This work proposed a hybrid multi-objective approach, GDPSO, combined with two different local search approaches: Local Search and Tabu Search to solve the multi-objective PECTP, denoted as HMGDPSOLTS. The process of HMGDPSOLTS is different from [3] which solves the single-objective PECTP. The pseudo-code of HMGDPSOLTS is provided in Figure 2.

Proposed Hybrid Approach - HMGDPSOLTS

input: A problem case
Initializing No_of_Generation to 0
Creating an archive set for keeping non-dominated solutions
Generating the first swarm of the solutions
for every solution in the first swarm **do**
    Applying local search to each solution
    Computing objective value of each objective function of each solution
end for
Computing crowding distances and ranks of all solutions in the first swarm
Placing non-dominated solutions into the archive set
while not meet the termination condition **do**
    for Every solution in the swarm **do**
        Preserving p_{best} as the personal best of each solution
    end for
    Preserving g_{best} as the global best of the swarm
    for every solution in the swarm **do**
        Applying crossover process to p_{best} and each solution
        Applying crossover process to g_{best} and each solution
        Applying mutation process with the probability of mutation at p_m to each solution
        Applying local search process to each solution
        Applying tabu search process to each solution
        Computing objective value of each objective function of each solution
    end for
    Computing crowding distance and rank of all solutions in the swarm and the archive set
    Placing non-dominated solutions into the archive set
    Setting No_of_Generation increasing by one
end while
output: Yielding non-dominated solutions in the archive set

Fig. 2: The pseudo code of HMGDPSOLTS

3.1 Multi-Objective Genetic-based Discrete Particle Swarm

The first key part in the proposed hybrid method is the multi-objective genetic-based discrete particle swarm optimization to solve the multi-objective PECTP, and the process is different from the original GDPSO that solves the PECTP in terms of single-objective function. The implementation of the multi-objective has the property known as Pareto dominance, [4], [6], [7], [8]. This property is used to compare two solutions. A solution x is indicated to be Pareto optimal when there is no other solution y in search space (S) such that $f(y)$ dominates $f(x)$. In this case, it also says that x is non-dominated concerning S and keeping in the archive set. The archive set is formed to keep the distinctly non-dominated solutions. Finally, the non-dominated solution is selected from the archive set.

3.2 Local Search Approach

Local search (LS) is a heuristic approach for solving difficult optimization problems as it helps to reduce the exploring of the search space, including quickly seeking the feasible solution. This work used LS from [4] as a basic framework, displayed in Figure 3.

Local Search Approach
input: Solution s from the current swarm
1: Generating a sorted list of events
2: **if** the current solution is infeasible **then**
3: Investigating the first item of the sorted list
4: **while** not meet the termination condition **and**
5: the current event still has an untried move left **do**
6: Computing the moves of s by assigning each time slot to the current event
7: **if** moving leads to decreasing of the number of hard constraint violations **then**
8: Moving to next event and going to line no. 4
9: **end if**
10: **end while**
11: **else {**the current solution is feasible}
12: Investigating the first item of the sorted list
13: **while** not meet termination condition **and**
14: the current event still has an untried move left **do**
15: Computing the moves of s by assigning each time slot to the current event
16: **if** moving leads to decreasing of the number of soft constraint violations with no hard constraint violations **then**
17: Moving to next event and going to line no. 13
18: **end if**
19: **end while**
20: **end if**
output: Yielding an improved solution

Fig. 3: The pseudo code of a local search approach

3.3 Tabu Search Approach

Tabu Search (TS) takes a probable solution to a problem and investigates its immediate neighbor solutions. TS is applied after the process of LS is completed to further improve the effectiveness of the solution, and this work used TS based on the TS approach from [4] as shown in Figure 4.

Tabu Search Approach
input: Solution s from the current swarm
1: Assigning solution s as the best solution
2: Building a tabu list
3: Initializing $TSCount$ to 0
4: **while** not meet the termination condition **do**
5: Initializing i to 0
6: **while** $i \leq$ 10% of all solutions **do**
7: Assigning s_i as the i-th move of solution s
8: Computing objective values of all objective functions of solution s_i
9: **end while**
10: **if** there is some solution s_j that has been dominated by the solution s and the solution s_j dominate or not dominate the solution s_i **then**
11: Assigning the solution s_j to be the solution s
12: Assigning the item at index j of tabu list equal to $TSCount$
13: Increasing $TSCount$ by one
14: **else**
15: Assigning the best solution s_j among all s_i ,which is not in the tabu list list yet, to solution s
16: Assigning the item at index j of the tabu list equal to $TSCount$
17: **end if**
18: Assigning the best solution so far to be the solution s
19: **end while**
output: Yielding the solution s

Fig. 4: The pseudo-code of a Tabu search algorithm.

4 Experiments

The experimental results of a proposed hybrid method to solve the multi-objective PECTP on Metaheuristic Network (MN) datasets, known as a standard testing benchmark, are reported in this section. These datasets can be divided into 3 categories: 5 easy classes, 5 medium classes, and 1 hard class. Moreover, the proposed approach was compared with the related algorithms, and the number of evaluations was used to accomplish the fairness of comparison with other algorithms. The nature of the three classes is specified in Table 1.

The parameters, according to [3] and [4] have been tuned up for each class differently. The terminating condition was the number of evaluations, specifying as 20,000 for easy cases, 10,000 for medium case 1 to 4, 14,000 for medium case 5 and 30,000 for hard case. For each problem case, all experiments were run repeatedly 20 times. In case of GDPSO, the swarm size, N, was set to 10, while the mutation probability, p_m, was set to 0.1. What is more, the time limit (tst_{max}) and the number of maximum steps (s_{max}) were used to stop the process of local search as follows. tst_{max} was fixed to 100 for easy cases, 1,000 for medium cases and 10,000 for hard case, respectively, and s_{max} was specified to 200 for easy cases, 1,000 for medium cases and 2,000 for hard case, respectively. Finally, the number of maximum iterations, tss_{max}, was set as the termination condition of tabu search, setting to 20 for easy cases, 30 for medium cases, and 80 for hard case.

Table 1. The Characteristics for each category of MN datasets

Characteristic	Small Class	Medium Class	Hard Class
The number of events	100	400	400
The number of rooms	5	10	10
The number of features	5	5	10
The number of students	80	200	400

4.1 Comparison with the Related Algorithms on Multi-Objective PECTP

A multi-objective Genetic-based Discrete Particle Swarm Optimization (GDPSO) and a hybrid multi-objective Genetic-based Discrete Particle Swarm Optimization with a LS algorithm (HMGDPSOLS) have been coded in Python and compared with the proposed approach to provide a clearer overview of the comparison. The experiments of those algorithms were run on the same group of machines to replicate the same testing environment, resulting in a fair comparison of results in each algorithm, including the parameter as discussed above. The abbreviations and descriptions of all 5 compared algorithms are described in Table 2.

Table 3 and Table 4 report the comparison results of proposed HMGDPSOLTS with all related algorithms on easy, medium, and hard cases respectively in terms of the average values of the number of soft constraint violations in each objective function. The best solution for all datasets is highlighted, and the proposed hybrid approach acquired more beneficial results than all related algorithms in all cases except Easy5 instance, which got the same average value with HNSGA2LTS as they both were not violated all constraints resulting in the average value of three objective functions equal to zero. To sum up, the comparison results clearly pointed out that the proposed method was able to outperform all other algorithms.

Table 2. The abbreviations and descriptions of the related algorithms on multi-objective PECTP

Abbreviations	Description
HMGDPSOLTS	The proposed hybrid approach in this paper.
MGDPSO	A multi-objective Genetic-based Discrete Particle Swarm Optimization.
HMGDPSOLS	A hybrid multi-objective Genetic-based Discrete Particle Swarm Optimization with a LS algorithm.
HNSGA2LTS	A hybrid multi-objective genetic algorithm with a new local search approach for solving the post-enrolment-based course timetabling problem by [4] in 2016.
GSNSGA	Guided search non-dominated sorting genetic algorithm by [9] in 2011.

Table 3. Comparison of HGDPSOLTS with the related algorithms on the multi-objective PECTP running on easy cases

Dataset	Algorithms	Average		
		f1	f2	f3
Easy01	**HMGDPSOLTS**	**0**	**0**	**0**
	MGDPSO	**0**	**0**	3.25
	HMGDPSOLS	**0**	**0**	0.20
	HNSGA2LTS	**0**	**0**	0.08
	GSNSGA	1.33	6.74	9.91
Easy02	**HMGDPSOLTS**	**0**	**0**	**0**
	MGDPSO	**0**	**0**	6.40
	HMGDPSOLS	**0**	**0**	1.65
	HNSGA2LTS	**0**	**0**	0.64
	GSNSGA	1.63	5.75	5.90
Easy03	**HMGDPSOLTS**	**0**	**0**	**0**
	MGDPSO	**0**	**0**	2.90
	HMGDPSOLS	**0**	**0**	1.75
	HNSGA2LTS	**0**	**0**	0.20
	GSNSGA	0.65	2.06	7.38
Easy04	**HMGDPSOLTS**	**0**	**0**	**0**
	MGDPSO	**0**	**0**	3.50
	HMGDPSOLS	**0**	**0**	2.40
	HNSGA2LTS	**0**	**0**	0.20
	GSNSGA	1.02	1.14	20.46
Easy05	**HMGDPSOLTS**	**0**	**0**	**0**
	MGDPSO	**0**	**0**	3.05
	HMGDPSOLS	**0**	**0**	2.00
	HNSGA2LTS	**0**	**0**	**0**
	GSNSGA	1.52	2.04	15.10

Table 4. Comparison of HGDPSOLTS with the related algorithms on the multi-objective PECTP running on medium and hard cases

Dataset	Method	Average		
		f1	f2	f3
Medium01	HMGDPSOLTS	**0**	**0**	**0**
	MGDPSO	8.05	11.85	0.10
	HMGDPSOLS	3.55	6.10	**0**
	HNSGA2LTS	72.47	110.90	5.82
	GSNSGA	8.74	138.76	32.52
Medium02	HMGDPSOLTS	**0**	**0**	**0**
	MGDPSO	2.10	3.00	0.05
	HMGDPSOLS	1.25	1.05	0.15
	HNSGA2LTS	74.47	111.49	5.31
	GSNSGA	13.00	176.60	21.00
Medium03	HMGDPSOLTS	**0**	**0**	**0**
	MGDPSO	2.45	1.75	0.10
	HMGDPSOLS	1.85	1.05	0.25
	HNSGA2LTS	106.62	135.28	6.97
	GSNSGA	6.90	145.81	16.69
Medium04	HMGDPSOLTS	**0**	**0**	**0**
	MGDPSO	6.05	2.85	0.05
	HMGDPSOLS	0.35	0.95	**0**
	HNSGA2LTS	59.74	101.28	5.30
	GSNSGA	7.15	88.81	22.38
Medium05	HMGDPSOLTS	**0**	**0**	**0.20**
	MGDPSO	0.65	0.20	5.75
	HMGDPSOLS	**0**	0.20	6.35
	HNSGA2LTS	124.47	108.72	8.95
	GSNSGA	23.15	150.40	43.15
Hard01	HMGDPSOLTS	**0**	**0**	**51.75**
	MGDPSO	**0**	**0**	115.50
	HMGDPSOLS	**0**	**0**	95.85
	HNSGA2LTS	587.97	446.32	37.95
	GSNSGA	39.72	345.94	124.64

4.2 Comparison with the Related Algorithms on single-Objective PECTP

To provide a more complete comparison, the proposed HMGDPSOLTS approach was compared with other algorithms from the published work on single-objective PECTP as most previous works of PECTP were in the form of single-objective optimization. The results of HMGDPSOLTS were transferred into single-objective experimental results by combining three objective values into a single objective value, and the abbreviations and descriptions of all 19 compared algorithms are in Table 5.

Table 6 offers the comparison results of the proposed HMGDPSOLTS with the 18 algorithms from the literature review in form of single-objective PECTP on easy cases. The comparison results revealed that the proposed HMGDPSOLTS approach gave a better result than RRLS, FMHO, GHH, and HAS in all easy cases. The rest of the related algorithms had no difference in terms of performance because they did not violate all constraints, resulting in the value of three objective functions equal to zero. Having said that, it can illustrate the considerable difference in medium and hard cases.

Table 5. The abbreviations and descriptions of the related algorithms on single-objective PECTP

Abbreviations	Description
HMGDPSOLTS	The proposed hybrid approach in this paper.
HGDPSOLTS	An Outperforming Hybrid Discrete Particle Swarm Optimization for Solving the Timetabling Problem by [3] in 2019.
HGALTS	Hybrid genetic algorithm with local search and tabu search approach by [10] in 2015.
MHSA	Modified harmony search algorithm by [11] in 2012.
HAS	Harmony search algorithm by [11] in 2012.
GSGA	Guided search genetic algorithm by [12] in 2009.
HGHH1	Hybrid graph-based hyper-heuristic with local search on complete solution by [13] in 2009.
HGHH2	Hybrid graph-based hyper-heuristic with local search during solution construct by [13] in 2009.
MA	Memetic algorithm by [14] in 2008.
GAWLS	Genetic algorithm with local search by [15] in 2008.
HEA	Hybrid evolutionary approach by [16] in 2007.
GHH	Graph-based hyper-heuristic by [17] in 2007.
RII	Random iterative improvement by [18] in 2007.
VNS	Variable neighborhood search by [19] in 2005.
FMHO	Fuzzy multiple heuristic ordering by [20] in 2005.
TSHH	Tabu-search hyper heuristic by [21] in 2003.
EALS	Evolutionary algorithm with local search by [22] in 2002.
MMAS	Max-min ant system by [5] in 2002.
RRLS	Random restart local search by [5] in 2002.

The experimental results in Table 7 have pointed out that the proposed hybrid approach was able to outperform 17 other algorithms on all medium cases, while it took the same performance as HGDPSOLTS as both showed no soft violation in all medium cases. For a hard instance, the number of soft constraint violations of the proposed HMGDPSOLTS was equal to 23, and it still can beat all 18 related algorithms, which “x%Ifea” is the percentage of runs that cannot seek a feasible solution (infeasible solution).

Table 6. Comparison of HGDPSOLTS with the related algorithms on the single-objective PECTP running on easy cases

Algorithm	Easy01	Easy02	Easy03	Easy04	Easy05
HMGDPSOLTS	**0**	**0**	**0**	**0**	**0**
HGDPSOLTS	**0**	**0**	**0**	**0**	**0**
HGALTS	**0**	**0**	**0**	**0**	**0**
MHSA	**0**	**0**	**0**	**0**	**0**
HAS	3	4	2	3	1
GSGA	**0**	**0**	**0**	**0**	**0**
HGHH1	2	2	1	1	**0**
HGHH2	**0**	**0**	**0**	**0**	**0**
MA	**0**	**0**	**0**	**0**	**0**
GAWLS	2	4	2	**0**	4
HEA	**0**	**0**	**0**	**0**	**0**
GHH	6	7	3	3	4
RII	**0**	**0**	**0**	**0**	**0**
VNS	**0**	**0**	**0**	**0**	**0**
FMHO	10	9	7	17	7
TSHH	1	2	**0**	1	**0**
EALS	**0**	3	**0**	**0**	**0**
MMAS	1	3	1	1	**0**
RRLS	8	11	8	7	5

Table 7. Comparison of HGDPSOLTS with the related algorithms on the single-objective PECTP running on medium and hard cases

Algorithm	Medium 01	Medium 02	Medium 03	Medium 04	Medium 05	Hard01
HMGDPSOLTS	**0**	**0**	**0**	**0**	**0**	**23**
HGDPSOLTS	**0**	**0**	**0**	**0**	**0**	25
HGALTS	137	132	194	114	160	789
MHSA	168	160	176	144	71	417
HAS	296	236	255	231	207	-
GSGA	240	160	242	158	124	801
HGHH1	310	419	332	324	162	80% Ifea
HGHH2	257	259	192	235	112	80% Ifea
MA	227	180	235	142	200	-
GAWLS	254	258	251	321	276	1027
HEA	221	147	246	165	135	529
GHH	372	419	359	348	171	1068
RII	242	161	265	181	151	100% Ifea
VNS	317	313	357	247	292	100% Ifea
FMHO	243	325	249	285	132	1138
TSHH	146	173	267	169	303	80% Ifea
EALS	280	188	249	247	232	100% Ifea
MMAS	195	184	248	164.5	219.5	851.5
RRLS	199	202.5	77.5 %Ifea	177.5	100 %Ifea	100%Ifea

Furthermore, it is noted that 9 comparator algorithms were unable to seek a feasible solution on a hard instance. To conclude, the proposed hybrid approach, HMGDPSOLTS, has shown the outperformance of the experimental results in all cases compared with all related algorithms on both the single-objective and multi-objective functions.

5 Conclusion

To sum up, the proposed hybrid algorithm has mainly been tested for its performance in solving the multi-objective PECTP on the standard testing benchmark, MN datasets. A hybrid approach integrates local search and tabu search techniques into a genetic-based discrete particle swarm optimization, denoted HMGDPSOLTS. Overall, the empirical results showed that the proposed hybrid method for solving the single-objective and multi-objective PECTP gave an outstanding performance, and it was able to get the best feasible solution of no soft constraint violation, resulting in the value of three objective functions equal to zero. It outperforms all published work on the same testing benchmark. What is more, the satisfactory performance of the proposed hybrid approach arises from the two parts. The first one is the designing of the solution representation with discrete variables, and this gives rise to a marked effect on the performance in terms of quickly seeking a feasible solution more effectively. The second part is the appropriate hybridization of LS and TS algorithms, and this brings about the ability to seek the neighbor solutions of a local search and a tabu search in the forms of exploitation and avoidance from the local optima.

In future work, the aims are to test the proposed hybrid method to solve the PECTP in terms of both single-objective and multi-objective optimization problems on real-world datasets such as the datasets from the real-life university in Thailand and to consider other soft constraints such as the utilization of rooms to minimize the cost of teaching and learning in the university.

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