Original Research Article

Meta-Heuristic Solutions to a Student Grouping Optimization Problem faced in Higher Education Institutions

Abstract

Combinatorial problems which have been proven to be NP hard are faced in Higher Education Institutions and researches have extensively investigated some of the well-known combinatorial problems such as the timetabling and student project allocation problems. However, NP hard problems faced in Higher Education Institutions are not only confined to these categories of combinatorial problems. The majority of NP hard problems faced in institutions involve grouping students and/or resources, albeit with each problem having its own unique set of constraints. Thus, it can be argued that techniques to solve NP hard problems in Higher Education Institutions can be transferred across the different problem categories. As no method is guaranteed to outperform all others in all problems, it is necessary to investigate heuristic techniques for solving lesser known problems in order to guide stakeholders or software developers to the most appropriate algorithm for each unique class of NP hard problems faced in Higher Education Institutions. To this end, this study described an optimization problem faced in a real university that involved grouping students for the presentation of semester results. Ordering based heuristics, genetic algorithm and the ants colony optimization algorithm were used to find feasible solutions to this problem, with the ants colony optimization algorithm performing better or equal in 75% of the test instances and the genetic algorithm producing better or equal results in 38% of the test instances.

Keywords Genetic Algorithm; Heuristics; Ants Colony Optimization; Student Grouping

1 Introduction

NP hard problems, among which include the University Course Timetabling Problem, Examination Timetabling Problem and Student Project Allocation Problem are faced annually in Higher Education Institutions. These problems and strategies to tackle them efficiently have been researched extensively.

However, there is a dearth of research on a combinatorial problem that involves grouping students for the presentation of semester results.

In some Higher Education Institutions, it is necessary to present the examination results of students in a programme. The document presented in a tabular form usually contains students in rows and courses as column headers, where the value of Table(i,j) is the examination score of student i in course j. Given that students register/write exams for different courses and there is only a fixed number of courses that could appear as column headers for the result presentation document to be legible, it becomes necessary to group students into subsets such that the union of the courses students took exams for in each group is not more than the number required for the creation of a legible document. As each group will have a unique set of course headers and may need to start on a new page in the document, the argument is that fewer groups will need fewer pages to be presented which will save resources for institutions that store printed copy of result summaries and also result in smaller sizes of the documents in electronic form. The Student Result Grouping (SRG) problem in its simplest form is thus to find the student groupings such that the number of groups are minimized. Institutions may have additional constraints and the Student Result Grouping problem from the university used as the case study in this research is described in the next section.

The SRG problem in the case study university has been solved by greedily assigning or creating groups based on the order students were stored in the database, but this research aims to use heuristic techniques such as the genetic algorithm and the ants colony optimization algorithm to find more suitable solutions to this problem.

2 Student Result Grouping (SRG) Problem

A dataset containing a list of students with courses they took examinations for as shown in Table 1 and a list of courses with the year the courses were introduced to students as shown in Table 2 represents the information available to produce a suitable grouping.

Student	**Course**
11100011	CMP301
11100011	MTH101
11200012	CMP436
11200012	CMP421

Table 1: List of students with the courses the students registered

Student	**Course**
CMP301	3^{rd}
MTH101	1^{st}
CMP436	4^{th}
CMP421	4^{th}

Table 2: Courses and the year the courses are introduced to students

Assuming that we are to generate groupings for fourth year students, new courses are fourth year courses while other courses are categorised as old. In the case study university, students are not allowed the register or take examinations for courses they have not been introduced to. Consequently, fourth year students can register for any course but third year students can register for only first, second and third year courses.

After examinations, the student grouping problem involves grouping students in a programme such that:

1. All students are assigned to a group.
2. The number of unique courses taken by all students in each group is less than 26.
3. The number of unique new courses taken by all students in each group is less than 13.
4. The number of unique old courses taken by all students in each group is less than 13.

The numbers in the objectives above were determined to be the most appropriate for legible presentation of results in an A4 sheet by the case study institution.

Fourth year students in the case study university can register courses from any level, thus presenting results for this set of students is a harder problem compared to students in lower levels.

2.1 Mathematical Formulation

The Student Result Grouping Problem is made up of a set of students $\{S_1 \ \cdots \ S_m\}$, set of courses $\{C_1 \ \cdots \ C_n\}$ and set of years $\{Y_1 \ \cdots \ Y_o\}$; Y being the years a student can spend in the university ($Y_1 = first\ year\ students$ and $Y_o = final\ year\ students$).

Students are grouped according to the number of years currently spent in the university $SY_j \in \{S_1 \ \cdots \ S_m\}$ and each course $C_i \in \{C_1 \ \cdots \ C_n\}$ is introduced to students SY_j in a particular year $Y_j \in \{Y_1 \ \cdots \ Y_o\}$.

Exams are taken for Courses. CY_j is the set of courses introduced to students SY_j in year Y_j. Students are not allowed to take exams for courses they have not been introduced to.

For each student $S_k \in SY_j$, course C_i is classified as old if $C_i \notin CY_j$, otherwise ($C_i \in CY_j$), it is classified as new.

The Student Result Grouping Problem groups all students in a particular year (SY) to subgroups SG. SG is a set of groups $\{SG_1 \ \cdots \ SG_k\}$ with each group in SG a subset of the students in SY; $SG \in SY$ and CG the courses students in SG took exams for. The Student Result Grouping Problem groups students whilst ensuring that:

1. All students are assigned to a group.
   $SG_1 \cup SG_2 \cup \cdots \cup SG_k = SY$
2. No student is assigned to more than one group
   $n(SG_1) + n(SG_2) + \cdots + n(SG_k) = n(SY)$
3. The number of unique courses taken by all students in each group is less than 26
   $n(CG) < 26$
4. The number of unique new courses taken by all students in each group is less than 13
   $n(CG;\ if\ CG_i\ is\ classified\ as\ new) < 13$
5. The number of unique old courses taken by all students in each group is less than 13
   $n(CG;\ if\ CG_i\ is\ classified\ as\ old) < 13$

2.2 Data

The dataset downloadable from https://doi.org/10.6084/m9.figshare.12116667 is in the format shown in Table 3 with each row showing a student, a course and the year the course was introduced to the student.

Student	Course	Year
111011	CMP201	2
111011	CMP421	4
...	...	...
...	...	...
...	...	...
303101	CMP401	4

Table 3: An example instance in the dataset available from https://doi.org/10.6084/m9.figshare.12116667

Table 4 shows the description of instances in the dataset, which shows an overview of fourth year students' examination/course registrations from the Computer Science department of the case study institution.

Name	New Courses	Old Courses	No. of Students
RGD41107	28	15	140
RGD4152	13	20	97
RGD4185	27	20	121
RGD42118	8	0	25
RGD4263	19	20	132
RGD4296	23	17	193
RGD41118	10	1	18
RGD4196	26	17	185
RGD4241	8	21	67
RGD4274	20	23	147
RGD4141	9	17	68
RGD4174	29	19	149
RGD42107	26	16	123
RGD4252	9	24	95
RGD4285	19	21	128
RGD4163	26	17	128

Table 4: Description of instances in the Student Result Grouping dataset

3 Methods

Heuristic algorithms have successfully been used to solve NP hard problems such as the Student Project Allocation Problem [1, 2, 3] and the Nurse Rostering Problem [4, 5].

Heuristic techniques that find satisfactory solutions to the Examination and Course timetabling problems have also been extensively investigated [6, 7, 8, 9]. Implementation of some of these algorithms are available as packages, for example DEAP - Distributed Evolutionary Algorithms in Python [10] is a python implementation of the Genetic algorithm. This study explores the use of some well known algorithms to solve the combinatorial problem in this research, and compares the quality of resulting solutions.

3.1 Evaluation/Fitness function

The fitness or evaluation function is arguably the most important aspect of a heuristic algorithm. It should be a function that not only evaluates the quality of a solution but also guides an algorithm towards optimal solutions. For example, in the fitness function in this study, penalty for groups that exceed the required number of unique courses is higher in a group with more students compared to a group with fewer students. The reason being that reducing the number of students in a group can guide the algorithm to a solution with fewer required number of unique course violations (unfit penalty).

Three penalties, unfit penalty, unassigned penalty and size penalty are used in the fitness function to determine the quality of a solution to the student result grouping problem in this research.

Proposition 3.1. *The **unfit penalty** evaluates if the number of unique new and old courses (cardinality of the set of new and old) offered by students grouped together exceeds the the allowed limit (13). This is computed with equations 3.1 and 3.2*

$$gp(old|new) = \begin{cases} n(CG_{old|new}) - 13 & if\ n(CG_{old|new}) \geq 13 \\ 0 & otherwise \end{cases} \tag{3.1}$$

$$up = \sum_{i=1}^{m} (gp_i(new) + gp_i(old)) \times n(SG_i); m\ is\ the\ no.\ of\ student\ groups \tag{3.2}$$

Equation 3.1 is used to compute the penalties of new and old courses in groups, while the unfit penalty is determined by the sum of group penalties for all groups in the solution as shown in Equation 3.2.

Proposition 3.2. *The **size penalty** as shown in Equation 3.3 guides algorithms to better solutions by ensuring that the meta-heuristic algorithm favours larger groups instead of smaller groups.*

$$sp = \sum_{i=1}^{m}(n(SY) - n(SG_i)) \times n(SG_i); m\ is\ the\ no.\ of\ student\ groups \tag{3.3}$$

Proposition 3.3. *The **unassigned penalty** penalizes solutions that do not assign groups to all students. It is simply evaluated as the number of students not assigned to a group.*

$$ap = n(SY) - \sum_{i=1}^{m}(n(SG_i)); m\ is\ the\ no.\ of\ student\ groups \tag{3.4}$$

The final fitness function is the weighted sum of individual penalties as shown in Equation 3.5.

$$f(x) = 1000 \times ap + (log_2(sp) + up \times 1000) \times n(SG) \tag{3.5}$$

The unfit penalty favours smaller groups because fewer students in a group results in fewer unique courses while the size penalty favours larger groups. As the size penalty is not as a result of a constraint violation, but help guide heuristic algorithms to a solution with fewer number of groups, its weight is scaled down compared to the unfit penalty, ensuring that meta-heuristic algorithms will try to reduce the number of groups only when the unique courses in all groups does not exceed the allowed limit.

3.2 Hardest First Ordering Heuristics

This is a graph-based technique that has been employed in solving a number of NP Hard problems faced in Higher Education Institutions (HEIs), particularly the Education Timetabling Problem. Early techniques [11, 12] that solved timetabling problems ordered events to be scheduled based on the number of constraint violations scheduling that event may cause, or how difficult scheduling that event is, in terms of student or lecturer clashes. For example, using the largest degree first graph heuristic, events with more common students are scheduled first while the least saturated degree schedules events with fewer available timeslots first [12].

In the university timetabling problem, the largest degree first and least saturated degree heuristics are variations of the hardest first heuristic, with difference only in how the hardest event to be scheduled is determined; largest degree first uses events with higher number of student groups, while least saturated degree first uses events with fewer available timeslots.

The constraints for the Student Grouping Problem in this study is simpler that the constraints for the Educational Timetabling Problem. The hardest student to be scheduled is simply the student who has taken the highest number of examinations.

The hardest first heuristics thus generates Student Grouping by greedily assigning the hardest student (student with the most courses) to its best fitting group (group that results in the least penalty) with no constraint violation. When no such group exists, a new group is created for the student. The pseudocode for the Hardest first heuristic is shown in Algorithm 1.

Algorithm 1: Pseudocode for Student Grouping by the Hardest First Ordering heuristics

Input: List of students and courses offered to be grouped
Output: Array of student grouped into subsets

$students$ = list of students in decreasing order of the number of courses registered
SG = Initialization of student group as an empty array
for $i \leftarrow 1$ ***to*** $length(students)$ **do**
    if $students[i]$ *can be assigned to any group in* SG *without any constraint violation* **then**
        Assign $students[i]$ to its best fitting group in SG
    else
        Assign $students[i]$ to a newly created group, and add group to SG
return SG

3.3 Ants Colony Optimization

The Ants Colony Optimization (ACO) [13] algorithm is inspired from the way ants navigate to a food source through cooperation. Ants drop pheromone trails on promising paths for other ants to follow, and if the path is still promising more pheromones are deposited on the trail, this increasing the likelihood that other ants will follow the trail. Using this concept, an ant traverses a path to a full solution to an optimization problem. The quality of the solution is determined and then the path is updated based on the quality of the found solution. Over several iterations and ant traversals, the ACO converges to always guide ants to follow the path with the highest pheromone trail, which in turn will lead to an optimal solution.

A number of variations to the ACO exists, and have been used to solve meta heuristic problems such as the University Course Timetabling Problem [14, 8], Student Project Allocation Problem [1], Nurse Rostering Problem [15]. However, the following concepts as described in [1] are the basis of all ACO algorithms.

Representation: The solution search space for an optimization problem can be represented as a graph. An ant traversal from the start node to the end node forms a solution to the optimization problem. For the student grouping problem in this study, each node visited on the graph assigns a student to a group, thus the graph can be represented as an nxm matrix where n rows is the number of groups and m columns is the number of students to be grouped. The number of groups n is determined by the number of groups in a solution found by the Hardest First Ordering heuristics algorithm, ensuring that final solutions cannot have more groups than the number of groups found using the Hardest First Ordering algorithm.

Initialization: The weight of edges on the graph representing the solution space of an optimization problem determines the probability that an ant will follow that edge. In the Max-Min ant system [14] which used in this study, the maximum edge weight is $T_{max} = 10$ and the minimum edge weight is $T_{min} = 0.1$, with edges (values in the representation matrix) initialized to T_{max}.

Traversal: From an initially empty solution, as an ant traverses the solution space represented as a graph by visiting nodes, each node visited adds a student grouping to the initially empty solution to form an updated partial solution. At the end of an ant traversal, a complete solution to the student grouping problem is found. An ant decides the node that will be added to the partial solution based on a probability determined by the level of pheromone trail and if visiting that node does not result in a constraint violation. Thus, nodes whose edges have higher T values are more likely to be visited than those with lower T values. Here lies the difference between the Hardest First Ordering heuristic algorithm and the Ant Colony optimization algorithm, the hardest first ordering heuristic simply assigns a student to its best fitting group while the ants colony optimization assigns a student to a group based on a probability controlled by a T value that is updated as the ant colony optimization algorithm progresses over a number of iterations.

Algorithm 2: Pseudocode for ants' traversal in an iteration of the Ants Colony optimization Algorithm

Initialize the number of ants as $numAnts$
$bestSolution$ = ant traversal of solution space to generate a solution
for $i \leftarrow 2$ ***to*** $numAnts$ **do**
    $antSolution$ = ant traversal of solution space to generate a solution
    if $quality(antSolution) < quality(bestSolution)$ **then**
        $bestSolution$ = $antSolution$
return $bestSolution$

Update: After each iteration, the edges that form a path to the final solution are updated based on the quality of the solution. This depicts the process of ants dropping pheromone trails on promising paths, as higher T values increases the likelihood of subsequent ants following that path. The reward determined from Equation 3.6 is added to the T values on the solution path. In cases when the T value becomes greater than T_{max} the T value is set to T_{max}.

$$reward = \begin{cases} 1 & if\ globalBest \geq currentQuality \\ \frac{1}{currentQuality - globalBest} & otherwise \end{cases} \tag{3.6}$$

Evaporation: To avoid convergence to a local minimum the edge weights are reduced after each ant traversal. This depicts the effect of wind reducing the pheromone trails from previously promising paths not followed when a more optimal path is found. Evaporation is particularly important in the ants colony optimization algorithm in this study because there are no negative rewards as shown in Equation 3.6, so evaporation is the only way to reduce the trail (T value) on non-optimal paths which have been initialized to T_{max}. T values are updated through evaporation using Equation 3.7, where ρ in the range 0.1 to 0.9 controls the rate of evaporation. Higher evaporation rate speeds up convergence but reduces the solution space searched. In cases where the T value becomes less than T_{min}, the T value is set to T_{min}.

$$T_{new} = T_{old} \times (1 - \rho) \tag{3.7}$$

Algorithm 3: Pseudocode of the Ants Colony optimization for solving the Student Result Grouping Problem

n = number of groups determined by the number of groups in the solution by hardest first heuristic algorithm
m = number of students
T_{max} = 10, T_{min} = 0.1, ρ = 0.9, $globalBest$ = None
SG = $n \times m$ matrix with values initialised to T_{max}
for $i \leftarrow 1$ ***to*** $numIterations$ **do**
    $cycleBest$ = ant traversal as described in Algorithm 2
    Reduce pheromone trail in SG by evaporation
    Update pheromone trail in $cycleBest's$ solution path
    if $quality(cycleBest) < quality(globalBest)$ **then**
        $globalBest$ = $cycleBest$
return $globalSolution$

3.4 Genetic Algorithm (GA)

Inspired from natural evolution the Genetic Algorithm for local search [16] creates an initial population of solutions to an optimization problem, and updates the population in subsequent generations through mutation, crossover and selection operators. These genetic operators which are used in solving the student result grouping problems is described subsequently.

Representation: Unlike the ACO and hardest first ordering heuristic algorithms described in previous sections, final solutions are not constructed in a way such that no constraint is violated. An individual in the population as shown in Fig 1 is simply represented as a list of integers where the position i on the list represents $Student_i$ and the value in the i^{th} position represents the group $Student_i$ has been assigned to. The length of an individual is the number of students to be grouped and the number of unique values (allele) in the list of integers is the number of groups in the solution.

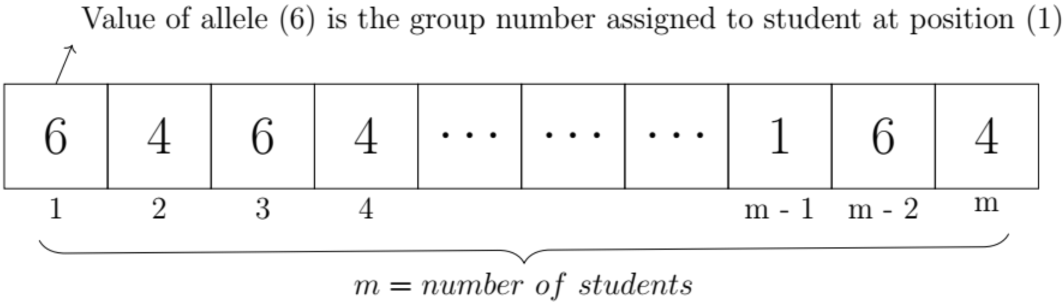
Heuristic information that is used in the ACO to determine the maximum number of groups is not used in the GA solution. Allele values (group a student is assigned to) is set to a random number in the range not greater than the number of students to be grouped, thus in the worst case, the final number of groups will be equal to the number of students.

As heuristic information is not used to generate the initial population of the GA, the quality of solutions is significantly worse than the first iteration of the ACO but a wider solution space is searched.

Evaluation: Individuals are evaluated by the fitness function shown in Equation 3.5. The fitness function is especially important for the GA to guide the algorithm towards better solutions. For example, if two individuals have the same number of groups, the evaluation function ensures that the fitter individual is the individual that needs fewer modifications to result in a fewer number of total groups.

Crossover: The crossover operator combines two individuals (parents) in the current population to generate two new individuals (offsprings) that will make up the population of the next generation. Single point crossover, two-point crossover, and uniform crossover are popular approaches to mate parents to produce offsprings through crossover. Magalhães-Mendes [17] compared the efficiency of different crossover approaches for a job scheduling problem, with experiments showing the single point crossover to produce the best average performance. However, in a study [1] that solved the student project allocation problem, the type of crossover operator did not have any significant

Figure 1: An individual in a GA population that represents a solution to the Student Result Grouping Problem



influence on the performance of the genetic algorithm, emphasizing that no method is guaranteed to outperform others in all problems.

Mutation The mutation operator changes a single allele in an individual. In this study, the mutation operator changes the value of an allele to a random integer not greater than the total number of students to be grouped.

Selection: A subset of individuals from the parents (individuals in the current generation) and offsprings (determined through mutation and crossover operators) are selected to make up the population of the next generation. The python library DEAP [10] that is used in this study implements a number of selection techniques. Amongst which are tournament and roulette wheel selection methods that are widely used for single objective genetic algorithms such as the student grouping problem in this study.

In tournament selection which is regarded as one of the most popular selection strategy for genetic algorithms [18] given a tournament size n, a random number of n individuals are selected from the parents and offsprings and the best individuals in each m tournaments make up the individuals in the next generation.

In roulette wheel selection, from a set of individuals (parents and offsprings), an individual is selected for the next generation by a probability proportional to its fitness. The probability of a fitter individual to be selected is higher than less fit individuals.

Razali and Geraghty [19] has shown that tournament selection can outperform other selection techniques for some optimization problems, thus this strategy is used in this study.

Algorithm 4: Pseudocode of the genetic algorithm for solving the student result grouping problem

```
m = population size
create the initial population with m number of individuals
while stopping condition not met do
    Generate offsprings by crossover and mutation operations on parents
    Evaluate fitness of offsprings
    Select individuals form parents and offsprings for the next generation by tournament
      selection whilst preserving the fittest individual
return fittest individual in the final population
```

Using the building blocks of the genetic algorithm as previously described and implemented in DEAP python library, the algorithm is run until 20 non improving generations is reached. The pseudocode of the genetic algorithm is shown in Algorithm 4.

4 Result and Discussion

Table 5 and Table 6 show the result of grouping students with the Hardest First Ordering, the Genetic Algorithm, Ants Colony Optimization and the Random Ordering meta heuristic techniques. In the majority of cases, the ants colony optimization algorithm performed better than other algorithms, however the Hardest First Ordering heuristic can produce a good enough solution with fewer trials compared to others.

	HFO			RO		
Instance	**Min**	**Max**	**Avg**	**Min**	**Max**	**Avg**
RGD41107	95.423	95.423	95.423	86.44	171.93	108.66
RGD4152	118.14	118.14	118.14	75.18	108.17	90.25
RGD4185	175.34	175.34	175.34	128.75	260.89	183.31
RGD42118	4.70	4.70	4.70	4.70	4.70	4.70
RGD4263	191.29	191.29	191.29	156.53	249.02	193.43
RGD4296	109.16	109.16	109.16	104.45	174.86	141.71
RGD41118	4.25	4.25	4.25	4.25	4.25	4.25
RGD4196	136.30	136.30	136.30	104.01	192.17	149.45
RGD4241	147.09	147.09	147.09	104.50	194.42	150.24
RGD4274	171.90	171.90	171.90	166.85	302.35	233.21
RGD4141	50.19	50.19	50.19	33.08	67.81	49.89
RGD4174	98.64	98.64	98.64	100.04	179.63	134.71
RGD42107	65.03	65.03	65.03	60.88	115.93	83.16
RGD4252	13435.17	13435.17	13435.17	14443.08	18726.77	16668.17
RGD4285	176.58	176.58	176.58	198.65	287.94	244.73
RGD4163	60.59	60.59	60.59	57.62	84.50	69.98

Table 5: Result of grouping students for the presentation of examination scores whilst satisfying the SRG problem constraints listed in Section 2 with the Hardest First Ordering (HFO) and Random Ordering (RO) meta-heuristic techniques

The algorithms, apart from the GA are guaranteed to produce a feasible solution (all grouping conditions are met) when such a grouping exists. Partial solutions are generatively updated in such a way that a student is assigned to a group that meets all assignment conditions, and when no such group exists, a new group is created. In the random and hardest first ordering heuristics, students are grouped greedily (assigned to the best fitting group), while in the ants colony optimization algorithm, assignment is based on a probability controlled by the pheromone trail. Thus, the quality of these algorithms is largely dependent on the order in which students are assigned to groups.

The GA does not update partial solutions ensuring that each update does not break feasibility but generates a complete random solution and iteratively updates the solution through mutation and crossover operations until an optimal solution is found. As a result of this, the majority of individuals in the initial generations of the Genetic Algorithm are infeasible solutions.

Generating solutions for the GA is faster that other algorithms in this study as each student assignment to a group does not require an evaluation to check for feasibility, but the GA requires more iterations to converge to an optimal solution. The fitness function is also important because even though the main aim is to have minimal number of groups, from the fitness function, the GA should be able to identify which solution is closer the feasibility even if they have the same number of student groups.

Given that 26 columns (13 for new courses and 13 for old courses) are available to show student results, 13 fixed number of columns are reserved for new and old courses. In special cases such as in the RGD4252 instance, it is not possible to find a feasible solution because a student in that instance took exams for more than 13 new courses. Thus, it may be necessary to allow groups to

	GA			ACO		
Instance	**Min**	**Max**	**Avg**	**Min**	**Max**	**Avg**
RGD41107	89.12	98.69	92.25	69.76	91.73	83.61
RGD4152	75.78	84.32	78.27	58.00	78.09	66.37
RGD4185	129.15	164.32	143.53	127.20	160.73	134.17
RGD42118	4.70	4.70	4.70	4.70	4.70	4.70
RGD4263	125.66	218.49	175.16	132.36	161.31	139.11
RGD4296	101.17	143.23	113.64	99.53	108.43	104.50
RGD41118	4.25	4.25	4.25	4.25	4.25	4.25
RGD4196	101.35	136.45	126.60	101.32	113.00	103.21
RGD4241	123.20	154.45	134.55	104.26	115.17	108.99
RGD4274	166.01	239.39	209.11	178.53	191.91	184.68
RGD4141	33.08	51.43	44.58	33.08	34.10	33.33
RGD4174	96.00	143.21	105.09	95.40	104.47	97.89
RGD42107	60.50	89.86	72.05	57.97	59.19	58.40
RGD4252	14417.77	14417.77	14417.77	14459.32	15560.84	14811.29
RGD4285	158.29	237.22	196.17	180.56	240.65	207.61
RGD4163	58.86	84.58	66.25	57.25	57.75	57.38

Table 6: Result of grouping students for the presentation of examination scores whilst satisfying the SRG problem constraints listed in Section 2 with the Genetic Algorithm (GA) and the Ants Colony Optimization (ACO) meta-heuristic techniques

have flexible number of columns for new or old courses, so that in special cases columns reserved of new or old courses may be changed dynamically.

As the ACO outperformed other algorithms as shown in Table 6. Table 7 shows the quality of solutions achieved when the number of columns for new and old courses were dynamically determined. The quality of solutions when the columns are dynamic are better that those achieved with fixed number of columns and feasible solution were found for all instances in the dataset used in this study.

Instance	**Min**	**Max**	**Average**
RGD41107	70.59	91.47	86.27
RGD4152	59.79	78.89	71.23
RGD4185	127.16	160.42	132.84
RGD42118	4.70	4.70	4.70
RGD4263	130.81	166.45	137.03
RGD4296	98.98	110.66	103.34
RGD41118	4.25	4.25	4.25
RGD4196	98.98	110.66	103.34
RGD4241	104.58	123.63	111.27
RGD4274	183.42	244.98	198.40
RGD4141	33.08	34.10	33.30
RGD4174	96.11	104.27	98.39
RGD42107	57.97	59.30	58.50
RGD4252	453.06	529.19	495.70
RGD4285	183.63	235.45	211.56
RGD4163	57.25	58.09	57.33

Table 7: Result of grouping students for presentation of results using the Ants Colony Optimization Algorithm with dynamic number of columns

5 Conclusions

A number of NP hard problems are faced annually in Higher Education Institutions, among these problems include the timetabling and project allocation problems which have been researched extensively. The student result grouping problem is similar to other NP hard problems faced in HEIs as it also involves grouping students albeit with its own unique constraints. Thus, techniques used in solving other NP hard problems can be adapted to solve the student result grouping problem investigated in this study.

This study elaborately described the student result grouping problem faced in a case study Higher Education Institution, and found suitable solutions to this problem by ordering heuristics (hardest first and random ordering), ants colony optimization and the genetic algorithm, demonstrating the possibility of solving these kind of problems with well-known heuristic techniques that have been used in solving other categories of NP hard problems.

The genetic and the ants colony optimization algorithms performed better than ordering based techniques and an adaptation of the problem in the case study institution improved the quality of final solutions. Ordering based heuristics can however be used to find a quick good enough solution.

In the case study institution, the student result grouping problem was previously solved by greedily assigning or creating groups based on the order students were stored in the database. In most instances, the final solutions were worse than any of the techniques investigated in this study. Thus, research on other lesser known combinatorial problems faced in institutions which report on adequate methods that can be used to find suitable solutions to these problems will be particularly beneficial to education software developers.

References

[1] Patrick Kenekayoro, Promise Mebine, and Bodouowei Godswill Zipamone. Population Based Techniques for Solving the Student Project Allocation Problem. *International Journal of Applied Metaheuristic Computing (IJAMC)*, 11(2):192–207, 2020.

[2] Marco Chiarandini, Rolf Fagerberg, and Stefano Gualandi. Handling preferences in student-project allocation. *Annals of Operations Research*, pages 1–40, 2018.

[3] Augustine Kwanashie, Robert W. Irving, David F. Manlove, and Colin T. S. Sng. Profile-Based Optimal Matchings in the Student/Project Allocation Problem. In *International Workshop on Combinatorial Algorithms*, pages 213–225. Springer, Cham, oct 2015.

[4] Mohammed A. Awadallah, Ahamad Tajudin Khader, Mohammed Azmi Al-Betar, and Asaju La'aro Bolaji. Global best Harmony Search with a new pitch adjustment designed for Nurse Rostering. *Journal of King Saud University - Computer and Information Sciences*, 25(2):145–162, jul 2013.

[5] Ghaith M. Jaradat, Anas Al-Badareen, M. Ayob, Mutasem Al-Smadi, Ibrahim Al-Marashdeh, Mahmoud Ash-Shuqran, and Eyas Al-Odat. Hybrid Elitist-Ant System for Nurse-Rostering Problem. *Journal of King Saud University - Computer and Information Sciences*, 31(3):378–384, jul 2019.

[6] Jingpeng Li, Edmund K Burke, and Rong Qu. A pattern recognition based intelligent search method and two assignment problem case studies. *Applied Intelligence*, 36(2):442–453, 2010.

[7] HY Al Tarawneh and Masri Ayob. Using Tabu search with multi-neighborhood structures to solve University Course Timetable UKM case study (faculty of engineering). In *Data Mining and Optimization (DMO) ...*, number June, pages 28–29, 2011.

[8] Patrick Kenekayoro and Godswill Zipamone. Greedy Ants Colony Optimization Strategy for Solving the Curriculum Based University Course Timetabling Problem. *British Journal of Mathematics & Computer Science*, 14(2):1–10, jan 2016.

[9] Ayla Gülcü and Can Akkan. Robust university course timetabling problem subject to single and multiple disruptions. *European Journal of Operational Research*, 283(2):630–646, jun 2020.

[10] Félix Antoine Fortin, Francois Michel De Rainville, Marc-André Gardner, Marc Parizeau, and Christian Gagné. DEAP: Evolutionary Algorithms Made Easy. *Journal of Machine Learning Research*, 13:2171–2175, 2012.

[11] Rong Qu, Edmund K. Burke, and Barry McCollum. Adaptive automated construction of hybrid heuristics for exam timetabling and graph colouring problems. *European Journal of Operational Research*, 198(2):392–404, oct 2009.

[12] Edmund Burke, Barry MacCloumn, Amnon Meisels, Sanja Petrovic, and Rong Qu. A Graph-Based Hyper Heuristic for Timetabling Problems. *European Journal Of Operational Research*, 176:177–192, 2010.

[13] M Dorigo, V Maniezzo, and A Colorni. Ant system: optimization by a colony of cooperating agents. *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on*, 26(1):29–41, 1996.

[14] Krzysztof Socha, Joshua Knowles, and Michael Sampels. A MAX - MIN Ant System for the University Course Timetabling Problem. In *Lecture notes in computer science: Proceedings of the 3rd international workshop on ant algorithms,*, pages 1–13. Springer Berlin, 2002.

[15] Razamin Ramli. A Hybrid Ant Colony Optimization Algorithm for Solving a Highly Constrained Nurse Rostering Problem. *Journal of Information and Communication Technology*, 18(3):305–326, 2020.

[16] Nico Ulder, Emile Aarts, Hans-Jürgen Bandelt, Peter van Laarhoven, and Erwin Pesch. Genetic local search algorithms for the traveling salesman problem Parallel Problem Solving from Nature. In Hans-Paul Schwefel and Reinhard Männer, editors, *International Conference on Parallel Problem Solving from Nature*, volume 496 of *Lecture Notes in Computer Science*, pages 109–116. Springer Berlin / Heidelberg, 1990.

[17] Jorge Magalhães-Mendes. A Comparative Study of Crossover Operators for Genetic Algorithms to Solve the Job Shop Scheduling Problem. *WSEAS Transactions on Computers*, 12(4):164–173, 2013.

[18] Vladimi Filipović. Fine-grained tournament selection operator in genetic algorithms. *Computing and Informatics*, 22(2):143–161, 2012.

[19] Noraini Mohd Razali and John Geraghty. Genetic Algorithm Performance with Different Selection Strategies in Solving TSP. In *Proceedings of the World Congress on Engineering*, volume 2, pages 1134–1139, London, 2011.