Final Report Assignment Based on Students' Preferences to Topics and Partners

Fang-Rong Hsu[1], Wan-Rong Chen[1](✉), Yu-Hsun Kuo[1], and Rong-Chang Chen[2]

[1] Department of Information Engineering and Computer Science, Feng Chia University, Taichung, Taiwan
P1000166@o365.fcu.edu.tw

[2] Department of Distribution Management, National Taichung University of Science and Technology, Taichung, Taiwan

Abstract. To evaluate the learning performance of students, a final report is usually assigned. Students are asked to form a group which includes several students and they are assigned a specific topic to prepare a report. The way of assignment greatly influences on the results. The purpose of this study is to present a novel optimization approach to final report assignment which considers the preferences of students to topics as well as their partners. Initially, students are asked to indicate their preferences to some specific topics and their preferred co-operative partners. After aggregating preference data, a scoring system is used to evaluate the assignment. Mathematical Programming (MP) is employed and an evolutionary method is used to find solutions. Results from this study show that the proposed approach presented in this study can get good solutions efficiently.

Keywords: Assignment problem · Mathematical programming · Optimization · Preference-based · Choice-based

1 Introduction

One of the most popular teaching activities to evaluate the learning performance of students on a specific subject is to assign a final report to students. Generally, the way of final report is conducted by deciding the students into different groups, selecting their topics, and then making an oral or written report. The final report can help teachers to understand the students' insights and whether they acquire adequate knowledge or not from the class. Accordingly, the teacher can make a score for the subject. However, an inappropriate way of assigning the final report may affect the expected learning performance.

In the past, there were several ways to decide the groups of final reports: assigning directly by the teacher, drawing lots, and finding partners by themselves [1]. The advantage of assigning directly by teacher is its simplicity, but the disadvantage is that the students may feel unfair or dislike their group members; drawing lots is simple and fair, but the drawback is that students may not like their partners and lacks the willingness to cooperate. The upside of finding partners by students themselves is that they can find

Y. Yau and F. Hage Chehade (Eds.): DESD 2022, ASSEHR 691, pp. 213–220, 2023.
https://doi.org/10.2991/978-2-494069-37-4_28

group members who are close to each other, but it is easy to form a coterie, and someone being a loner or feeling bad to reject people will be sacrificed. On the other hand, the schemes for deciding topics can be generally divided into two types: deciding by drawing lots and deciding by students themselves. The former fails to consider the willingness of students, while the latter is unfair. In addition, both schemes fail to consider overall satisfaction.

Given that many drawbacks of these above schemes to grouping and assigning topics, we proposed a novel method based on students' preferences to determine the topics and groups. This method not only considers students' choices but also is fairness. This objective is to decide final report by most satisfying the preferences of students. First, collecting students' preferences to their preferred group members and topics. Second, applying a scoring system to evaluate this method. The scheme is not complex and it is been proven to be effective in getting good results [1–3].

The remainder of this paper is organized as follows. The final report assignment problem is described in detail in Sect. 2. The proposed approach is presented in Sect. 3. In Sect. 4, a reference case is set up and a number of experimental are performed. In addition, results and some discussion are addressed. Finally, concluding remarks are drawn in Sect. 5.

2 The Problem

Given the number of students, the number of final report topics, and the number of students allowed in a topic, the problem to be tackled is to find an optimized assignment aiming to best satisfy all the students' preferences to report topics and their preferred partners.

For easy description, an example is given below. Suppose that there are four students, designated by S1, S2, S3, and S4, respectively. There are two report topics, which are represented by T1 and T2, and the number of students allowed in each topic is two. The preferences of students to topics and preferred partners are shown in Table 1 and Table 2, where a "1" stands for the first choice, "2" for the second choice, "3" for the third choice, and the like. A scoring system is used to evaluate the solutions, where a value of "$1^2 = 1$" is given for the first choice, "2^2" is given for the second choice, "3^2" is given for the third choice, and so on. The objective is to find a solution with a minimal value of the total score.

Table 1 shows the preferences of students to topics. The first choices of students S1 and S2 on the topics are T1, while the first choices of students S3 and S4 are T2. On the other hand, the first choice of student S1 on partners is S2, the second choice is S3, and the third choice is S4, and more, as illustrated in Table 2.

To further illustrate the problem, two solutions are shown and compared, as shown in Table 3. In solution1, students S1 and S2 are assigned topic T1, while students S3 and S4 are assigned topic T2; In solution 2, students S1 and S3 are assigned topic T1, while students S2 and S4 are assigned topic T2.

From Table 1 and Table 2 we can calculate the total scores of solutions 1 and 2 (see Table 4). Since the total scores of the solution 1 is lower than the solution 2, the solution 1 is a better solution. In this paper, we will find some optimized solutions which have lower values of the topic and partner scores.

Table 1. A student-topic preference matrix with four students and two topics.

	T1	T2
S1	1	2
S2	1	2
S3	2	1
S4	2	1

Table 2. A student-student preference matrix with four students.

	S1	S2	S3	S4
S1		1	2	3
S2	1		3	2
S3	3	1		2
S4	2	3	1	

Table 3. Two possible solutions.

	T1	T2
Solution 1	S1, S2	S3, S4
Solution 2	S1, S3	S2, S4

Table 4. Solutions and their corresponding scores.

Solution 1	Topic score	Partner score	Solution 2	Topic score	Partner score
S1	1	1	S1	1	4
S2	1	1	S2	4	4
S3	1	4	S3	4	9
S4	1	1	S4	1	9
Total	4	7	Total	10	26

To find the best solution without losing the generality, suppose that there are M students and N final report topics in a course. Each report topic allows N_T students to form a group and to cooperate with each other to complete a report. Let $S = \{1, 2, \ldots, M\}$ be the set of students and let $T = \{1, 2, \ldots, N\}$ be the set of final report topics in the course. For $i \in S$ and $j \in T$, we designate c_{ij} as the preference coefficient given by student i to being assigned topic j. Moreover, we define d_{ik} as the preference coefficient given by student i to becoming partners with student k, where $k \neq i$. If c_{ij} or d_{ik} has not been assigned an integer value (i.e. student i has not included topic j or student k in their list of preferences), then c_{ij} or d_{ik} is assigned a penalty value B_1 or B_2 (suitably large), respectively. The mathematical formulation of the assignment problem can therefore be expressed as

Objective Functions:

$$\text{Minimize } Z_1 = \sum_{i=1}^{M} \sum_{j=1}^{N} f(c_{ij}) x_{ij} \tag{1}$$

$$\text{Minimize } Z_2 = \sum_{i=1}^{M} \sum_{j=1}^{N} P_i x_{ij} \tag{2}$$

where

$$P_i = \sum_{k=1}^{N_T - 1} \frac{g(d_{ik}) + g(d_{ki})}{2} \quad i = 1, \ldots, M \tag{3}$$

Subject to:

$$\sum_{j=1}^{N} x_{ij} = 1 \quad i = 1, \ldots, M \tag{4}$$

$$\sum_{i=1}^{M} x_{ij} = N_T \quad j = 1, \ldots, N \tag{5}$$

$$x_{ij} = \begin{cases} 1 & \text{if student } i \text{ is assigned topic } j, \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

There are two objective functions. The first objective is to minimize the topic score, as shown in Eq. (1). The second objective is to minimize the partner score, as expressed in Eq. (2). Note that $f(c_{ij})$ in Eq. (1) or $g(d_{ik})$ in Eq. (2) can be an arbitrary function of preference coefficient c_{ij} or d_{ik}, respectively. Usually, a square function is employed [1–3]. Equation (4) requires that each student is exactly assigned one topic. Equation (5) requires that each topic allows exactly N_T students. The decision variable is x_{ij}, being either 0 or 1. If student i is assigned topic j, $x_{ij} = 1$, as shown in Eq. (6).

3 The Proposed Approach

The problem formulated in Sect. 2 is a bi-objective combinatorial optimization problem [4–10], which is generally difficult to solve when the number of the decision variable becomes large. Instead of using complex algorithms to solve the bi-objective combinatorial optimization problem, an overall fitness function is proposed and a solver based on evolutionary computation is used to efficiently obtain good solutions. As shown in Eq. (7), The objective is to minimize the product of normalized total topic score and normalized total partner score.

Overall Fitness Function:

$$F_{Overall} = F_T \times F_P$$

$$= \left(\frac{\sum_{i=1}^{M} \sum_{j=1}^{N} f(c_{ij}) x_{ij}}{NB_1} \right) \left(\frac{\sum_{i=1}^{M} \sum_{j=1}^{N} P_i x_{ij}}{MB_2} \right) \quad (7)$$

The overall fitness function expressed in Eq. (7) is a non-smooth function. Consequently, an evolutionary solving method might be more adequate to be used to find solutions. In this paper, we use the Excel Programming Solver to solve the combinatorial optimization problem. One of the most advantages for the Excel Solver is easy to use. However, the standard Microsoft Excel Solver has a limit of 200 decision variables for both linear and nonlinear problems. For a larger size problem, Python or other programming language may be used to get solutions.

To ensure a good solution is obtained, the following steps are taken:

(1) First, randomly get an initial solution.
(2) Keep the solution from step (1) and restart the Evolutionary method from that solution in a reasonable length of time. Repeat the Evolutionary method from the solution obtained at last run several times until the solution is unchanged.
(3) Tighten the convergence criterion and restart the Evolutionary method. Repeat this step several times until a better solution cannot be obtained.
(4) Increase the population size and restart the Evolutionary method. Repeat this step several times until a better solution cannot be obtained.
(5) Increase the mutation rate and restart the Evolutionary method. Repeat this step several times until a better solution cannot be obtained.

4 Results and Discussion

A reference case is set up to examine the results. At the reference case, there are 30 students (designated as S1, S2, …, S30) and 10 topics (designated as T1, T2, …, T10) in the class. Each topic allows three students to co-operate with ($N_T = 3$). Students are asked to indicate five choices on topics and eight choices on their preferred possible partners. A square function is used to evaluate the assignment results, i.e., "1" is given for the first choice, "4" for the second choice, and "9" for the third choice, and the like. B_1 and B_2 are both set to be 100.

The convergence criterion is set to be 10^{-4} initially. To find a better solution, the convergence criterion is changed to 10^{-5} and then 10^{-6}. The population is varied from 100 to 200, while the mutation rate is changed from 0.1 to 0.2.

Table 5. The solution and its topic scores for the reference case.

T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
S11	S4	S1	S6	S7	S8	S25	S24	S13	S5
S29	S30	S17	S18	S9	S12	S2	S10	S22	S14
S16	S15	S3	S21	S20	S19	S23	S28	S26	S27
4	1	4	1	1	1	1	1	1	1
1	1	1	1	1	1	4	1	1	1
1	1	1	4	1	1	1	9	1	9

Table 6. The solution and its partner scores for the reference case.

T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
S11	S4	S1	S6	S7	S8	S25	S24	S13	S5
S29	S30	S17	S18	S9	S12	S2	S10	S22	S14
S16	S15	S3	S21	S20	S19	S23	S28	S26	S27
100	36	9	100	4	4	100	4	100	4
1	9	1	25	100	100	9	16	100	100
9	1	4	100	1	49	36	4	25	9
100	100	100	9	100	100	16	100	1	36
9	9	4	36	100	9	25	1	1	9
4	100	100	1	9	100	100	100	36	1

The solution for the reference case is shown in Table 5 and Table 6. As we can see, the result is quite good though we use an overall fitness function rather than a bi-objective solving method. All the topics assigned to students are in the list of preferences. However, it is harder to let all the partners of students be in their preference list.

Using the method presented in Chen and Hu [11], the Pareto optimal solution can be obtained. The Pareto solution (also called Pareto noninferior solution), where none of the objective functions can be improved in value without degrading some of the other objective values, is shown in Fig. 1. The "optimal" solution is marked by "1". The Pareto solution can offer managers extensive selections of candidate assignments, facilitating the multi-objective decision.

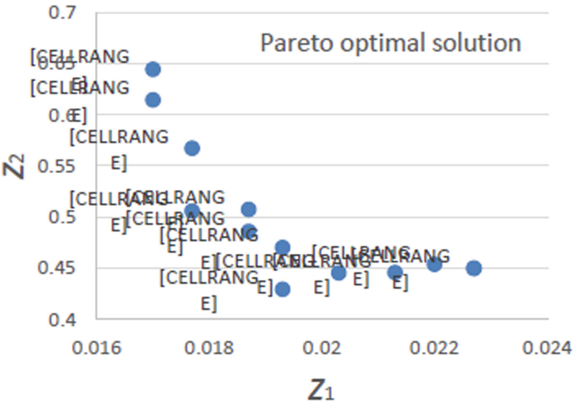

Fig. 1. The Pareto optimal solution for the reference case.

5 Conclusions

To evaluate the learning performance of students, a final report is usually assigned. Students are generally divided into some groups with several students and they are assigned a specific topic to present a report. The way of assignment greatly influences on the learning performance. Education needs innovative methods to boost learning motivation and willingness of students. If we can employ methods which consider students' preferences, positive effects are very likely to occur. In this study, a novel optimization approach to final report assignment which considers the preferences of students to topics and their partners is proposed. After aggregating preference data, a scoring system is used to evaluate the assignment. An evolutionary method is then employed to find solutions to the assignment optimization problem. Results from this study show that the proposed approach is easy to implement and can obtain goods solutions efficiently.

Acknowledgments. The authors wish to express their appreciation to Pin-Jung Lai and Yi-Ching Hsiao for their help during the course of this paper. This work was supported by the Ministry of Science and Technology.

References

1. Chen, R. C, 2012. Grouping optimization based on social relationships. *Mathematical Problems in Engineering*, Article ID: 170563, 1–19.
2. Chen, R. C., Huang, M. R., Chung, R. G., & Hsu, C. J. (2011). Allocation of short-term jobs to unemployed citizens amid the global economic downturn using genetic algorithm. *Expert Systems with Applications*, *38*(6), 7535–7543.
3. Harper, P. R., de Senna, V., Vieira, I. T., & Shahani, A. K. (2005). A genetic algorithm for the project assignment problem. *Computers & Operations Research*, *32*(5), 1255–1265.
4. Korte, B. H., Vygen, J., Korte, B., & Vygen, J. (2011). *Combinatorial optimization* (Vol. 1). Berlin: Springer.

5. Artigues, C., Jozefowiez, N., & Sarpong, B. (2018). Column generation algorithms for bi-objective combinatorial optimization problems with a min–max objective. *EURO Journal on Computational Optimization*, *6*(2), 117–142.
6. Jesus, A. D., Paquete, L., & Figueira, J. R. (2018). Finding representations for an unconstrained bi-objective combinatorial optimization problem. *Optimization Letters*, *12*(2), 321–334.
7. Lai, X., & Xia, X. (2019). Multi-objective evolutionary algorithm on simplified bi-objective minimum weight minimum label spanning tree problems. *International Journal of Computational Science and Engineering*, *20*(3), 354–361.
8. Blot, A., Kessaci, M. É., & Jourdan, L. (2018). Survey and unification of local search techniques in metaheuristics for multi-objective combinatorial optimisation. *Journal of Heuristics*, *24*(6), 853–877.
9. Jesus, A. D., Paquete, L., & Liefooghe, A. (2021). A model of anytime algorithm performance for bi-objective optimization. *Journal of Global Optimization*, *79*(2), 329–350.
10. Shao, Y., Lin, J. C. W., Srivastava, G., Guo, D., Zhang, H., Yi, H., & Jolfaei, A. (2021). Multi-objective neural evolutionary algorithm for combinatorial optimization problems. *IEEE Transactions on Neural Networks and Learning Systems.*
11. Chen, R. C., & Hu, T. T. (2015). A decision-making mechanism considering carbon footprint and cost to fulfil orders for multi-site global companies. *International Journal of Shipping and Transport Logistics*, *7*(3), 295–318.