An Educative Approach to Booth Assignment for a School Carnival

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Abstract. School carnival is one of the most important activities for the school anniversary celebration. A good allocation of booths may determine success or failure of this activity. In dealing with the allocation of booths in the school carnival, drawing lots is among the most popular ways to determination of the booth locations. This way is easy to do, but there are some flaws. For example, it leaves out the preferences of the student groups and cannot fulfil most of them. Consequently, quite a lot of students may feel that they are not respected. To improve this situation, we present an educative approach, which is fair and can satisfy the most students' preferences, to booth assignment of a school carnival. First, we provide the layout to student groups to realize where they want to set up their booths. Second, according to their preferences, we present a mathematical model which aims to meet most student groups' preferences. Finally, we employ genetic algorithm (GA) to get feasible solutions. Results based on a number of experiments show that the proposed approach can easily generate a number of good solutions which satisfy the preferences of most student groups.

Keywords: School carnival · Educative approach · Booth assignment · Genetic algorithm · Optimization

1 Introduction

To celebrate the school anniversary, a carnival is often held to attract as many people as possible to enter the campus and join all kinds of activities. In order to make the school carnival a great success, the allocation of booths (including location and size) to student groups may play a critical role since an improper allocation may fail to satisfy the needs of booth applicants and thus to degrade the quality of the school carnival. In consideration of booth allocation, drawing lots maybe is the most often used method to determine the booths of applicants. This way is easy to perform. However, some possible drawbacks should be taken into consideration. For example, student groups

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cannot choose the locations by their personal preferences or needs. Some groups like the pop dancing club prefer booths located at the corner, while other groups such as the pop music club prefer booths near the center of the booth areas. Taking a famous university in central Taiwan as an example, a school carnival is held and about 60–100 student groups join the event every year. Some of these groups expect their booth locations to be near to the main entrance, then they will possibly have higher visit rates. A randomly assigned booth location may not meet their needs. Moreover, they may feel that they are not respected since their preferences are not taken into consideration.

To improve the situation mentioned above, we present a creative and educative approach in this paper. The approach considers the preferences of student groups. First, we collect and aggregate their preferences to booths by providing a layout. They are asked to indicate their choices on the booths. Based on the preferences of student groups, we present an optimization model and some optimization techniques are employed to find optimized solutions to the booth assignment problem.

The remainder of this paper is organized as follows: In Sect. 2, we describe the problem in detail and the formulation for the problem is presented. Section 3 introduces the solving process. In Sect. 4, we conduct some experiments based on a reference case and some factors influencing the results are discussed. Finally, in Sect. 5, some concluding remarks are drawn.

2 The Problem

To begin with this section, we explain briefly the booth assignment problem and subsequently present a mathematical formulation of the problem.

School carnival is one of the most popular activities for the school anniversary celebration. In each year, the organizer provides a number of booths for student groups to sell, to promote, or to communicate with other attendants. In Taiwan, it is a general practice that about 60–100 booths are organized in a university carnival.

Suppose that there are s student groups and b booths in a school carnival. Each booth is assigned to at most one student group, and vice versa. Each student group can indicate their preferred booths with an integer number that a value of one stands for a first choice, two for a second choice, and so on up to a pre-assigned number, N_p. Furthermore, each group is asked to choose at least one booth in each area, as illustrated in Fig. 1, where the carnival is composed of four areas.

For easy description, let $S = \{1, 2, \ldots, s\}$ be a set of student groups that apply the booths and let $B = \{1, 2, \ldots, \mathrm{b}\}$ be a set of booths provided by the school organizer. For $i \in S$ and $j \in B$, we define p_{ij} as the preference coefficient given by student group i to being assigned booth j. Moreover, we define w_i as the priority weight of student group i. Note that the constraints for $s \geq b$ and $s < b$ are different. The mathematical programming formulation of the assignment optimization problem can be described as:

Objective:

$$\text{Minimize} F \sum_{i \in S} \sum_{j \in B} w_i p_{ij} x_{ij} \tag{1}$$

Constraints:

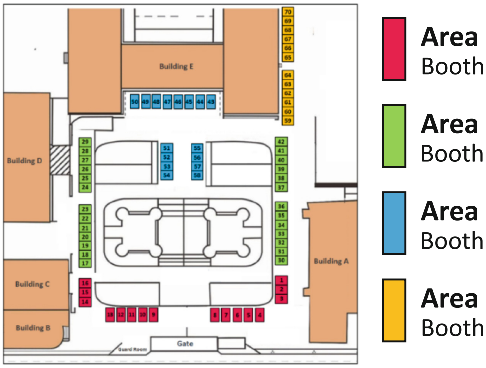

Fig. 1. A schematic diagram of the layout of a school carnival

(1) $s \geqq b$

$$\sum_{j \in B} x_{ij} \leq 1 \forall i \in S \tag{2}$$

$$\sum_{i \in S} x_{ij} = 1 \forall j \in B \tag{3}$$

(2) s < b

$$\sum_{j \in B} x_{ij} = 1 \forall i \in S \tag{4}$$

$$\sum_{i \in S} x_{ij} \leq 1 \forall j \in B \tag{5}$$

$$x_{ij} \in \{0, 1\} \forall i \in S, j \in B \tag{6}$$

where

$$x_{ij} = \begin{cases} 1 \text{ if booth } j \text{ is assigned to student group } i, \\ 0 \text{ otherwise} \end{cases} \tag{7}$$

and

$$\forall i \in S,\ j \in B\, p_{ij} = M \text{ } if \text{ } p_{ij} \notin \{1, 2, \ldots, N_p\} \tag{8}$$

The objective function is to minimize the total scoring value in Eq. (1), where the preferences to booths and the priority weights of student groups are considered. The values of p_{ij} are based on preferences (choices). For example, if a booth is one group's first choice, p_{ij} is equal to 1. Otherwise, p_{ij} will be given an integer number greater than 1. Previous studies [1–3] show that a square function is a good one to express the preferences and can obtain good solutions. Consequently, we will use the square function to calculate the scoring value. For comparison, a linear function and a cube function will also be tested to investigate their influences on the results. Equation (2) requires that each student group is assigned at most one booth, where $s \geq b$. Due to the space limitation, some applying groups may be denied. Equation (3) ensures that one booth is assigned exactly to one student group. On the other hand, when $s < b$, each student group is assigned exactly one booth, as shown in Eq. (4). If an assigned booth is not in the list of applicants' preferences, a big integer number M will be given.

The problem stated above forms a special case of the generalized assignment problem (GAP)[1, 2, 4–9], which is concerned with combinatorial optimization [10, 11]. One of the most challenging issues in combinatorial optimization is to effectively deal with the combinatorial explosion [10, 11]. Heuristic algorithms may be more suitable than exact algorithms to find solutions when the number of variables is large. Amongst the most powerful heuristic algorithms, genetic algorithm (GA) [1–3, 12–15] is one of the most powerful methods to find feasible solutions. Furthermore, not a few previous studies stated that GA is effective in solving the generalized assignment problem [1, 2, 8]. We will, therefore, employ GA to solve the booth assignment problem.

3 The Proposed Appraoch

Figure 2 shows the proposed approach to the booth assignment problem. In the first step, the preferences of student groups must be collected and aggregated to decide the preference coefficients. Then GA is employed to solve the problem and their solutions are compared with those from integer programming (IP). Finally, solutions are adjusted or selected according to the needs of the organizer to facilitate implicit multi-objective decision-making.

We will divide the booths into several areas by the foot traffic and numbered every booth. After that, we can provide a complete layout to the student groups to write their choice list. When collecting the information, one needs to ask the student groups to abide by some restrictions on writing their preferences to booths. Each group can indicate a fixed number of choices in the application form about the booth, and they have to write at least one choice in each area. In general, five choices are enough. After collecting and aggregating every group's preference, we can make an intact choice list. According to the list, we can decide the preference coefficient p_{ij}. This research uses some functions to calculate the preference coefficients and to compare with the influences on results: a linear function $\{1, 2, 3, 4, 5, M\}$, a square function $\{1^2, 2^2, 3^2, 4^2, 5^2, M\}$ and a cube function $\{1^3, 2^3, 3^3, 4^3, 5^3, M\}$, where M is a suitably large integer number. In addition, we also discuss the influences of different M values.

To find solutions by using GA, the first step is to encode a chromosome. The representation of the chromosome is illustrated in Fig. 3. Since there are b booths and each

Fig. 2. The procedure for solving the assignment optimization problem.

Fig. 3. Representation of a chromosome.

booth is assigned to at most one student group, the number of genes is thus equal to *b*. As illustrated in Fig. 3, there are *a* areas and $n_1 + n_2 + \ldots + n_a = b$. If the values of the first two genes are 33 and 21, respectively, then the first two booths are assigned to student group 33 and group 21, and the like.

The initial population is generated by random. The population number is fixed in the evolution process. The mutation is performed by the swap method, which can avoid of generating infeasible solutions. If the generation number is reached, the program will stop computing and output results. Since GA can produce a lot of different solutions for different trials, we can compare the results and according to the organizer's objectives to select the most suitable solution. One apparent advantage of GA as stated in Harper et al. [1] is that GA can generate a number of different solutions and thus facilitate the multi-objective decision-making.

4 Results and Discussion

The GA program was developed by using VB.NET. The program was run on an Intel(R) Core(TM) i5- 6198DU CPU @ 2.30 GHz and with 4.0 GB RAM. The operating system we used during the course of this paper is Windows 10. To ensure that the GA program can give accurate results, a variety of experiments based on small-size data were performed and their results were compared with those from integer programming. The results were the same or nearly the same, indicating that the correctness of the GA program.

To investigate the results of the GA approach, a reference case is set up. There are 70 booths ($b = 70$) and the numbers of the student groups are 63 and 77 ($s = 63$ or 77), respectively. Sometimes the supply exceeds the demand, while another time the demand is higher than the supply. The proposed approach is applied to the scenario of a famous university in Taichung, Taiwan. Previously, the booths were assigned by drawing lots, which did not consider the preferences of student groups. Quite a lot of students were not very satisfied with their booths which are assigned randomly. Therefore, this paper applies a new preference-based scheme, where student groups are allowed to indicate at most five choices to their preferred booths and give them a number from 1 to 5, where a value of one stands for the first choice, a two the second choice, and so on. The crossover rate is 0.9, the mutation rate is 0.05, and the generation number is 50,000. Ten trials are performed for each case.

The results for the reference case are shown in Table 1, where "Not" indicates that the assignment is not in the list of preferences of student groups. As we can see from this table, most of the assignment results satisfy the student groups' preferences. The dissatisfaction rate is only about $4.4/70 \times 100\% = 6.3\%$, a very low rate as compared to those from drawing lots. The influences of different penalty values and preference

Table 1. The assignment results with different penalty values M with $s = 77$ and $b = 70$.

M	Choice (Average)					
	1	2	3	4	5	Not
100	30.9	16.2	5.2	8.5	4.8	4.4
200	31.1	16.5	4.8	8.0	5.2	4.4
500	30.1	17.2	4.9	8.6	4.9	4.3

Table 2. The influences of different preference functions on the results with $s = 77$ and $b = 70$.

P_{ij}	Choice (Average)					
	1	2	3	4	5	Not
$\{1, 2, 3, 4, 5\}$	31.3	16.9	4.3	7.8	5.0	4.7
$\{1^2, 2^2, 3^2, 4^2, 5^2\}$	30.6	16.6	5.1	8.5	5.0	4.2
$\{1^3, 2^3, 3^3, 4^3, 5^3\}$	30.3	16.2	6.0	8.3	4.8	4.4

Table 3. The influences of different population numbers on the results with $s = 77$ and $b = 70$.

N_p	Choice (Average)					
	1	2	3	4	5	Not
20	31.5	16.7	4.4	8.2	4.1	5.1
30	31.4	16.1	4.7	8.4	4.8	4.6
50	30.9	16.2	5.2	8.5	4.8	4.4

functions on the results are also tested in this paper. The influences of the penalty values M are not quite apparent, as shown in Table 1.

As for the preference functions, a square function leads to a lower rate of choices that are not in the preference list. Therefore, a square function seems to be a very suitable one when considering the preference coefficients (Table 2).

The influences of different population numbers N_p on the results are shown in Table 3. A higher population number can generate a better solution, as indicated in this table. However, a higher population number also requires more computational time. The ratio of required computational time is about 1:1.45:2.32 (population number 20:30:50).

Tables 4 and 5 show the results for s $< b$ and $s \geq b$, respectively. As we can see from these two tables, most of the assigned booths are in the list of preferences of student groups. Over 60% of student groups are assigned the top two preferred booths. In addition, when $s \geq b$, the results are quite stable with a very low coefficient of variation C_v.

Table 4. The results with $s = 63$ and $b = 70$ in the reference case

	Choice					
	1	2	3	4	5	Not
Average	30.1	14.8	3.6	7.7	3.9	3.5
Best	32.0	–	–	–	–	2
Worst	27.0	–	–	–	–	6
C_v	0.05	0.21	0.33	0.34	0.28	–

Table 5. The results with $s = 77$ and $b = 70$ in the reference case.

	Choice					
	1	2	3	4	5	Not
Average	31.4	16.1	4.7	8.4	4.8	4.6
Best	33.0	–	–	–	–	4
Worst	30.0	–	–	–	–	5
C_v	0.03	0.06	0.27	0.20	0.22	–

5 Concluding Remarks

In dealing with the allocation of booths in the school carnival, drawing lots is one of the most popular ways to determine the booths. This way is easy to perform. However, there exist some drawbacks. For example, it fails to consider the booth preferences of the student groups and cannot satisfy most of them. The students, therefore, may feel that they are not respected since their choices are not considered. To remedy this situation, we propose an optimization approach in this paper. As a first step, we provide the layout to student groups to collect their preferences to booths. Subsequently, we present a mathematical model which aims to meet most student groups' preferences. Finally, we employ genetic algorithm to get solutions. Results based on a number of experiments show that GA can generate a number of good solutions which satisfy the preferences of most student groups. In addition, a square function is a suitable one to calculate the preference coefficients.

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