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Optimization of the Allocation of Students into Academic Programmes using Goal Programming

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The rapid rate of technological development and the growing complexity of society in recent years have brought renewed awareness of the importance of higher education. As this sector is increasing in size and quality, higher education administrators are facing difficulties in allocating students into certain programmes. However, the modelling to determine the number of student enrolment is given less priority. Hence there is a need of a systematic approach and dynamic planning for the efficient allocation of students in programmes offered by institutions of higher learning. This research represents a goal programming model where each constraint is given the priority for the optimization problem of the student enrolment in an institution of higher learning by considering the number of expertise of lecturers and the capacity students for each programme. This goal programming model was applied to one of the departments of a faculty in a public university in Malaysia. The data was collected from the programme coordinator and the Academic Affairs Office. Then, the LINGO Software was used to run the model. The results of the pre-emptive model were then compared to the current allocation of students using the weighted Mean Absolute Percentage Error (MAPE). The successful application represents the ability of the goal programming model to comply with the student intake admission and goal constraints of the academic programmes.

Keywords: affirmative, allocation, constraints, decision, goal, priority, weighted mean, pre-emptive

I. INTRODUCTION

Higher education has shown its rapid expansion both in size and quality recently. Due to the factors, there is a need to have systematic approaches and a dynamic planning in the allocation of students in universities and a good planning for the efficient resource allocation in the higher education administration.

Recently in terms of education sectors, researchers emphasize more on other issues such as e- learning (Lin *et. al.,* 2014), blended learning (Luca, 2006), Web Course Tools (WebCT) (Adeyinka & Mutula, 2010), multi choice of course planning (Kırış, 2014), Massive Open Online Course (MOOC) (Vihavainen *et. al.,* 2012) and many others. However, the modelling on emphasizing the main academic thrust of an institution should not be left out (Hassan, 2015a). One of the issues on academic thrust that must be taken into account is the determination of the number of student enrolment in a faculty.

The allocation of students is very essential in the higher educational level of decision-making problem (Dolan & Schmidt, 1994). It is necessary to have a group of students to be allocated in a class, but there are some limits in assigning students in a class due to several constraints. Hence, without a proper planning there will be a surplus or inadequate number of student enrolment in each class (Joiner, 1980). Therefore, some mathematical models must be developed in order to design an efficient and

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effective student allocation in a university programme. There are multiple of conflicting objectives to manage the allocation of student in universities. According to Ignizio (1978), a goal programming model has the capability in handling multiple objectives of optimization problems in many fields of studies. In Malaysia, it has been applied to food product distributions (Hassan & Ayop), library funding (Hassan & Loon, 2012), tourism activities (Hassan & Halim, 2012), the management of pineapple nutrient (Hassan & Sahrin, 2012), stock market and the management of chilli nutrient (Hassan *et. al.,* 2012a; 2012b), the production of rubber and bakery (Hassan *et. al.,* 2013a; 2013b), cucumber fertilizer and library acquisition (Hassan *et. al.,* 2013c; 2013d).

Thus, this research used a pre-emptive weighted goal programming model to optimize the allocation of students into academic programmes of mathematical sciences as a continuation of a series of studies by Hassan (2015b; 2016a; 2016b). The three academic programmes involved in this study are Computational Mathematics (P1), Management Mathematics (P2) and Mathematics (P3). The programmes are offered by the Faculty of Computer and Mathematical Sciences (FCMS) in one of the public universities in Malaysia. The weighted method was used to apportion the students into the academic programmes in the faculty that would reflect the research thrust of the faculty. Error analysis was performed based on the deviation from the aspired levels and then the values was compared against the current value by using a weighted mean absolute percentage error (MAPE) analysis.

II. METHODOLOGY

The data for students of Computational Mathematics, Management Mathematics and Mathematics were taken from March 2018 session. The data collected is shown in Table I.

Table I shows the data for three programmes namely P1, P2 and P3 for all semesters which were Semester 1 to Semester 7, the number of students for the first year that intakes from matriculation and diploma, the number of lecturers, the capacity of the first year students and the capacity of student proportionate to the number of classes for session March 2018. The data was obtained from the coordinator of programmes and the office of Academic Affairs.

TABLE I. Data of Number of Students and Lecturers at the Department of Mathematics

	P 1	P2	P3
Semester 1	1	1	1
Semester 2	53	37	4
Semester 3	9	65	106
Semester 4	36	43	33
Semester 5	23	36	111
Semester 6	22	66	96
Semester 7	10	33	39
First Year from Diploma	27	74	110
First Year from Matriculation	36	29	5
Lecturers	9	12	17
Students to lecturer ratio	22	27	25
Capacity of First Year Students	70	110	140
Capacity of Student Proportionate to The Number of Classes	200	330	420

In this model, the number of the first-year students was the summation of students from Semester 1 until Semester 3, whereas, Semester 4 and Semester 5 were the second-year students, and Semester 6 and Semester 7 were the third year students. The data for the capacity of student proportionate to the number of classes were obtained from the total capacity for FCMS students which was 950 students. This total was then divided into three programmes accordingly to their priority as well as capacity of the first-year students.

III. MODEL DEVELOPMENT

Listed below are the input parameters, constraints, and the objective function of the model in allocating students of mathematical sciences department in UiTM Negeri Sembilan, Seremban Campus, into three academic programmes of P1, P2 and P3 for the first-year students.

Input parameters

c_1 = Capacity of the first-year students in P1

c_2 = Capacity of the first-year students in P2

c_3 = Capacity of the first-year students in P3

r_1 = Student-to-lecturer ratio for P1

r_2 = Student-to-lecturer ratio for P2
r_3 = Student-to-lecturer ratio for P3
t_1 = Total capacity of students in P1 proportionate to the number of classes
t_2 = Total capacity of students in P2 proportionate to the number of classes
t_3 = Total capacity of students in P3 proportionate to the number of classes
e_1 = Number of students enrolling into year two of P1
e_2 = Number of students enrolling into year two of P2
e_3 = Number of students enrolling into year two of P3
h_1 = Number of students enrolling into year three of P1
h_2 = Number of students enrolling into year three of P2
h_3 = Number of students enrolling into year three of P3

Variables

x_1 = Number of diploma students admitted into P1
x_2 = Number of diploma students admitted into P2
x_3 = Number of diploma students admitted into P3
y_1 = Number of matriculation students admitted into P1
y_2 = Number of matriculation students admitted into P2
y_3 = Number of matriculation students admitted into P3
a_1 = Total number first year students in P1
a_2 = Total number first year students in P2
a_3 = Total number first year students in P3
d_1 = Total number of students enrolled in P1
d_2 = Total number of students enrolled in P2
d_3 = Total number of students enrolled in P3
l_1 = Number of lecturers required for P1
l_2 = Number of lecturers required for P2
l_3 = Number of lecturers required for P3
X = Total number of the first-year diploma students admitted into the departments
Y = Total number of the first-year matriculation students admitted into the departments
A = Total number of the first-year students admitted into the department.

Constraints

Non-negativity Constraints:

$x_j \geq 0,\ y_j \geq 0,\ d_j \geq 0,\ l_j \geq 0$ for all $j = 1,2,3$,

Hard Constraints

The constant values of the hard constraints are obtained and calculated from the data given by the program coordinators. Then, the hard constraints that constructed in this model that must be fulfilled are as follow:

1) Total numbers of the second- and third-year students

$d_1 - x_1 - y_1 = 91, d_2 - x_2 - y_2 = 178,$
$d_3 - x_3 - y_3 = 285,$

2) The minimum number of the first-year students from diploma and matriculation for each programme

$x_1 > 20, x_2 > 20, x_3 > 20, y_1 > 20,$
$y_2 > 20, y_3 > 20, d_1 > 0, d_2 > 0, d_3 > 0$

3) Minimum number of lecturers for each programme

$l_1 > 5, l_2 > 5, l_3 > 5$

Soft Constraints

The aspiration values on the right-hand side of the soft constraints are obtained from the program coordinators. The set of soft constraints are then constructed in the model formulation as the goals where the soft constraints will have positive deviations of overachievement, d_i^+ and negative deviations of underachievement, d_i^-. This model will attempt to fulfill these soft constraints by minimizing the deviations where the values of these deviations will be discussed in the next section. The soft constraints in this model are as follows:

1) First year allocation

$x_1 + y_1 + d_1^- - d_1^+ = 70,$
$x_2 + y_2 + d_2^- - d_2^+ = 110,$
$x_3 + y_3 + d_3^- - d_3^+ = 140$

2) Total capacity of student allocation

$d_1 + d_4^- - d_4^+ = 200,$
$d_2 + d_5^- - d_5^+ = 330,$
$d_3 + d_6^- - d_6^+ = 420$

3) Students-to-lecturer ratio

$22l_1 - d_1 + d_7^- - d_7^+ = 0,$
$27l_2 - d_2 + d_8^- - d_8^+ = 0,$
$25l_3 - d_3 + d_9^- - d_9^+ = 0$

4) Lecturer allocation

$l_1 + l_2 + l_3 + d_{10}^- - d_{10}^+ = 38$

Goal and Priority

First priority (P1):
Allocation of the first-year students for each programme: To obtain the targeted number of total students for each programme for the first-year students.

$x_1 + y_1 + d_1^- - d_1^+ = 70,$
$x_2 + y_2 + d_2^- - d_2^+ = 110,$
$x_3 + y_3 + d_3^- - d_3^+ = 140$

Second Priority (P2):

Total capacity in the allocation of students in each programme:

To obtain the total number students.

$d_1 + d_4^- - d_4^+ = 200,\ d_2 + d_5^- - d_5^+ = 330,\ d_3 + d_6^- - d_6^+ = 420$

Third priority (P3):

Student-to-lecturer ratio.

$23l_1 - d_1 + d_7^- - d_7^+ = 0,$
$27l_2 - d_2 + d_8^- - d_8^+ = 0,$
$25l_3 - d_3 + d_9^- - d_9^+ = 0$

Fourth priority (P4):

Total lecturer allocation:

To obtain number of lecturers that teach mathematics in the faculty.

$l_1 + l_2 + l_3 + d_{10}^- - d_{10}^+ = 38$

Objective function

Minimize $P_1 + P_2 + P_3 + P_4$

where each priority is given weight according to the three programmes as follows:

$P_1 = 3d_1^- + 3d_1^+ + 2d_2^- + 2d_2^+ + 1d_3^- + 1d_3^+$
$P_2 = 1d_4^- + 1d_4^+ + 2d_5^- + 2d_5^+ + 3d_6^- + 3d_6^+$
$P_3 = 1d_7^- + 1d_7^+ + 2d_8^- + 2d_8^+ + 3d_9^- + 3d_9^+$
$P_4 = d_{10}^+$

IV. RESULTS AND DISCUSSIONS

The data on the number of students and lecturers for the three programmes namely P1, P2 and P3 in the Faculty of Computer and Mathematical Sciences (FCMS) at UiTM Negeri Sembilan, Seremban Campus was analysed using LINGO Software to get the optimized student allocation for the programmes. There were four goals involved in this research. The goals were assigned with the priority and was attached with weight. The result of deviation variables is shown in Table II while the result of the number of students and lecturers from the pre-emptive model is shown in Table III.

TABLE II. The deviation variables

Priority	Weight	Deviation Variables	
Priority 1 (First year students' allocation)	3	$d_1^- = 0$	$d_1^+ = 0$
	2	$d_2^- = 0$	$d_2^+ = 0$
	1	$d_3^- = 5$	$d_3^+ = 0$
Priority 2 (Total capacity of students)	1	$d_4^- = 39$	$d_4^+ = 0$
	2	$d_5^- = 42$	$d_5^+ = 0$
	3	$d_6^- = 0$	$d_6^+ = 0$
Priority 3 (The number of students-to-lecturer ratio)	1	$d_7^- = 0$	$d_7^+ = 0$
	2	$d_8^- = 0$	$d_8^+ = 0$
	3	$d_9^- = 0$	$d_9^+ = 0$
Priority 4 (The number of lecturers)	-	$d_{10}^- = 3$	$d_{10}^+ = 0$

Table II indicates that the first priority is for the admission of the first-year students with declining weights in P1, P2 and P3. The corresponding deviation variables were $d_1^- = 0, d_1^+ = 0, d_2^- = 0, d_2^+ = 0, d_3^- = 5, d_3^+ = 0$. It shows that the admission into P1 and P2 was optimum. On the other hand, P3 had an underachievement of 5 students which means another additional 5 students are needed to meet the aspired value.

The second priority was the total student capacity with declining weights in P3, P2 and P1. The corresponding deviational variables were $d_4^- = 39, d_4^+ = 0, d_5^- = 42, d_5^+ = 0, d_6^- = 0, d_6^+ = 0$. Thus, the pre-emptive model optimized the student capacity of P3 as it was assigned with highest weightage among the three programmes. The values of $d_4^- = 39$ and $d_5^- = 42$ show that P2 had an underachievement of 39 students while P1 had an underachievement of 42 students.

For the third priority which was student-to- lecturer ratio with declining weights in P3, P2 and P1, the deviation variables were $d_7^- = 0, d_7^+ = 0, d_8^- = 0, d_8^+ = 0, d_9^- = 0, d_9^+ = 0$. This shows that the third priority of students-to-lecturer ratio of 23:1, 27:1 and 25:1 were fully achieved in this model.

On the other hand, the fourth priority of lecturer allocation shows the deviation variables $d_{10}^- = 3, d_{10}^+ = 0$. This indicates that the priority was overachieved with three extra lecturers.

Table III summarizes the output obtained for the pre-emptive weighted goal programming model. The model suggests a mix of 110 diploma and 25 matriculation students to be admitted into P3 in order to fulfil the admission capacity of 135 students. This is required as the highest priority and weightage given towards this requirement. Whereas, P1 shows only the mix of 45 diploma and 25 matriculation students filled up 70 available places.

TABLE III. Number of students and lecturers from the pre-emptive model

	P1	P2	P3
Number of the first-year matriculation students	45	85	110
Number of the first-year diploma students	25	25	25
Number of the first-year student to be admitted	70	110	135
Number of lecturers in each programme	7	11	17
Number of total students	161	288	420

This situation occurred because filling up the capacity of the P1 was given the least weightage, compared to P2 and P3. Furthermore, the number of lecturers required in each programme had to correspond to the total number of students in the particular programme.

To validate the results, the current values and the values of the preemptive weighted model are compared by using the weighted Mean Absolute Percentage Error (MAPE) analysis as shown as follow:

$$\frac{\Sigma w_i \frac{|e_i|}{X_i} \times 100}{\Sigma w_i}$$

The values for each parameter are listed in Table IV.

TABLE IV. Error calculation for the pre-emptive weighted goal programming model

Priority	Weight	Program	Aspiration (X)	Preemptive	Error (e)	Current	Error (e)
1	3	P1	70	70	0	63	7
	2	P2	110	110	0	103	7
	1	P3	140	135	5	111	29
2	1	P1	200	161	39	154	46
	2	P2	330	288	42	281	49
	3	P3	420	420	0	396	24
3	1	P1	23	23	0	23	0
	2	P2	27	27	0	27	0
	3	P3	25	25	0	25	0
4	-	P1					
		P2	38	35	0	38	0
		P3					

Table IV shows that the first priority error calculation for the pre-emptive model was less than the error calculation for the current model. Other than that, the results of pre-emptive model for the second priority and the third priority also show less error compared to the current model. However, the fourth priority indicates the current model had less error compared to pre-emptive model.

TABLE V. MAPE values based on priorities

Priorities	Pre-emptive model (%)	Current (%)
First year students	1.7857	14.1450
Total capacity of students	7.4924	11.6400
Students-to-lecturer ratio	0	0
Number of lecturers	7.8947	0
Average	4.2932	6.4463

By comparing the values of MAPE of the current practice and the MAPE values for the pre-emptive method, the average percentage for the pre-emptive model gives better results which are closer to the aspiration values. If the MAPE values are to be categorized according to priorities, the values are as shown in Table V.

Based on the weighted MAPE values above, the first priority indicated that the pre-emptive error was lower than the current value. While the second priority, the weightage MAPE value for the pre-emptive model was also lower than the current value. Lastly, the third priority was similar for both MAPE which for the current and pre-emptive model. For the fourth priority, the current MAPE value was 0% while the pre-emptive model was 7.8947%, as the model indicates that there were extra three lecturers and this goal had been given the lowest priority.

V. SUMMARY

Recently, higher education in Malaysia has expanded in size and improved on quality. It is necessary for authorities involved to make a proper planning on the enrolment of students in order to ensure effective and efficient system in the administration of universities. Consequently, it may assist the administrators of universities especially UiTM Negeri Sembilan, Seremban Campus to provide a proper planning in determining the number of student enrolment in the faculty for every semester, which will ensure the system runs effectively. The pre-emptive weighted goal programming model using LINGO software successfully obtained the good results, and error analyses using weighted mean absolute percentage Error (MAPE) verified its optimality. Thus, it is shown that the mathematical programming model proposed can be used for policy-making in the process of decision making for the future allocation of students to academic programmes in any department of any university.

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