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 (Kiriş, 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
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 |
|-----------------------------------------------|---|---|---|
| Semester 1 | P1 | P2 | P3 |
| Semester 2 | 1 | 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

\[ c_1 = \text{Capacity of the first-year students in P1} \]
\[ c_2 = \text{Capacity of the first-year students in P2} \]
\[ c_3 = \text{Capacity of the first-year students in P3} \]
\[ r_1 = \text{Student-to-lecturer ratio for P1} \]
\[ r_2 = \text{Student-to-lecturer ratio for P2} \]
\[ r_3 = \text{Student-to-lecturer ratio for P3} \]
\[ t_1 = \text{Total capacity of students in P1 proportionate to the number of classes} \]
\[ t_2 = \text{Total capacity of students in P2 proportionate to the number of classes} \]
\[ t_3 = \text{Total capacity of students in P3 proportionate to the number of classes} \]
\[ e_1 = \text{Number of students enrolling into year two of P1} \]
\[ e_2 = \text{Number of students enrolling into year two of P2} \]
\[ e_3 = \text{Number of students enrolling into year two of P3} \]
\[ h_1 = \text{Number of students enrolling into year three of P1} \]
\[ h_2 = \text{Number of students enrolling into year three of P2} \]
\[ h_3 = \text{Number of students enrolling into year three of P3} \]

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

**Constraints**

**Non-negativity Constraints:**
\[ x_j \geq 0,\ y_j \geq 0,\ d_j \geq 0,\ l_j \geq 0 \text{ for all } j=1,2,3 \]

**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**
\[ d_1^+ + d_2^+ - d_3^- = 200, \]
\[ d_2^+ + d_3^+ - d_1^- = 330, \]
\[ d_3^+ + d_1^+ - d_2^- = 420. \]
3) **Students-to-lecturer ratio**
\[ 22l_1 - d_1 + d_2^- - d_2^+ = 0, \]
\[ 27l_2 - d_2 + d_3^- - d_3^+ = 0, \]
\[ 25l_3 - d_3 + d_1^- - d_1^+ = 0. \]
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.

\[ d_1^* + d_2^* - d_3^* = 200, \]
\[ d_2^* + d_3^* - d_4^* = 330, \]
\[ d_3^* + d_4^* - d_5^* = 420 \]

**Third priority (P3):**

Student-to-lecturer ratio.

\[ 23l_1 - d_1 + d_1^+ - d_1^- = 0, \]
\[ 27l_2 - d_2 + d_2^+ - d_2^- = 0, \]
\[ 25l_3 - d_3 + d_3^+ - d_3^- = 0 \]

**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:

\[ P_1 = 3d_1^- + 3d_1^+ + 2d_2^- + 2d_2^+ + 1d_3^- + 1d_3^+ \]
\[ P_2 = 1d_4^- + 1d_4^+ + 2d_5^- + 2d_5^+ + 3d_6^- + 3d_6^+ \]
\[ P_3 = 2d_7^- + 2d_7^+ + 3d_8^- + 3d_8^+ + 4d_9^- + 4d_9^+ \]
\[ P_4 = d_{10}^+ \]

**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.

| Priority   | Weight | Deviation Variables |
|------------|--------|---------------------|
| Priority 1 | 3      | \( d_1^- = 0 \)    |
| (First year students’ allocation) |        | \( d_1^+ = 0 \)    |
| Priority 2 | 1      | \( d_2^- = 39 \)   |
| (Total capacity of students)     |        | \( d_2^+ = 0 \)    |
| Priority 3 | 2      | \( d_3^- = 42 \)   |
| (The number of students-to-lecturer ratio) |        | \( d_3^+ = 0 \)    |
| Priority 4 | 3      | \( d_4^- = 0 \)    |
| (The number of lecturers)         |        | \( d_4^+ = 0 \)    |

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 devational variables were \( d_2^- = 39, d_2^+ = 0, d_3^- = 0, d_3^+ = 42, d_3^- = 0, d_3^+ = 0 \). 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 \( d_3^- = 39 \) and \( d_3^+ = 42 \) 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 \( d_2^- = 0, d_2^+ = 0, d_3^- = 0, d_3^+ = 0, d_3^- = 0, d_3^+ = 0 \). 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

| Program | 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:

$$\frac{\sum w_i |e_i|}{\sum w_i} \times 100$$

The values for each parameter are listed in Table IV.

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

| Priority | Weight | Program | Aspiration | Preemptive | Error (%) |
|----------|--------|---------|------------|------------|-----------|
| 1        | 3      | P1      | 70         | 70         | 63        | 7         |
| 2        | P2     | 110     | 110        | 103        | 7         |
| 3        | 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          | 306       | 24        |

| Priority | Weight |
|----------|--------|
| 3        | 1      |
| 2        | P2     |
| 3        | P3     |

| Priorities | Pre-emptive model (%) | Current (%) |
|------------|------------------------|-------------|
| First year students | 1.7857 | 14.4450 |
| 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.
VI. REFERENCES

Adeyinka, T. & Mutula, S. 2010, A proposed model for evaluating the success of WebCT course content management system. Computers in Human Behavior, vol. 26, no. 6, pp. 1795–1805.

Dolan, R. C. & Schmidt, R. M. 1994, Modeling institutional production of higher education. Economics of Education Review, vol. 13, no. 3, pp. 197–213.

Hassan, N. 2015a, Student enrollment allocation into academic programs using preemptive goal programming, in Proceedings of the 17th International Conference on Mathematical and Computational Methods in Science and Engineering. (MACMESE'15) Kuala Lumpur, pp. 139–143.

Hassan, N. 2015b, A weighted multi-criteria distribution model for student enrollment into academic programmes. Pakistan Journal of Statistics, vol. 31, no. 5, pp. 539–546.

Hassan, N. 2016a, A preemptive goal programming for allocating students into academic departments of a faculty. International Journal of Mathematical Models and Methods in Applied Sciences, vol. 10, pp. 166–170.

Hassan, N. 2016b, Allocation of students into academic programs using mathematical programming. International Journal of Mathematics and Computers in Simulation, vol. 10, pp. 77–81.

Hassan, N. & Ayop, Z. 2012, A goal programming approach for food product distribution of small and medium enterprises. Advances in Environmental Biology, vol. 6, no. 2, pp. 510–513.

Hassan, N., Azmi, D. F., Guan, T. S. & Hoe, L. W. 2013d, A goal programming approach for library acquisition allocation. Applied Mathematical Sciences, vol. 7, no. 140, pp. 6977 – 6981

Hassan, N. and Halim, B. A. 2012, Mathematical modelling approach to the management of recreational tourism activities at Wetland Putrajaya. Sains Malaysiana, vol. 41, no. 9, pp. 1155–1161.

Hassan, N., Hamzah, H. H. M & Zain, S. M. M. 2013a, A goal programming approach for rubber production in Malaysia. American-Eurasian Journal of Sustainable Agriculture, vol. 7, no. 2, pp. 50–53.

Hassan, N., Hassan, K. B., Yatim, S. S. & Yusof, S. A. 2013c, Optimizing fertilizer compounds and minimizing the cost of cucumber production using the goal programming approach. American-Eurasian Journal of Sustainable Agriculture, vol. 7, no. 2, pp. 45–49.

Hassan, N. & Loon, L. L. 2012, Goal programming with utility function for funding allocation of a university library. Applied Mathematical Sciences, vol. 6, no. 110, pp. 5487–5493.

Hassan, N., Pazil, A. H. M., Idris, N. S. & Razman, N. F. 2013b, A goal programming model for bakery production. Advances in Environmental Biology, vol. 7, no. 1, pp. 187–190.

Hassan, N., Safai, S., Raduan, N. H. M & Ayop, Z. 2012b, Goal programming formulation in nutrient management for chilli plantation in Sungai Buloh, Malaysia. Advances in Environmental Biology, vol. 6. No. 12, pp. 4008–4012.

Hassan, N. & Sahrin, S. 2012, A mathematical model of nutrient management for pineapple cultivation in Malaysia. Advances in Environmental Biology, vol. 6, no. 5, pp. 1868–1872.

Hassan, N., Siew, L. W. & Shen, S. Y. 2012a, Portfolio decision analysis with maximin criterion in the Malaysian stock market. Applied Mathematical Sciences, vol. 6, no. 110, pp. 5483–5486.

Ignizio, J. P. 1978, A review of goal programming: A tool for multiobjective analysis. Journal of the Operational Research Society, vol. 29, no. 11, pp. 1109–1119.

Joiner, C. 1980, Academic planning through the goal programming model. Interfaces, vol. 10, no. 4, pp. 86–92.

Kiriş, Ş. 2014, AHP and multichoice goal
programming integration for course planning’, International Transactions in Operational Research, vol.21, no. 5, pp. 819-833.

Lin, T. C., Ho, H. P. & Chang, C. T. 2014, Evaluation model for applying an e-learning system in a course: An analytic hierarchy process—Multi-choice goal programming approach. Journal of Educational Computing Research, vol. 50, no. 1, pp. 135-157.

Luca, J. 2006, Using blended learning to enhance teaching and learning, in Proceedings of the 8th Australasian Conference on Computing Education—Volume 52.

Vihavainen, A., Luukkainen, M. & Kurhila, J. 2012, Multi-faceted support for MOOC in programming’, in Proceedings of the 13th Annual Conference on Information Technology Education.