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Modified Hungarian Method in Optimizing Preference Levels in Lecturer-To-Course Assignment

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Abstract Effective allocating lecturers to courses is vital in Higher Education Institutions, ensuring that faculty expertise and resources are used to their best advantage. Previous studies have often utilized the Hungarian method for this task, but the Modified Hungarian Method (MHM) has yet to be extensively explored. Moreover, incorporating lecturer preferences, which range across four distinct levels from having never taught the course to having participated in training for the course, into the assignment process has yet to be previously implemented. This paper introduces a mathematical programming method to enhance the formulation of the MHM model. The preference-based MHM (P-MHM) model incorporates lecturers' course preferences, aiming to maximize the preferences obtained from lecturer-to-course assignments. We gathered preference data from Mathematics lecturers at UiTM Shah Alam via an online survey, which served as the input for the P-MHM model. This model was solved using MATLAB's intlinprog function, producing an optimal assignment where lecturers are assigned to a maximum of three courses. The optimal results of the P-MHM model determine the most suitable course assignments for each lecturer based on their preference levels. The model seeks to enhance educational quality and improve overall academic outcomes by aligning lecturer capabilities with the courses offered.

Keywords Preferences; Higher Education Institutions; Lecturers-to-Courses Assignment; Mathematical Programming; Modified Hungarian Method.

Mathematics Subject Classification 90C90.

1 Introduction

A lecturer is crucial in defining the academic journey for students, offering a unique combination of knowledge, enthusiasm, and commitment. Especially for those in the mathematics department with a strong foundation in basic and advanced mathematics, lecturers do more than teach theory but also deliver practical insights and real-life examples that enhance the educational experience. Lecturers advocate teaching methodologies that promote critical thinking, problem-solving, and active engagement, all deepening students' comprehension of intricate subjects and motivating them to extend their learning outside the classroom. Preferences can be defined as something preferred, one's first choice, or giving priority or advantage to one person or country over others [1]. Lecturers' preferences are a key factor in allocating and assigning lecturers to teach the courses. The Hungarian Method (HM) has also been applied to assign lecturers to courses. HM is a combinatorial optimization algorithm designed to solve assignment problems by allocating resources to tasks that optimize a specific objective, such as minimizing costs [2]. It is an essential technique in operations research, computer science and economics. The Modified Hungarian Method (MHM) improves upon the original by incorporating changes that tackle particular constraints or enhance effectiveness in certain situations.

Previous studies on lecturers to courses have broadly utilized HM, but MHM use still needs improvement. Our study is the first to propose the MHM optimization model [3]. HM typically addresses balanced assignment problems, while MHM is designed to handle unbalanced scenarios, such as unequal numbers of lecturers and courses. As educational institutions aim for higher standards and greater efficiency, there is an increasing interest in adopting sophisticated optimization models to pair lecturers with courses based on their preferences. This paper introduces an adaptation and modification of the MHM model to tackle the lecturer-course assignment problem, focusing on addressing the imbalance caused by an unequal number of lecturers and courses. The model's primary goal is to maximize preference levels by aligning course assignments with lecturers' individual preferences. By treating preferences as key factors, the preference-based MHM (P-MHM) model ensures optimal lecturer-course matching, essential for improving teaching quality in Higher Education Institutions. Acknowledging that lecturers have different levels of preference for various courses, the model leverages these preferences to enhance teaching effectiveness. Insights from our survey on lecturers' preferences enable the university to make well-informed, data-driven assignment decisions. This optimized approach significantly improves the institutions efficiency in teaching and learning, contributing to academic excellence and quality enhancement.

2 Related Works

Assigning lecturers to courses is a critical function within academic institutions that impacts educational quality and faculty satisfaction. The preferences of lecturers, which can include factors such as timing, content expertise, pedagogical interests, and career development opportunities, play a vital role in this process. A well-considered assignment strategy accommodating these preferences can increase motivation, improve classroom performance, and create a more cohesive academic environment. However, balancing individual lecturer preferences with the institution's operational requirements and educational goals presents a complex challenge. Preferences of lecturers can be in the form of teaching format as, according to [4], understanding lecturers' preferred teaching formats may help develop relevant solutions with educational technologies. The goal is to include the individual lecturers preferences, which the lecturers need to decide which approach is suitable to teach, such as face-to-face classes, online classes, or mixed (face-to-face and online classes), subject to the requirements of the courses. According to [5], lecturers conducted synchronous and asynchronous online assessments to meet the needs of the students.

Researchers have recently delved into various optimization models and algorithms to tackle the complex problem of assigning tasks effectively. One of the methods is the Hungarian method (HM), which Kuhn and Munkres developed in the 1950s; HM is an effective algorithm that uses a cost matrix to solve assignment problems, striving to either minimize the total cost or maximize the total benefit while adhering to the task-resource assignment constraints [2]. HM is widely applied across various fields, including logistics, resource allocation, and scheduling. However, its use in education, such as assigning lecturers to courses, still needs improvement. In universities, the number of lecturers and courses varies each semester, necessitating using the Modified Hungarian Method (MHM) to handle unbalanced assignments. However, research on addressing unbalanced lecturer-course assignments incorporating preferences through the MHM still needs to be expanded.

Few studies have explored the assignment of academic staff or lecturers to specific courses. Most of these studies employ the HM to address balanced assignment problems, where the number of rows and columns in the assignment table is equal. More recently, in 2023, [6] focused on assigning Mathematics/Statistics Department lecturers to postgraduate courses by implementing HM using manual computation, in which HM effectively produces the optimal solution. Meanwhile, [7] tackled the teacher assignment problem by efficiently assigning teachers to classes at minimal cost. The Course and Lecturer Assignment Problem Solvation (CLAPS) process at a tertiary institution is discussed by [8], where the authors assign several courses to an equal number of faculties, which leads to the least expensive allocation and assignment for the lecturer-course assignment problem. [9] used HM to reduce lecturer preparation time and to match lecturers based on individual expertise. The study's findings indicate that this strategy can increase teaching quality because lecturer-to-course assignments are based on expertise.

In addition, [10] applied the HM to solve the AP in Nigerian universities, and the assignment model in course allocation resulted in a 13.20% increase in lecturers' efficacy in analyzing each issue for business decisions. Furthermore, the HM and LINGO software creates an optimal assignment schedule for staff-subject allocation, with the solution providing a minimum and maximum feasible outcome for assigning the staff to the courses [11]. The Hungarian Method (HM) model's objective is to maximize the teaching-learning process's overall effectiveness. Table 1 outlines previous studies from 2017 to 2023 concerning assigning and allocating lecturers using HM. Historically, the assignment and allocation of lecturers to courses with unbalanced assignments where the number of lecturers does not match the number of courses, such as an unequal number of rows and columns, has yet to be extensively studied. In recent years, the number of lecturers has increased in response to higher student enrollment, driven by rapid technological advancements and a growing emphasis on education. This study aims to employ the MHM model to allocate lecturers to specific clusters within the mathematics courses according to their preference levels, ultimately benefiting all involved parties. The past related studies on MHM are shown in Table 2. This represents the most recent application of MHM, which has been utilized in six previous studies across various domains. In recent research by [12], MHM is used for resource block (RB) allocation in cluster-based Device to Device (D2D) multicasting within 5G networks. The approach addressed by the authors interference in underlay D2D communications is to enhance the quality of service by developing an intelligent clustering algorithm to maximize the network sum rate.

Table 1: Past Studies Related to Assignment and Allocation of Lecturers Using HM.

Author	Year	The Uses of HM	Solution Methods	Software Used	Assignment Problem
[11]	2017	Staff-subject Allocation	HM	LINGO	Compare using HM and techniques to solve the allocation based on the rating of the academic staff.
[10]	2020	Assign lecturers to courses	HM;LP	does not stated	Aiming to maximize lecturers effectiveness rating to enhance the quality of education.
[9]	2021	Assign Lectures to courses	HM	JAVA language	Aiming to minimize lecturers preparation time and to match the lecturer per individual expertise.
[8]	2021	Assign Lectures in different faculty to courses	HM	QM and TORA	Aiming to maximize effectiveness in knowledge and minimize cost allocation of lecturers.
[7]	2022	Assign teachers to classes	HM	QM	Aiming to maximize lecturers effectiveness and minimize class preparation.
[6]	2023	Assign Lectures to postgraduate courses	HM	No software used	Aiming ensure equity and effectiveness in postgraduate course assignment among lecturers.

Additionally, [13] implemented MHM to minimize training delays in federated learning over wireless channels, a process complicated by the training's overall performance and the varying privacy needs of each client. Furthermore, MHM has been successfully applied in various problem domains, including networking, where it has improved upon existing models. This is evident in its ability to manage sizeable maximum waiting times, ensuring the participation of all client models in each communication round for optimal training outcomes. Meanwhile, [14] applied MHM in multi-agent pursuit-evasion scenarios under uncertainty, demonstrating superior performance over traditional nearest-neighbor-based assignment algorithms. Similarly, [15] used MHM to evaluate the reuse of significant buildings in Egypt by comparing four notable buildings repurposed for various activities, highlighting the method's efficiency in maximizing the buildings' utility while preserving their intrinsic value. Besides that, MHM has been effectively utilized on the Internet-of-Things (IoT) sector, as demonstrated by [16] and [17]. [16] applied MHM to allocate subchannels to IoT devices, significantly reducing interference and total transmission power. [17] implemented MHM in Parked Vehicle Edge Computing (PVEC) for IoT, efficiently selecting parked vehicles for various energy and service requirements. After implementing algorithms, the simulation results confirmed a significant decrease in total transmission power.

Table 2: Past Studies Related to MHM

Authors	Area of Application	Solution Methods	Software/System Used	Multi-Objective	Optimization Model for Assignment Problem
[15]	Fuzzy Assignment problem	MHM; α-Cut Method	Manual Calculation (not using any software)	Multi-objective (get the optimum solution of the fuzzy AP and assignment cost in the fuzzy)	Achieve minimum assignment cost to get the best benefit of building reuse
[17]	Internet-of Things (IoT)	MHM; Lyapuunov optimization	PVEC system	Multi-objective (two-stage service migration algorithm for PVEC networks and the serving PV selection in parking lots)	Assign subchannels to the Internet-of-Things (IoT) devices and selecting Parked Vehicle Edge Computing (PVEC) with various energy and services
[16]		MHM; improved K-means method; alternating iterative method; golden section search method	does not stated by authors	Multi-objective (minimize the total transmission power between different IoT devices and the limited number of channels of a UAV)	MHM based dynamic many–many matchings (HD4M) algorithm
[14]	Assignment of Redundant Pursuers	MHM; Markov Localization	CVX: MATLAB	Multi-objective (minimize total capture time of the uncertainties and minimize maximum capture time)	Assign pursuers and control methods in multi-agent pursuit-evasion under uncertainty
[13]	Federated learning training	MHM; Greedy Matching with a Better Alternative (GMBA)	CIFAR-10; FahionMNIST	Multi-objective (minimize FL training delay over wireless channels and for each client's differential privacy (DP) requirement)	Reduce federated learning training delays across wireless channels, which were limited by overall training performance and each client's differing privacy requirements
[12]	Device to device (D2D) multicasting	MHM	network simulator	Maximize the obtained sum rate of the network	Frame a suitable D2D multicasting in underlay cellular network with appropriate resource

As shown in Table 2, past studies have applied MHM in various areas of applications. Still, none are concerned with lecturers-to-course assignment problems and particularly the use of mathematical programming model to implement MHM in solving the problem. In our study, we introduced the use of MHM in solving lecturers-to-courses assignment problems, which deals with assigning lecturers to courses based on optimal solutions found using MHM optimization models. We proposed five variants of MHM models, whose objective function is to maximize the lecturers' preference levels or to maximize the lecturers' competency score. We also consider multiple objectives involving both solved using goal programming methods [3]. In this paper, we present the preference-based MHM (P-MHM) model. The P-MHM model aims to address the unbalanced problem of lecturers about course assignments.

3 Materials and Methods

This study is divided into four phases: Data Collection and Analysis, Enhanced Formulation of MHM, Computational Experiments, and Analysis of Results, as illustrated in Figure 1. Data were gathered between March and August 2023 via an online survey distributed to 39 lecturers from the Mathematics Department at the College of Computing, Informatics and Mathematics, Universiti Teknologi MARA (UiTM), Shah Alam. The study involves 35 undergraduate Mathematics courses. The questionnaire has a section on preference levels, using a Likert scale to rate responses. Based on [18], Likert scales allow researchers to collect quantitative data on subjective traits, which can be summarized and visualized like other quantitative data. The Likert scale is among educational and social science research's most commonly used and essential psychometric tools [19]. Besides that, the Likert scale is a fundamental measurement tool widely employed in social science research, particularly within qualitative methodologies [20]. The specific Likert scales for preferences are provided in Table 3.

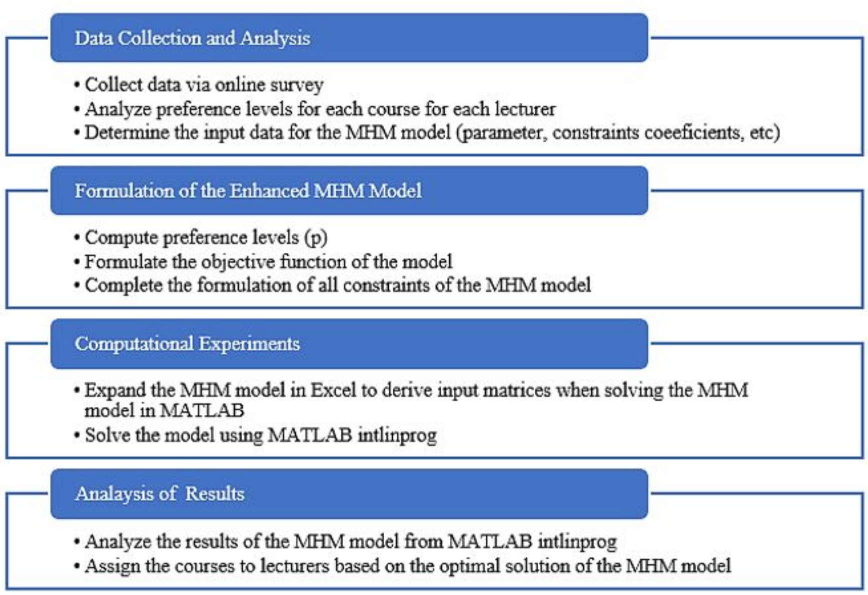

Figure 1: Steps in Methodology.

Table 3: Likert Scale for Lecturer's Preferences for a Course

Scale	Description	Justification
1	Strongly Unpreferred	This course has never been taught, learned, or exposed to before.
2	Unpreferred	This course has never been taught (only learned in university, self-taught, etc.)
3	Preferred	This course has been taught before.
4	Strongly Preferred	Have attended training (MATLAB, MAPLE, LINGO, etc.) for this course.

Data analysis involved calculating the average preference levels for each course for each lecturer. Preferences (p) were converted to percentages, where a level of 1 corresponded to $p_{ij} = 0.25$ is $p_{ij} = 0.53, p_{ij} = 0.75$ and 4 is $p_{ij} = 1$. The MHM optimization model was expanded in Excel using the data gathered and preference levels (p_{ij}) as the model's objective function coefficients. The input matrices derived from the Excel model were then used to solve the model using the preferences levels of lecturers on courses. The formulation of the enhanced MHM model is as follows.

The MHM Model for Maximizing Preference Levels (P-MHM Model)

Our study has developed five variants of the enhanced MHM model for lecturer-to-course assignment problems, one is the MHM model for maximizing preference levels (P-MHM model). The P-MHM model formulation is as follows.

P-MHM Model Formulation

Notation − Sets, Indices, Parameters, and Input Variables:

m: number of lecturers ($m = 39$)
n : number of courses ($n = 35$)
i : index for lecturers
j : index for courses
p_{ij}: lecturer i preferences to get course j

$$x_{ij} = \begin{cases} 1, \text{lecturer } i \text{ is assigned course } j \\ 0, \text{ otherwise} \end{cases}$$

$$\text{Maximize } Z_1 = \sum_{i=1}^{m} \sum_{j=1}^{n} p_{ij} x_{ij} \tag{1}$$

subject to

$$\sum_{i=1}^{m} x_{ij} \geq 1, j = 1, 2, 3...n \tag{2}$$

$$\sum_{j=1}^{n} x_{ij} \geq 1, i = 1, 2, 3...m \tag{3}$$

$$\sum_{i=1}^{m} x_{ij} \leq 3, j = 1, 2, 3...n \tag{4}$$

$$\sum_{j=1}^{n} x_{ij} \leq 3, i = 1, 2, 3...m \tag{5}$$

$$x_{ij} = 0, 1, i = 1, 2, 3...m; j = 1, 2, 3...n \tag{6}$$

Model Description

The objective function is presented in Equation (1) to maximize lecturers' preference levels for courses. Constraint (2) ensures that one lecturer should be assigned to at least one course. On the other hand, Constraint (3) guarantees that a course must be assigned to at least one lecturer. Constraint (4) restricts the ability of one lecturer to be transferred to at most three courses. Meanwhile, Constraint (5) dictates that one course can only be assigned to at most three lecturers. Finally, Constraint (6) presents the restriction on the value of decision variables in which the binary decision variables only take the binary value of either 0 or 1.

Before solving the P-MHM model using MATLAB, the model's expansion was carried out to determine vectors and matrices, which are the parameters of the MATLAB intlinprog. These vectors include vectors of the objective function coefficients (f) and Right-Hand-Side (RHS) of inequality constraints (b). Matrix denotes the technology matrix or coefficients of the inequality constraints (A). Input vectors and matrices of MATLAB intlinprog are shown in Figure 2.

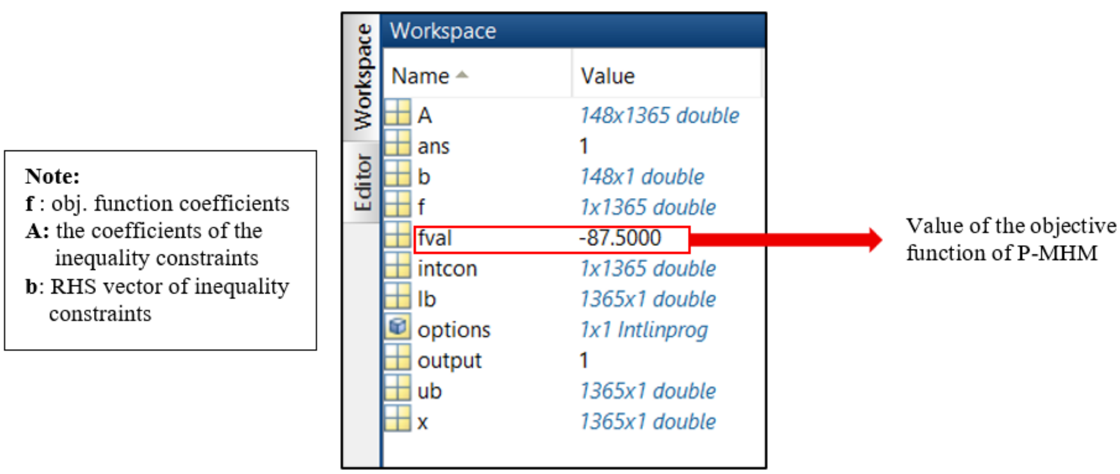

Figure 2: MATLAB matrices.

4 Results and Discussion

The demographic profiles, which include gender, age of lecturer, and current position of lecturer, are depicted in Figure 3, Figure 4, and Figure 5, respectively. Figure 3, six male lecturers (15%) and 33 female lecturers (85%) participated in the survey. Meanwhile, Figure 4 displays the distribution of respondents' age for 39 respondents from UiTM Shah Alam, where the respondents from the age group of 31-40 years old being the highest where there are 24 respondents (61%) while the lowest is from the age group of 22-30 years old with only one respondent (3%). Figure 5 shows the current position of lecturers, with 34 out of 39 (87.2%) respondents being senior lecturers and 4 (10.2%) being associate professors. In addition, 1 (2.6%) respondent had a lecturer position, and no respondents were professors.

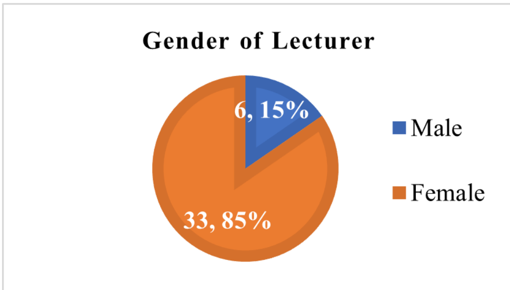

Figure 3: Gender of Lecturer

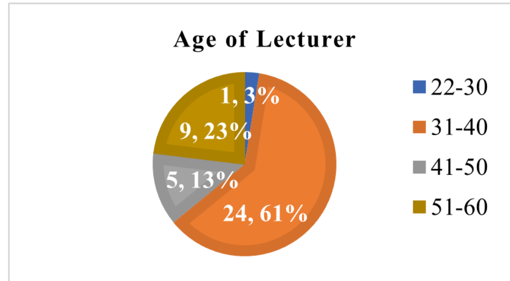

Figure 4: Age of the Lecturer

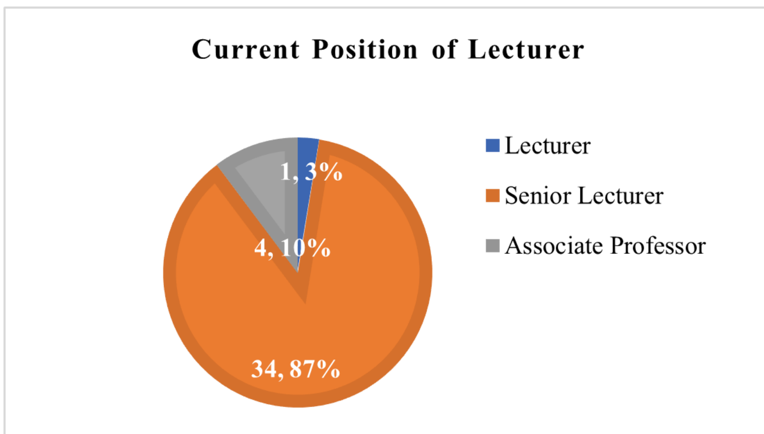

Figure 5: Current Position of Lecturer.

Table 4 lists the undergraduate Mathematics courses. The first digit of the code (4, 5, and 6) represents the year this course is offered, whether it is the first, second, or third year of the undergraduate program.

The MATLAB intlinprog generates optimal solutions that contain the objective function value (fval) and the values of the decision variables which has either a value of '1' or '0'. Note that the objective function of P-MHM is to maximize the preference levels of lecturers for courses. The fval value for the P-MHM model is as shown in Figure 2, which is -87.50. Note that the MATLAB default minimizes the objective function; thus, the command minimizes the negative of the objective function of P-MHM. Therefore, the maximum preference level of lecturers for courses is 87.50. The values of '1's and '0's obtained from MATLAB intlinprog are transferred to an Excel spreadsheet better to illustrate the assignment of each lecturer to courses. The results obtained based on the maximization of total lecturers' preference levels are displayed in Table 5, where each lecturer is assigned one to three classes.

Table 4: List of Undergraduate Mathematics Courses in UiTM Shah Alam

No.	First Year Courses	No.	Second Year Courses	No.	Third Year Courses
1	MAT402(Business Mathematics)	16	MAT512(Number Theory)	31	MAT612(Partial Differential Equations)
2	MAT406(Foundation Mathematics)	17	MAT522(Ordinary Differential Equations)	32	MAT631(Complex Analysis with Computational Applications)
3	MAT415(Discrete Mathematics)	18	MAT523(Linear Algebra II)	33	MAT 652(Algebraic Structures)
4	MAT417(Mathematics)	19	MAT525(Coding and Cryptography)	34	MAT633(Fuzzy Set Theory)
5	MAT421(Calculus I)	20	MAT530(Introduction to Mathematical Modelling)	35	MAT668(Graph Theory with Applications)
6	MAT422(Mathematical Logic and Proving Techniques)	21	MAT531(Advanced Mathematical Modelling)		
7	MAT423(Linear Algebra I)	22	MAT538(Applied Mathematics)		
8	MAT435(Calculus for Engineers)	23	MAT560(Vector Calculus)		
9	MAT438(Foundation of Applied Mathematics)	24	MAT565(Advanced Differential Equations)		
10	MAT441(Calculus II)	25	MAT570(Mathematics Economics)		
11	MAT455(Further Calculus for Engineers)	26	MAT571(Real Analysis)		
12	MAT472(Foundation of Mechanics)	27	MAT575(Introduction to Numerical Analysis)		
13	MAT480(Further Differential Equations)	28	MAT578(Mathematical Methods)		
14	MAT491(Calculus III)	29	MAT580(Further Differential Equations)		
15	MAT495(Partial Derivatives and Approximation Methods)	30	MAT583(Applied Numerical Methods)		

In contrast, up to three lecturers can only teach each course. Based on Table 5, lecturers SA3, SA4, SA13, SA21, and SA26 are assigned only one course each, while only SA7 is assigned two courses. The remaining lecturers, SA1, SA2, SA5, and the rest, have been assigned three courses each. The results reflect that courses have been assigned to suit the preferences of lecturers. Besides that, it was also found that this optimal solution for lecturers to course assignments also displays that these courses reflect the areas of expertise of the lecturers. Table 5 also summarizes the lecturer-to-course assignments of all the lecturers involved.

Table 6 shows the compilation of results shown in Table 5. Examples of the optimal assignments include, for instance, Lecturers SA3 and SA4, which are assigned only one course, MAT455 (Further Calculus for Engineers) for SA3, and MAT565 (Advanced Differential Equations) for SA4. Meanwhile, some lecturers have been assigned two courses. For example, Lecturer SA7 is assigned two courses, namely MAT491 (Calculus III) and MAT560 (Vector Calculus). Lecturers can be assigned up to three courses. For instance, Lecturer SA36 is assigned to MAT402 (Business Mathematics), MAT531 (Advanced Mathematical Modelling), and MAT565 (Advanced Differential Equations), whereas Lecturer SA37 is assigned MAT406 (Foundation Mathematics), MAT578 (Mathematical Methods), and MAT580 (Further Differential Equations). Several lecturers are also assigned to teach courses at various levels of the undergraduate program such as lecturers SA1, SA5, SA17, SA18, SA20, SA31, and SA35 have three different levels with the first digit of the course code (4, 5, or 6). The courses might be in different course levels. Conversely, lecturer SA27 gets to teach all first-year courses with the first digit of 4, whereas a few lecturers teach courses with second- and third-year courses with the first digit of 5 and 6. For instance, lecturers SA11, SA19, and SA29. Overall, this structured assignment of courses to lecturers based on their preference levels enhances the student learning experience and fosters faculty development, highlighting the value of a strategic approach to lecturer-course assignments in the Mathematics department.

The analysis of the optimal solutions from the P-MHM model presented in Tables 5 and Table 6 emphasizes the alignment between lecturers' expertise and their assigned courses. A key contribution of this study is integrating a preference-based approach into the lecturer-to-course assignment process and adapting the MHM algorithm to handle complex data inputs efficiently. Furthermore, this research offers valuable insights into lecturers' profiles and preference levels, presenting new perspectives for enhancing teaching quality and academic performance across multiple disciplines, extending beyond Mathematics. The P-MHM model aims to minimize assignment mismatches and to improve lecturer satisfaction by factoring in lecturer preferences.

Table 6: Result of Lecturer-to-Course Assignment Based on Lecturer Preferences

Lecturer	Courses			Lecturer	Courses		
SA1	MAT495	MAT522	MAT 612	**SA21**	MAT 583		
SA2	MAT 415	MAT530	MAT570	**SA22**	MAT441	MAT491	MAT538
SA3	MAT 455			**SA23**	MAT406	MAT422	
SA4	MAT 565			**SA24**	MAT423	MAT441	MAT523
SA5	MAT 472	MAT 578	MAT633	**SA25**	MAT530	MAT531	MAT560
SA6	MAT 402	MAT 438	MAT522	**SA26**	MAT531		
SA7	MAT491	MAT560		**SA27**	MAT417	MAT 435	MAT 455
SA8	MAT421	MAT 435	MAT633	**SA28**	MAT 472	MAT570	MAT583
SA9	MAT 415	MAT 472	MAT525	**SA29**	MAT512	MAT525	MAT 652
SA10	MAT 438	MAT538	MAT 575	**SA30**	MAT 480	MAT495	MAT 631
SA11	MAT 578	MAT 612	MAT 631	**SA31**	MAT422	MAT571	MAT 631
SA12	MAT406	MAT417	MAT 575	**SA32**	MAT421	MAT522	MAT570
SA13	MAT 583			**SA33**	MAT 402	MAT 480	MAT668
SA14	MAT423	MAT523	MAT560	**SA34**	MAT 438	MAT530	MAT538
SA15	MAT423	MAT 435	MAT523	**SA35**	MAT422	MAT525	MAT668
SA16	MAT417	MAT491	MAT 612	**SA36**	MAT 402	MAT531	MAT 565
SA17	MAT 415	MAT571	MAT 652	**SA37**	MAT 480	MAT 565	MAT 580
SA18	MAT480	MAT512	MAT633	**SA38**	MAT406	MAT 578	MAT 580
SA19	MAT512	MAT571	MAT668	**SA39**	MAT421	MAT 455	MAT495
SA20	MAT441	MAT 575	MAT 652				

Table 5: Result from MATLAB of P-MHM

Courses	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35
Lecturers	MAT 402	MAT406	MAT 415	MAT417	MAT421	MAT422	MAT423	MAT 435	MAT 438	MAT441	MAT 455	MAT 472	MAT 480	MAT491	MAT495	MAT512	MAT522	MAT523	MAT525	MAT530	MAT531	MAT538	MAT560	MAT 565	MAT570	MAT571	MAT 575	MAT 578	MAT 580	MAT 583	MAT 612	MAT 631	MAT 652	MAT633	MAT668
A1															1		1														1				
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1 course 2 courses 3 courses

5 Conclusions

This article examines the assignment of lecturers to courses using the MHM optimization model, which incorporates lecturers' preferences. The analysis highlights the complexity and importance of optimizing lecturer-course assignments in Higher Education Institutions. This study introduced an enhanced MHM optimization model (P-MHM) model to demonstrate the effectiveness of the MHM approach in managing these complex educational challenges. The model's objective is to maximize the preference levels of mathematics lecturers at UiTM Shah Alam. The findings emphasize the need for a structured approach to balance workloads, ensure thorough course coverage, and align assignments with lecturers' expertise. Through the P-MHM model, educational institutions can establish continuous evaluation mechanisms. Future research could expand the model to include a more comprehensive workload distribution. This could address not only academic positions and administrative roles but also the balance between teaching, research and community engagement. Factors such as credit hour allocation, course levels and student enrollment sizes could be incorporated to ensure equitable distribution. Beyond lecturer-course assignments, this model can be adapted to other fields and industries. The study highlights that prioritizing lecturer preferences is vital for sustainable university performance, demonstrating both the practicality and positive impact of addressing complex educational challenges.

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References

[1] Collins Dictionary, Definition of Preferences, *Collins Dictionary*, 2024. url https://www.collinsdictionary.com/dictionary/english/preference (accessed on Aug. 25, 2024).

[2] H. W. Kuhn, The Hungarian Method for the Assignment Problem, *Nav. Res. Logist. Q.*, vol. 2, no. 12, pp. 83-97, Mar. 1955, doi: 10.1002/nav.3800020109.

[3] N. S. Ibrahim, A. Shuib, and Z. A. Zaharudin, Modified Hungarian model for lecturer-to-course assignment, in *In AIP Conference Proceedings*, 2024, vol. 3086, p. 080001. doi: 10.1063/5.0208455.

[4] M. Burkhard, J. Guggemos, S. Seufert, and S. Sonderegger, When Lecturers have a Choice: Covid-19 Teaching Format Preferences in a Large-Scale Course of Freshmen Students in Switzerland, *Lect. Notes Informatics (LNI), Proc. - Ser. Gesellschaft fur Inform.*, vol. P-316, pp. 319-324, 2021.

[5] P. H. Wijayati et al., Preferences of Online Learning Assessment in Higher Education During the Pandemic Based on Perspectives of Students and Lecturers, *J. High. Educ. Theory Pract.*, vol. 22, no. 3, pp. 109-117, Mar. 2022, doi: 10.33423/jhetp.v22i3.5087.

[6] U. V. Udok and U. A. Victor-Edema, Application of assignment problem in postgraduate course allocation at Ignatius Ajuru University of Education, *Fac. Nat. Appl. Sci. J. Sci. Innov.*, vol. 5, no. 1, pp. 21-33, 2023.

[7] S. S. Ahmed, U. N. Mariga, S. Abdulmalik, I. S. Ango, and S. Umaru, The Use of Assignment Problem Models To Assign Teachers To Classes: A Case Study of Ado Bobi Primary School, *Trans. Niger. Assoc. Math. Phys.*, vol. 18, pp. 167-172, 2022.

[8] C. Mallick, S. K. Bhoi, K. K. Jena, K. S. Sahoo, M. Humayn, and M. H. Shahd, CLAPS: Course and Lecture Assignment Problem Solver for Educational Institution Using Hungarian Method, *Turkish J. Comput. Math. Educ.*, vol. 12, no. 10, pp. 3085-3092, 2021.

[9] N. Wattanasiripong and N. W. Sangwaranatee, Program for Solving Assignment Problems and Its Application in Lecturer Resources Allocation, *J. Phys. Conf. Ser.*, vol. 2070, no. 1, p. 012003, Nov. 2021, doi: 10.1088/1742-6596/2070/1/012003.

[10] O. Solaja, J. Abiodun, J. Ekpudu, M. Abioro, and O. Akinbola, Assignment Problem and Its Application In Nigerian Institutions: Hungarian Method Approach, *Int. J. Appl. Oper. Res.*, vol. 10, no. 1, pp. 1-9, 2020.

[11] S. Kabiru, B. M. Saidu, A. Z. Abdul, and U. A. Ali, An Optimal Assignment Schedule of Staff-Subject Allocation, *J. Math. Financ.*, vol. 07, no. 04, pp. 805-820, 2017, doi: 10.4236/jm f.2017.7 4042.

[12] P. Mukherjee and T. De, Interference aware D2D Multicasting using Modified Hungarian Method, in *2023 OITS International Conference on Information Technology (OCIT)*, Dec. 2023, no. Ocit, pp. 319-324. doi: 10.1109/OCIT59427.2023.10431269.

[13] K. Wei et al., Low-Latency Federated Learning Over Wireless, *IEEE J. Sel. Areas Commun.*, vol. 40, no. 1, pp. 290-307, 2022.

[14] L. Zhang, A. Prorok, and S. Bhattacharya, Pursuer Assignment and Control Strategies in Multi-agent Pursuit-Evasion Under Uncertainties, *Front. Robot. AI*, 8 : 691637, Mar. 2021.

[15] M. A. Elsisy, A. S. Elsaadany, and M. A. El Sayed, Using Interval Operations in the Hungarian Method to Solve the Fuzzy Assignment Problem and Its Application in the Rehabilitation Problem of Valuable Buildings in Egypt, *Complexity*, vol. 2020, pp. 1-11, Sep. 2020, doi: 10.1155/2020/9207650.

[16] Y. Liu, K. Liu, J. Han, L. Zhu, Z. Xiao, and X.-G. Xia, Resource Allocation and 3-D Placement for UAV-Enabled Energy-Efficient IoT Communications, *IEEE Internet Things J.*, vol. 8, no. 3, pp. 1322-1333, Feb. 2021, doi: 10.1109/JIOT.2020.3003717.

[17] S. Ge, M. Cheng, X. He, and X. Zhou, A Two-Stage Service Migration Algorithm in Parked Vehicle Edge Computing for Internet of Things, *Sensors*, vol. 20, no. 10, May 2020, doi: 10.3390/s20102786.

[18] L. South, D. Saffo, O. Vitek, C. Dunne, and M. A. Borkin, Effective Use of Likert Scales in Visualization Evaluations: A Systematic Review, *Comput. Graph. Forum*, vol. 41, no. 3, pp. 43-55, Jun. 2022, doi: 10.1111/cgf.14521.

[19] A. Joshi, S. Kale, S. Chandel, and D. Pal, Likert Scale: Explored and Explained, *Br. J. Appl. Sci. Technol.*, vol. 7, no. 4, pp. 396-403, Jan. 2015, doi: 10.9734/BJAST/2015/14975.

[20] B. Tanujaya, R. C. I. Prahmana, and J. Mumu, Likert Scale in Social Sciences Research: Problems and Difficulties, *FWU J. Soc. Sci.*, vol. 16, no. 4, pp. 89-101, Dec. 2022, doi: 10.51709/19951272/Winter2022/7.