*Malaysian Journal of Computing, 10 (2): 2308-2321, 2025*

*eISSN: 2600-8238*

# MODIFIED HUNGARIAN METHOD FOR LECTURER-TO-COURSE ASSIGNMENT: A MULTI-OBJECTIVE MATHEMATICAL PROGRAMMING MODEL FOR OPTIMIZING PREFERENCES AND COMPETENCY (PC MO-MHM)

**Nur Syahirah Ibrahim**[1]**, Adibah Shuib**[2*] **and Zati Aqmar Zaharudin**[3]

[1&2*]*Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA (UiTM), 40450 Shah Alam, Selangor, Malaysia*

[3]*Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA (UiTM) Cawangan Negeri Sembilan, Negeri Sembilan, Malaysia*

[1]2021672794@student.uitm.edu.my, [2*]adibah253@uitm.edu.my, [3] zati@uitm.edu.my

**ABSTRACT**

*Efficient lecturer-to-course assignment is crucial for ensuring both faculty satisfaction and optimal teaching outcomes in higher education institutions. This study presents an advanced optimization model based on the Modified Hungarian Method (MHM) to address this challenge by integrating lecturers' preference levels and competency scores. While previous research has primarily focused on the traditional Hungarian Method (HM), limited attention has been given to its modified version. Moreover, the incorporation of preference-competency-based criteria in lecturer assignments is still lacking. To bridge these gaps, this study develops a mathematical programming approach to refine the MHM framework. The proposed model, called the Preference-Competency Multi-Objective MHM (PC MO-MHM), aims to achieve two key objectives: maximizing lecturers' preferences and maximizing lecturers' competencies. Competency is assessed across three elements: knowledge, skills, and teaching motivation. Data were gathered through an online survey involving Mathematics lecturers teaching undergraduate courses at the public university in Malaysia. By utilizing the collected data on preference levels and competency scores, the PC MO-MHM model was implemented using MATLAB's intlinprog function to generate an optimized lecturer-to-course assignment plan, limiting each lecturer to a maximum of three courses. The findings highlight that the PC MO-MHM model effectively determines the most suitable course assignments based on lecturers' preferences and competencies. The enhanced MHM framework provides a practical tool for optimizing course-teaching assignment planning. The model potentially not only improves teaching quality but also minimizes mismatches between lecturers and courses, fostering better academic outcomes and increased faculty satisfaction. Ultimately, this study contributes towards refining lecturers' assignment processes, paving the way for more effective and efficient resource management in academia.*

**Keywords**: *Competency, Lecturers-to-Courses Assignment, Mathematical Programming, Modified Hungarian Method, Preferences.*

Received for review: 28-03-2025; Accepted: 26-09-2025; Published: 01-10-2025
DOI: 10.24191/mjoc.v10i2.5562

## 1. Introduction

Assignment problem concerns the optimal allocation of a set of resources, such as people, vehicles, machines, or computers, to a set of jobs or tasks, typically aiming to maximize total profit, benefit, efficiency, or reliability, or minimize total costs, time, or effort. The assignment problem may involve a balanced assignment problem, where the number of resources equals the number of jobs. Otherwise, the problem is called an unbalanced assignment problem. The assignment problem, which is a combinatorial optimization problem, is usually formulated as a Mathematical Programming (MP) model, such as linear programming, 0-1 programming, or integer programming model based on an efficient method in Operations Research called the Hungarian method. Manually solving an assignment problem is often time-consuming, while mistakes might occur. Thus, solving the assignment problem using the Hungarian method and the MP model can help to find the optimal solution in less time while minimizing errors.

Assignments of lecturers to courses to be taught are a classic assignment problem occurring in higher education institutions, aimed at balancing the lecturers' load and matching them with courses suitable for their teaching based on certain criteria. Many lecturer-to-course assignment problems have been tackled using MP models and the Hungarian method. However, existing approaches are still lacking in addressing the complex interaction between lecturers' preferences and competencies for the courses being assigned. In addition, with increasing student enrollments and a growing variety of courses, institutions also frequently encounter imbalances between available lecturers and course demands. This issue highlights the need for advanced approaches such as the Modified Hungarian Method (MHM), which provides a more effective solution for handling unbalanced assignment problems. While prior studies have primarily focused on HM, limited attention has been given to the potential of MHM in lecturer-to-course assignments. Although HM is effective in achieving balanced assignments and allocations, it struggles in scenarios where resources, such as the number of lecturers and available courses, are mismatched. To the best of our knowledge, this study is the first to apply the MHM optimization model specifically in this context (Ibrahim et al., 2024). Moreover, past research has typically considered either lecturer preferences or competencies in isolation, overlooking the advantages of integrating both.

Furthermore, existing MP models that incorporate competency and preference as dual objectives are still lacking. Another challenge in lecturer-to-course assignments arises from the varying levels of expertise among lecturers across different Mathematics courses, which further complicates the allocation and assignment process. Mathematics courses were chosen because Mathematics is considered essential for advancing Malaysia's national agenda and is recognized as a fundamental subject across all levels of education (Selamat et al., 2025). This paper introduces an enhanced MHM model to address these challenges, particularly dealing with the unbalanced assignment problem. The proposed Preference-Competency Multi-Objective MHM (PC MO-MHM) model is designed to achieve two main objectives which are to maximize the lecturers' preference levels based on preference scores and to maximize the lecturers' competency scores based on courses. Through these two objective functions, the proposed model ensures that lecturers are assigned to courses that best suit their expertise while meeting their preferences. Maximizing the lecturers' preferences and competencies can contribute to enhancing teaching effectiveness and academic quality.

## 2. Literature Review

Assignment of lecturers to courses in higher education is a complex process that requires balancing institutional requirements on courses offered with lecturers' preferences and competencies. Traditional methods, such as manual assignment or the Hungarian Method (HM) introduced by Kuhn (1955), provide effective solutions for balanced datasets. However, these methods often face limitations in unbalanced scenarios where the number of lecturers and courses is not equal. The traditional HM also lacks the flexibility to integrate multidimensional factors such as preferences and competency, which can be considered crucial for optimizing lecturer-course assignments. The Modified HM (MHM), through additional constraints and objectives, is well-suited for handling unbalanced assignment problems. Despite this strength, the utilization of MHM in lecturer-to-course assignments is still lacking. Previous studies that used MHM have primarily focused on either lecturers' preferences or competencies individually, rarely integrating both. Although multi-objective optimization techniques such as goal programming have demonstrated the advantages of considering multiple factors, their practical implementation in academic settings has been limited due to computational complexity and challenges in interpretability.

Matching lecturers to courses based on preference levels and competency scores is essential for effective educational management, in ensuring optimal resource allocation and enhanced teaching quality. The lecturer-to-course assignments' optimization involves distributing resources (lecturers) to jobs (courses to teach) to maximize objectives such as minimizing cost, such as differences in teaching loads of lecturers, or maximizing instructional effectiveness, where, for example, a lecturer is given three or more different courses to teach in one semester. Lecturer competency, as highlighted by Latip et al. (2020), directly influences student satisfaction and academic performance, while preferences, including scheduling considerations and subject expertise, contribute to lecturer satisfaction and teaching efficiency. The HM model for lecturers' assignments has been primarily implemented for a balanced assignment problem setting. For example, Solaja et al. (2020), who applied the HM, have demonstrated that aligning lecturer assignments with institutional needs improved teaching effectiveness in Nigerian institutions. Similarly, Kabiru et al. (2017) utilized HM with LINGO software to generate optimal staff-course schedules, while Udok and Victor-Edema (2023) validated HM's effectiveness in postgraduate Mathematics and Statistics course allocations through manual calculations. Research by Wattanasiripong and Sangwaranatee (2021) and Ahmed et al. (2022) leveraged HM-based approaches to optimize lecturer-to-course assignments, enhancing decision-making efficiency and teaching quality. The Course and Lecturer Assignment Problem Solvation (CLAPS) process at a tertiary institution is discussed by Mallick et al. (2021), 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. Nevertheless, despite its wide applications, HM remains limited in addressing unbalanced assignment problems, necessitating the adoption of more advanced models. These studies, which used HM, typically assume equal numbers of lecturers and courses, overlooking unbalanced scenarios where MHM would be more appropriate.

The MHM model has been successfully applied in various fields in solving the optimization of the unbalanced assignment problem. For instance, Zhang et al. (2021) utilized MHM in multi-agent pursuit evasion, while Wei et al. (2022) employed it to enhance federated learning in wireless networks. In IoT systems, Liu et al. (2021) and Ge et al. (2020) applied MHM to optimize subchannel allocation, whereas Mukherjee and De (2023) used it for resource allocation in 5G networks. Despite its effectiveness, MHM has not yet been explored for lecturer-to-course assignments. This study is the first to introduce MHM in this context, proposing five variants of the MHM model to optimize lecturer allocations. These models focus on maximizing either lecturers' preferences, competency scores, or both, utilizing goal programming techniques to address multiple objectives (Ibrahim et al., 2024). Among the proposed models, the novel Preference-Competency Multi-Objective MHM (PC MO-MHM) model is designed specifically for unbalanced lecturer-to-course assignments. This proposed model is a bi-objective model which pursues two objective functions: to maximize the lecturers' total preference scores and to maximize the lecturers' total competency scores measured based on knowledge, skills and teaching motivation. Unlike traditional HM-based approaches, the PC MO-MHM model employs the preemptive goal programming (GP) method to optimize based on the priority levels for the goals (objective functions), thus through a sequential procedure. The first objective function has the highest priority, the second objective function becomes the second-priority goal, the third becomes the third-priority goal, and so on. In PC MO-MHM, maximizing the lecturers' total preference scores is the priority goal, whereas maximizing the lecturers' total competency scores is the second priority goal. The model ensures that lecturers' preferences are maximized while ensuring that the preferences do not neglect lecturers' competency in teaching the assigned courses. Having the lecturers' preferences satisfied as much as possible can contribute towards lecturers' satisfaction, while having courses assigned based on preferences to these lecturers must also adhere to their competency or expertise in teaching those courses. In other words, it is important to meet both the lecturers' satisfaction and the goal of maintaining or enhancing the quality of teaching of those courses. Table 1 shows the summary of relevant past studies on HM and MHM models.

Table 1. Past Studies of Hungarian Method (HM) and Modified Hungarian Method (MHM) models

| **Hungarian Method (HM) model** | **Modified Hungarian Method (MHM) model** | | |
|---|---|---|---|
| **Authors** | **Area of Application** | **Authors** | **Area of Application** |
| Kabiru et al. (2017) | Staff-subject | Elsisy et al. (2020) | Fuzzy Assignment problem |
| Solaja et al. (2020) | Assign lecturers to courses | Ge et al. (2020) | Internet of Things (IoT) |
| Wattanasiripong and Sangwaranatee (2021) | Assign lecturers to courses | Liu et al. (2021) | Internet of Things (IoT) |
| Mallick et al. (2021) | Assign lecturers in different faculties to courses | Zhang et al. (2021) | Assignment of Redundant Pursuers |
| Ahmed et al. (2022) | Assign teachers to classes | Wei et al. (2022) | Federated learning training |
| Udok and Victor-Edema (2023) | Assign lecturers to postgraduate courses | Mukherjee and De (2023) | Device-to-Device (D2D) Multicasting |

Mixed Integer Linear Programming (MILP) models have been commonly employed in past studies to solve assignment problems. For example, Hanafi et al. (2024) proposed a MILP model to deal with the Exam-Invigilator Assignment Problem in Universiti Pertahanan Nasional Malaysia (UPNM). The model was solved using an algorithm implemented in XPress MP and a better solution and more efficient and effective resource utilizations were obtained. MILP was used by Cua et al. (2024) for the assignment and scheduling of healthcare workers, where worker skill levels and shifts were considered. The model minimizes the total costs and the optimal schedule found was validated through a scenario analysis. A Mixed Integer Goal Programming (MIGP) model refers to a multi-objective MILP with more than one objective function considered and some but not all the variables are constrained to be integer valued. The MIGP model is often solved using a certain goal programming (GP) approach. Shuib and Ibrahim (2021) proposed a MIGP model for the Vehicle Routing Problem with Time Windows (VRPTW) for optimal routes of blood collecting vehicles to adhere to all time windows for collection at blood donation sites. The model pursues four goals, namely, to minimize total distance traveled, to minimize total travel time, to minimize total waiting time of vehicles and to minimize the number of vehicles (routes). The model was solved using the preemptive GP technique, with results that include a reduced number of vehicles used. Haroune et al. (2023) utilized the MIGP model to produce an optimal schedule for a multi-project scheduling problem under shared multi-skill resource constraints. The model minimizes the total weighted tardiness and the undesirable goal deviations. Employees are assigned to projects with fixed percentages of time, in which all projects must be completed within the desired time horizon. A local search and tabu search (TS) algorithm are proposed to tackle large-scale instances where high-quality solutions are achieved.

## 3. Methodology

This study is structured into four key phases: data collection and analysis, development of the enhanced MHM model, computational experiments and result analysis. Data were gathered from March to August 2023 through an online survey involving 39 Mathematics Department lecturers, covering 35 undergraduate courses. Each lecturer assessed their competency in three elements, namely knowledge, skills and teaching motivation for every course. The following are the respective Likert scales for each of the preferences and three elements of competency of lecturers for each course, shown in Tables 2, 3, 4 and 5.

Table 2. 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. |

Table 3. Likert scale for the lecturer's Knowledge competency of a Course.

| Scale | Description | Justification |
|---|---|---|
| 1 | Beginner | Has a basic level of knowledge. |
| 2 | Competent | A person who has the knowledge, advanced than a beginner but not yet proficient. |
| 3 | Proficient | A person who is highly competent but not yet an expert. |
| 4 | Expert | Subject matter expert recognized by virtue of credentials, training, education, profession, publications, or experiences. |

Table 4. Likert scale for the lecturer's Skills competency of a Course.

| Scale | Description | Justification |
|---|---|---|
| 1 | Basic | Has a basic level of skills, which is expected to have some knowledge of the specified activity and its terminology and concepts. |
| 2 | Capable | Can carry out standard relevant tasks confidently and consistently without supervision. |
| 3 | Accomplished | Can carry out complex, specialist, or non-standard tasks confidently and consistently. |
| 4 | Authoritative | Widely recognized as an authority, external peers and by others in the organization for the knowledge and experience that have been demonstrated. |

Table 5. Likert scale for the lecturer's Teaching Motivation competency of a Course.

| Scale | Description | Justification |
|---|---|---|
| 1 | Basic | Has a basic level of skills, which is expected to have some knowledge of the specified activity and its terminology and concepts. |
| 2 | Capable | Can carry out standard relevant tasks confidently and consistently without supervision. |
| 3 | Accomplished | Can carry out complex, specialist, or non-standard tasks confidently and consistently. |
| 4 | Authoritative | Widely recognized as an authority, external peers and by others in the organization for the knowledge and experience that have been demonstrated. |

The data analysis phase involved computing the average preference levels and competency scores for each lecturer-to-course. Preference levels $(p)$ were converted into percentages, with a score of 1 corresponding to $p_{ij} = 0.25$, a score of 2 to $p_{ij} = 0.5$, a score of 3 to $p_{ij} = 0.75$, and a score of 4 to $p_{ij} = 1$. Similarly, Competency scores $q_{ij}$ were categorized based on the average score across the three competency elements. The classification is shown in Table

Table 6. Average Competency Scores.

| Score | Average Competency $(q_{ij})$ |
|---|---|
| 1 | $0 < q_{ij} \leq 0.25$ |
| 2 | $0.25 < q_{ij} \leq 0.50$ |
| 3 | $0.50 < q_{ij} \leq 0.75$ |
| 4 | $0.75 < q_{ij} \leq 1.00$ |

To derive these values, the sum of scores for the three competency elements for each course was divided by 12 (the maximum possible sum), resulting in a value between 0 and 1. For instance, if Lecturer SA1 received scores of 2 for knowledge, 4 for skills and 3 for teaching motivation, the average competency score was calculated as:

$$q_{ij} = \frac{(2+4+3)}{12} = 0.75.$$

Since this value falls within the range $0.50 < q_{ij} \leq 0.75$ , the final competency score for Lecturer SA1 was assigned as $q_{ij} = 0.75$ (Score 3). For both scores of preferences and competency of one lecturer to one course can be shown, for example, Lecturer SA1 has a score of course MAT422 with $p_{ij} = 1$ (Score 4) and $q_{ij} = 0.75$ (Score 3). The expansion of the MHM optimization model was carried out in Excel using the collected preference levels $(p_{ij})$ and competency scores $(q_{ij})$ as coefficients for the objective functions. The input matrices generated from the Excel model were subsequently used to solve the model in MATLAB utilizing the intlinprog function. The primary objectives of the enhanced MHM model are to maximize lecturers' preference scores and maximize the competency scores of lecturers in course assignments as a second objective. The formulation of the enhanced MHM model is presented as follows.

**The MHM Model for Preference-Competency Multi-Objective (PC MO-MHM Model)**

Our study has developed five variants of the enhanced MHM model for the lecturer-to-course assignment problem, in which one of them is the MHM model for maximizing preference and maximizing competency scores of lecturers, which is a dual objective (PC MO-MHM model). The PC MO-MHM model formulation is as follows.

PC MO-MHM Model Formulation

Notation – Sets, Indices, Parameters and Input Variables:

| | | |
|---|---|---|
| $m$ | : | number of lecturers $(m = 39)$ |
| $n$ | : | number of courses $(n = 35)$ |
| $I = \{1, \ldots, m\}$ | : | index for lecturers, $i \in I$ |
| $J = \{1, \ldots, n\}$ | : | index for courses, $j \in J$ |
| $p_{ij}$ | : | lecturer $i$ preferences to get course $j$ |
| $q_{ij}$ | : | lecturer $i$ competency to get course $j$ |
| $x_{ij}$ | = | $\begin{cases} 1, \text{lecturer } i \text{ is assigned course } j \\ 0, \text{otherwise} \end{cases}$ |

$$\text{Maximize } Z_1 = \sum_{i\epsilon I}\sum_{j\epsilon J} p_{ij}x_{ij} \quad (1)$$

$$\text{Maximize } Z_2 = \sum_{i\epsilon I}\sum_{j\epsilon J} q_{ij}x_{ij} \quad (2)$$

subject to

$$1 \le \sum_{i\epsilon I} x_{ij} \le 3 \qquad ,\forall j \in J \quad (3)$$

$$1 \le \sum_{j\epsilon J} x_{ij} \le 3 \qquad ,\forall i \in I \quad (4)$$

$$x_{ij} \in \{0,1\} \qquad ,\forall i \in I; \forall j \in J \quad (5)$$

Model Description

The objective function is presented in Equation (1), which is to maximize the lecturers' preference, while the second objective function, Equation (2), is to maximize the competency of lecturers for courses. Constraint (3) is to ensure that a lecturer $i$ should be assigned to at least one and at most three courses. On the other hand, Constraint (4) guarantees that a course $j$ must be assigned to at least one and at most three lecturers. Finally, Constraint (5) presents the restriction on the value of decision variables, in which the binary decision variables only take binary values of either 0 or 1.

Before solving the PC MO-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 the 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 as shown in Figure 1.

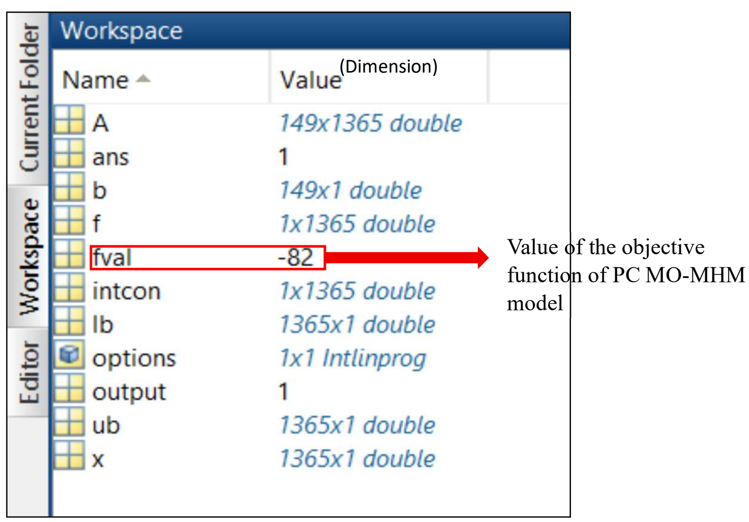


Figure 1. MATLAB Workspace for PC-MHM model.

The third phase, Computational Experiments, involved solving the expanded model using MATLAB's *intlinprog* solver. The input matrices and vectors generated in Excel were used as parameters for the solver, ensuring precise computation of the optimization problem. The final phase, analysis of results, focused on evaluating the output from MATLAB to determine the effectiveness of the enhanced MHM model in optimizing lecturer-to-course assignments.

Figure 1 provides an overview of the input matrices and vectors used in the computational process, emphasizing the reproducibility and robustness of the methodology.

## 4. Results and Discussions

Table 7 presents the list of Mathematics courses offered by the Mathematics Department of the university. The MATLAB *intlinprog* generates optimal solutions, which contain the objective function value (fval) and the values of the decision variables $x_{ij}$ which has either a value '1' or '0'. Note that the objective functions of PC MO-MHM are to maximize the preferences and maximize the competency score of lecturers for courses. The fval value for the PC MO-MHM model is as shown in Figure 1, which is -82. Note that MATLAB's default is to minimize the objective function; thus, the command is to minimize the negative of the objective function of PC MO-MHM. Thus, the maximum preferences and competency score of lecturers for courses is 82. The values of '1's and '0's obtained from MATLAB *intlinprog* are transferred to an Excel spreadsheet to better illustrate the assignment of each lecturer to courses.

Table 7. List of Mathematics Courses.

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

The results obtained are displayed in Table 8, where each lecturer is assigned one to three courses, while each course can only be taught by not more than three lecturers. Based on Table 8, lecturers SA3, SA4, SA13, SA21 and SA26 are assigned only one course each, while SA7 and SA10 are assigned two courses. The remaining lecturers, including SA1, SA2 and so forth, have been assigned three courses each. The results reflect that courses have been assigned to suit the preference levels and competency scores (scores obtained based on Knowledge, Skills and Teaching Motivation). Besides that, it is also found that this optimal solution of lecturers to course assignments also displays that these courses reflect the areas of expertise of the lecturers. Table 8 also summarizes the lecturer-to-course assignments of all the lecturers involved.

Table 8. The result from MATLAB for the Courses of Each Lecturer.

| 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 |
| SA1 | | | | | | 1 | | | | | | | | | 1 | | 1 | | | | | | | | | | | | | | | | | | |
| SA2 | | | 1 | | | | | | | | | | | | | | | | | 1 | | | | | 1 | | | | | | | | | | |
| SA3 | | | | | | | | | | | 1 | | | | | | | | | | | | | | | | | | | | | | | | |
| SA4 | | | | | | | | | | | | | | | | | | | | | | | | 1 | | | | | | | | | | | |
| SA5 | | | | | | | | | | | | | | | | | | | | | | | | | | | | 1 | 1 | | | | | 1 | |
| SA6 | 1 | | | | | | | | 1 | | | | | | | | 1 | | | | | | | | | | | | | | | | | | |
| SA7 | | | | | | | | | | | | | | | | | | | | | | | 1 | | | | | | | 1 | | | | | |
| SA8 | | | | | 1 | | | 1 | | | | | | | | | | | | | | | | | | | | | | | | | | 1 | |
| SA9 | | | | | | | | | | | | | 1 | | | 1 | | | | | 1 | | | | | | | | | | | | | | |
| SA10 | | | | | | | | | 1 | | | | | | | | | | | | | 1 | | | | | | | | | | | | | |
| SA11 | | | | | | | | | | | | | | | | | | | | | | | | | | | | 1 | | | 1 | 1 | | | |
| SA12 | | 1 | | 1 | | | | | | | | | | | | | | | | | | | | | | | 1 | | | | | | | | |
| SA13 | | | 1 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| SA14 | | | | | | | 1 | | | | | | | | | | | 1 | | | | | 1 | | | | | | | | | | | | |
| SA15 | | | | | | | 1 | 1 | | | | | | | | | | 1 | | | | | | | | | | | | | | | | | |
| SA16 | | | | 1 | | | | | | | | | | 1 | | | | | | | | | | | | | | | | | 1 | | | | |
| SA17 | | | 1 | | | | | | | | | | | | | | | | | | | | | | | 1 | | | | | | | 1 | | |
| SA18 | | | | | | | | | | | | 1 | | | | | | | | | | | | | | | | | | | | | 1 | | 1 |
| SA19 | | | | | | | | | | | | | | | | 1 | | | | | | | | | | 1 | | | | | | 1 | | | |
| SA20 | | | | | 1 | | | | | | | | | | | | | | | | | | | | | | 1 | | | | | | 1 | | |
| SA21 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | 1 | | | | | |
| SA22 | | | | | | | | | | 1 | | | | 1 | | | | | | | | 1 | | | | | | | | | | | | | |
| SA23 | | 1 | | | | 1 | | | | | | | | 1 | | | | | | | | | | | | | | | | | | | | | |
| SA24 | | | | | | | 1 | | | 1 | | | | | | | | 1 | | | | | | | | | | | | | | | | | |
| SA25 | | | | | | | | | | | | | | | | | | | | 1 | 1 | | 1 | | | | | | | | | | | | |
| SA26 | | | | | | | | | | | | | | | | | | | | | 1 | | | | | | | | | | | | | | |
| SA27 | | | | 1 | | | | 1 | | | 1 | | | | | | | | | | | | | | | | | | | | | | | | |
| SA28 | | | | | | | | | | | | 1 | | | | | | | 1 | | | | | | | | | | | | | | | 1 | |
| SA29 | | | | | | | | | | | | 1 | | | | 1 | | | 1 | | | | | | | | | | | | | | | | |
| SA30 | | | | | | | | | | | | | | | 1 | | | | | | | | | | | | | | 1 | | 1 | | | | |
| SA31 | | | | | | 1 | | | | | | | | | | | | | | | | | | | | 1 | | | | | | 1 | | | |
| SA32 | | | | | | | | | | 1 | | | | | | | 1 | | | | | | | | 1 | | | | | | | | | | |
| SA33 | 1 | | | | | | | | | | | | 1 | | | | | | | | | | | | | | | | | | | | | | 1 |
| SA34 | | | | | | | | | 1 | | | | | | | | | | | 1 | | 1 | | | | | | | | | | | | | |
| SA35 | | | | | | | | | | | | | | | | | | | 1 | | | | | | | | 1 | | | | | | | | 1 |
| SA36 | 1 | | | | | | | | | | | | | | | | | | | | | | | 1 | 1 | | | | | | | | | | |
| SA37 | | | | | | | | | | | | | 1 | | | | | | | | | | | 1 | | | | | 1 | | | | | | |
| SA38 | | 1 | | | | | | | | | | | | | | | | | | | | | | | | | | 1 | | 1 | | | | | |
| SA39 | | | | | 1 | | | | | | 1 | | | | 1 | | | | | | | | | | | | | | | | | | | | |

1 course

2 courses

3 courses

Table 9. Result of Lecturer to Course Assignment Based on PC MO-MHM Scores

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

Table 9 shows the compilation of results shown in Table 8. Examples of the optimal assignments include for instance, Lecturers SA3, SA4, SA13, SA21 and SA26 are assigned only one course, which is MAT455 (Further Calculus for Engineers), MAT565 (Advanced Differential Equations), MAT415 (Discrete Mathematics), MAT583 (Applied Numerical Methods) and MAT531 (Advanced Mathematical Modelling), respectively. Meanwhile, some lecturers have been assigned with two courses. For example, Lecturer SA7 is assigned two courses, namely MAT560 (Vector Calculus) and MAT583 (Applied Numerical Methods), while Lecturer SA10 is assigned MAT438 (Foundation of Applied Mathematics) and MAT538 (Applied Mathematics). Lecturers can be assigned up to three courses. For instance, Lecturer SA1 is assigned MAT422 (Mathematical Logic and Proving Techniques), MAT495 (Partial Derivatives and Approximation Methods) and MAT522 (Ordinary Differential Equations), whereas Lecturer SA2 is assigned MAT415 (Discrete Mathematics), MAT530 (Introduction to Mathematical Modelling) and MAT570 (Mathematics Economics). Several lecturers are also assigned to teach courses at various levels of the undergraduate program, with lecturers like SA17, S20, SA28, SA30 and SA31 assigned to the first digit of the code (4, 5 and 6), where code represents the year, the course is offered, which is the first year, second year or third year of undergraduate program. This suggests extensive experience and competence among these lecturers. Conversely, lecturers such as SA3, SA13, SA23, SA27 and SA39 specialize in first-year courses, whereas SA5, SA11, SA19 and SA35 focus on second and third-year courses, demonstrating their adeptness in higher-level Mathematics. Overall, this structured assignment of courses to lecturers based on preferences and competency ensures a better learning experience for students and supports faculty development, highlighting the importance of a strategic approach to lecturer-to-course assignments within the Mathematics department.

## 5. Conclusion

This study examines the assignment of lecturers to courses using the MHM model, which integrates both preference and competency scores to enhance assignment efficiency. The findings highlight the complexity and importance of optimizing lecturer assignments in higher education institutions. To address this challenge, the study proposes an enhanced MHM optimization model, referred to as the Preference-Competency Multi-Objective MHM (PC MO-MHM) model, which strategically incorporates lecturer preferences and competencies to improve assignment outcomes. The model's objective function aims to maximize preference and maximize the competency scores of Mathematics lecturers. The results highlight the need for a systematic assignment approach to ensure balanced workloads, comprehensive course coverage and alignment with lecturers' expertise. By adopting the PC MO-MHM model, institutions can implement continuous evaluation mechanisms to enhance decision-making in academic resource management. Future research could further refine this model by incorporating additional factors, improving scalability and exploring the applications to optimize both lecturer performance and student learning outcomes.

**Acknowledgement**

We thank the authors for their expertise and assistance throughout all aspects of our study and for their help in writing the manuscript.

**Funding**

The author(s) received no specific funding for this work.

**Author Contribution**

Nur Syahirah Ibrahim is responsible for all data analysis and writing the Methodology section. Aside from that, she has also contributed in preparing the review on the past studies on HM and MHM in the Literature Review.

Adibah Shuib has been responsible for organizing and writing the major parts of the Results and Discussion section. She has also been working together with Nur Syahirah Ibrahim and Zati Aqmar Zaharudin to finalize the Literature Review section.

Zati Aqmar Zaharudin has been in charge of the Introduction and Conclusion while assisting with the review of relevant studies for the Literature Review. All three authors, Nur Syahirah Ibrahim, Adibah Shuib and Zati Aqmar Zaharudin have worked together on the formulation of the PC MO-MHM model.

**Conflict of Interest**

The authors agree that this research was conducted in the absence of any self-benefits, commercial or financial conflicts and declare absence of conflicting interests.

**References**

Ahmed, S. S., Mariga, U. N., Abdulmalik, S., Ango, I. S., & Umaru, S. (2022). The Use of Assignment Problem Models To Assign Teachers To Classes : A Case Study of Ado Bobi Primary School. *Transactions of the Nigerian Association of Mathematical Physics*, *18*, 167–172.

Cua, K. A. S., Ong, A. A., A., & Magno, D. J. A. (2024). Mixed Integer Linear Programming Model for the Assignment and Scheduling of Healthcare Workers with the Consideration of Worker Skill Levels. *MSIE '24: Proceedings of the 2024 6th International Conference on Management Science* *and Industrial Engineering*, 39 – 45.

Elsisy, M. A., Elsaadany, A. S., & El Sayed, M. A. (2020). 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*, *2020*, 1–11.

Ge, S., Cheng, M., He, X., & Zhou, X. (2020). A Two-Stage Service Migration Algorithm in Parked Vehicle Edge Computing for Internet of Things. *Sensors*, *20*(10), 2786.

Hanafi, M. A. I, Syed Ali, S. A., Mat Jusoh, R, Ali, F., & Abd Rahman, N. (2024). Assignment Problem: A Case Study at Universiti Pertahanan Nasional Malaysia. *JOIV: International Journal on Informatics Visualization*, *8*(2), 686-691.

Haroune, M., Dhib, C., Neron, E., Soukha, A., Mohamed Babou, H., & Nanne, M. F. (2023). Multi-project scheduling problem under shared multi-skill resource constraints. *Transactions in Operations Research* (TOP), *31*, 194–235

Ibrahim, N. S., Shuib, A., & Zaharudin, Z. A. (2024). Modified Hungarian model for lecturer-to-course assignment. *In AIP Conference Proceedings*, *3086*, 080001.

Kabiru, S., Saidu, B. M., Abdul, A. Z., & Ali, U. A. (2017). An Optimal Assignment Schedule of Staff-Subject Allocation. *Journal of Mathematical Finance*, *07*(04), 805–820.

Kuhn, H. W. (1955). The Hungarian Method for the Assignment Problem. *Naval Research Logistics Quarterly*, *2*(1–2), 83–97.

Latip, M. S. A., Newaz, F. T., & Ramasamy, R. (2020). Students' Perception of Lecturers'

Competency and the Effect on Institution Loyalty: The Mediating Role of Students' Satisfaction. *Asian Journal of University Education*, *16*(2), 183.

Liu, Y., Liu, K., Han, J., Zhu, L., Xiao, Z., & Xia, X.-G. (2021). Resource Allocation and 3-D Placement for UAV-Enabled Energy-Efficient IoT Communications. *IEEE Internet of Things Journal*, *8*(3), 1322–1333.

Mallick, C., Bhoi, S. K., Jena, K. K., Sahoo, K. S., Humayn, M., & Shahd, M. H. (2021). CLAPS: Course and Lecture Assignment Problem Solver for Educational Institution Using Hungarian Method. *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*, *12*(10), 3085–3092.

Mukherjee, P., & De, T. (2023). Interference aware D2D Multicasting using Modified Hungarian Method. *2023 OITS International Conference on Information Technology (OCIT)*, *Ocit*, 319–324.

Selamat, A. S., Othman, Z. S., & Mamat, S. S. (2025). Secondary school students' attitude and its effects on mathematics achievement. *Malaysian Journal of Computing (MJoC)*, *10*(1), 2001-2011.

Shuib, A., & Ibrahim, P. M. (2021). A Mixed Integer Goal Programming (MIGP) Model For Donated Blood Transportation Problem – A Preliminary Study. *Malaysian Journal of Computing (MJOC*), *6*(2), 835-851.

Solaja, O., Abiodun, J., Ekpudu, J., Abioro, M., & Akinbola, O. (2020). Assignment problem and its application in Nigerian institutions: Hungarian method approach. *International Journal of Applied Operational Research*, *10*(1), 1–9.

Udok, U. V., & Victor-Edema, U. A. (2023). Application of assignment problem in postgraduate course allocation at Ignatius Ajuru University of Education. *Faculty of Natural and Applied Sciences Journal of Scientific Innovations*, *5*(1), 21–33.

Wattanasiripong, N., & Sangwaranatee, N. W. (2021). Program for Solving Assignment Problems and Its Application in Lecturer Resources Allocation. *Journal of Physics: Conference Series*, *2070*(1), 012003.

Wei, K., Li, J., Ma, C., Ding, M., Chen, C., Jin, S., Han, Z., & Poor, H. V. (2022). Low-Latency Federated Learning Over Wireless. *IEEE Journal on Selected Areas in Communications*, *40*(1), 290–307.

Zhang, L., Prorok, A., & Bhattacharya, S. (2021). Pursuer Assignment and Control Strategies in Multi-agent Pursuit-Evasion Under Uncertainties. *Frontiers in Robotics and AI*, 262.