MJFAS
Malaysian Journal of Fundamental and Applied Sciences

Mohd Rohaizad *et al.* | Malaysian Journal of Fundamental and Applied Sciences, Vol. 22 (2026) 260–273

RESEARCH ARTICLE

Validating the Adaptability of a Developed General University Course Timetabling Model through Practical Implementation

Siti Sarah Mohd Rohaizad[a], Zahidah Mohd Zaulir[a], Nur Aidya Hanum Aizam[a,b,*]

[a]Faculty of Computer Science and Mathematics, Universiti Malaysia Terengganu, 21030 Kuala Nerus, Terengganu, Malaysia; [b]Mathematical Modelling and Optimization Research Interest Group, Universiti Malaysia Terengganu, 21030 Kuala Nerus, Terengganu, Malaysia

Abstract Researchers have extensively studied the university course timetabling problem (UCTP) over the past decades, aiming to develop efficient, practical, and scalable scheduling that cater to the needs of academic institutions. This paper presents the implementation of a general Mixed-Integer Programming (MIP) model to solve UCTP using a dataset from an East Coast Malaysian public university. Building upon previous research that proposed a model with 24 constraints, this study aims to validate the original model to ensure its applicability and flexibility. Through the validation process, this study demonstrates how the model can be customized by selecting 13 relevant constraints based on East Coast Malaysian public university's specific scheduling requirements, institutional policies, and academic preferences. This approach ensures that the model remains both realistic and adaptable to various scheduling contexts. Two different case studies with the same dataset are explored: case study 1 focuses on generating a timetable based on the university's real timetabling requirements, while case study 2 integrates additional preferences and requests from lecturers and top university management to accommodate specific needs. The model is solved using AIMMS with the CPLEX 12.9 solver, ensuring feasible and optimal solutions. With minor modifications, this general model is adaptable and applicable to other universities' while addressing various institutional requirements and preferences.

Keywords: AIMMS, Management problem, Mathematical model, Mixed-integer programming, Scheduling.

Introduction

Timetabling research involves allocating resources to time slots and spaces while satisfying various constraints accordingly to each problem. Figure 1 illustrates different application fields of timetabling problems, with studies referenced from [1] to [15] providing examples of how these problems have been addressed. Among these problems, the University Course Timetabling Problem (UCTP) is particularly challenging, as it involves limited resources, overlapping schedules, and the preferences of both lecturers and management, all of which must be satisfied to enhance the quality of the timetable produced. It becomes more challenging as different institution requires different requirements and preferences. The difficulty increases further when additional and unique institutional requirements are incorporated. These challenges make it difficult to produce feasible timetables efficiently, particularly as the size and complexity of the problem increases.

Hence, a general model that incorporates most requirements typically found in universities is essential, as demonstrated in [16]. Most of the existing literature focuses on the timetabling problem of a single institution, which makes it time-consuming and demanding to develop a new model for each specific case. Thus, the model proposed in [16] can be directly applied to solve the UCTP for a specific institution.

***For correspondence:**
aidya@umt.edu.my

Received: 20 May 2025
Accepted: 19 Jan. 2026

Its application in this study to a public university on the East Coast of Malaysia not only reduces the time and effort required to produce a complete university timetable, but more importantly, serves to validate the applicability and practicality of the general model introduced. Basically, to address these challenges, optimization methods for UCTP are broadly classified into two categories; exact and heuristic methods. Figure 2 illustrates these commonly used methods along with examples of the different types of constraints considered in UCTP.

Exact methods, including integer programming (IP) [17, 18, 19], mixed-integer programming (MIP) [20, 21, 22], and binary integer programming (BIP) [23], guarantee an optimal solution by exploring all possibilities, but can be computationally intensive for complex problems. Meanwhile, heuristic methods, such as simulated annealing (SA) [24], genetic algorithms (GA) [25], and tabu search (TS) [26, 27], provide high-quality solutions with lower computational effort [28, 29]. These methods have been widely applied in previous studies to solve UCTP. Building on these methods, Figure 3 shows the timeline of research developments specific to one of the East Coast Malaysian public universities. The first model, based on [30] serves as the foundation, followed by reformulations and validations by other authors, which were applied in the current research. Therefore, this research is divided into two case studies: case study 1 addresses actual university requirements, while case study 2 incorporates additional lecturer and management preferences.

This paper is structured as follows: second section outlines UCTP requirements; third section presents the formulated model; and the following sections detail its application to the case studies, and the final section concludes the findings.

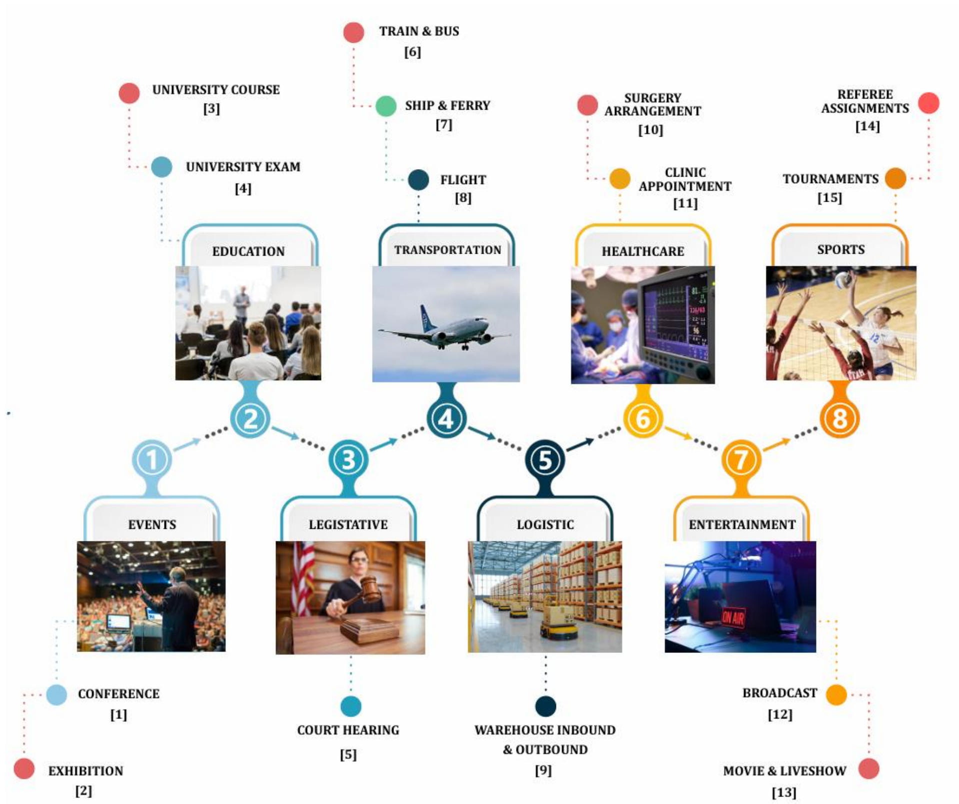

Figure 1. The various field in timetabling

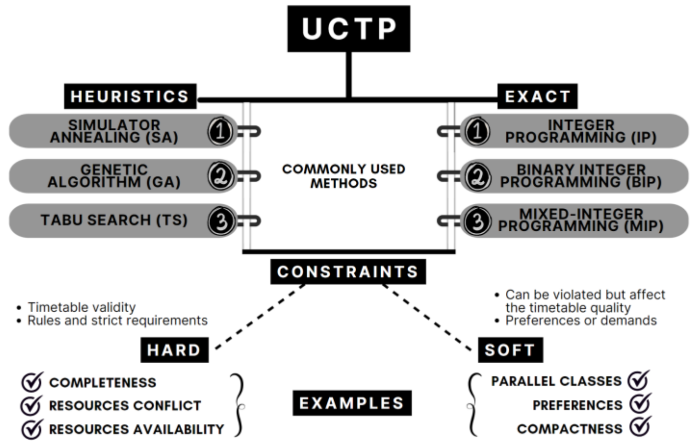

Figure 2. The overview of commonly used methods to solve UCTP

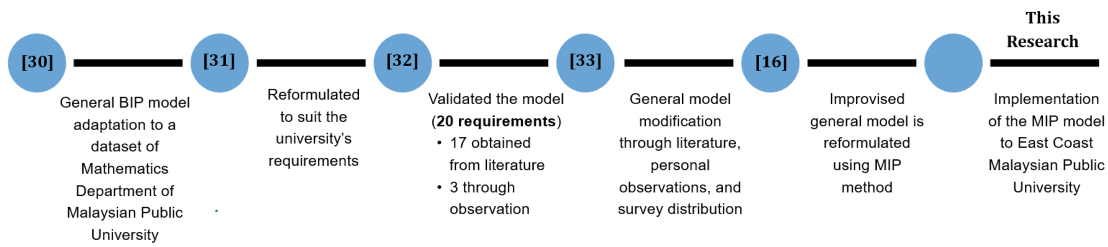

Figure 3. The timeline of UCTP research at East-Coast Malaysian public university

University Course Timetabling Problem

The real data used to validate the model came from one of the East Coast Malaysian public universities for the first semester of the 2017/2018 academic session. This university was selected because it represents a typical Malaysian public university in terms of academic structure, institutional policies, and resource limitation. Furthermore, the availability of complete and reliable real-world timetabling data made it suitable for validating the proposed model under realistic operational conditions. The official daily lecture hours usually begin at 8.00 AM and end at 7.00 PM and have been scheduled from Sunday to Thursday. However, laboratory sessions are held from 2.00 PM until 5.00 PM, which take place on Sunday and Monday, from 10.00 AM to 7.00 PM on Tuesday to Thursday. Courses are grouped into three categories: elective courses, program core courses, and university core courses. Each course has its specific attributes, like credit hours, lab and consecutive hour requirements, number of enrolled students, and assigned lecturers. Each institution has its own set of requirements that need to be considered when generating the course timetable. While some universities have similar scheduling needs, others may have different requirements based on their academic structure, policies, and available resources. In this research, we outline the specific requirements for the university of our focus as follows.

1. All lectures should be assigned to the respective time slot and room
2. Number of students cannot exceed the room capacity
3. Some time slots are unavailable for the assignment of lab
4. Some courses must be assigned according to their specific requirements for the room type
5. No student should attend more than one lecture in any time slot
6. No room should be used for more than one lecture in any time slot
7. No lecturer should teach more than one lecture in any time slot
8. Each lecturer cannot teach more than the limited number of their workload
9. Some lectures of the same course should be scheduled on the same day
10. Some lectures of the same course should not be scheduled on the same day except for some courses
11. Some lectures of the same course should be scheduled consecutively
12. Lectures with a large number of students are to be scheduled simultaneously
13. Some time slots are unavailable for the assignment of any courses (break hours)

By addressing these requirements, this study ensures that the generated timetable is practical, efficient, and suitable for real-world implementation. The problem is to assign the lectures to the available resources. The dataset includes as below.

Table 1. The obtained data of East-Coast Malaysian public university

Data Collection	
Course	508 courses
Lecturer	478 lecturers
Program	27 programs across 8 schools
Lecture	508 courses are divided into 2,895 lectures based on credit hours

Table 2. The available resources at East-Coast Malaysian Public University

Available Resources	
Time slots	55 one-hour time slots (8.00 AM to 7.00 PM: Sunday to Thursday)
Rooms	141 rooms (72 lecture rooms, 69 laboratories)

Mixed-Integer Linear Programming

In this research, a general university course timetabling model proposed in [16] is applied to a real-world dataset from an East Coast Malaysian public university. The model represents a general UCTP model incorporating a wide range of institutional requirements with the aim of maximizing preferences in course assignments. Out of the 24 constraints defined in this general model representing various UCTP requirements, 13 are selected based on a thorough analysis of the intended institutional requirements and academic preferences. The remaining constraints are excluded from this study. This strategic selection ensures that the model is aligned with the university's course timetabling requirements while demonstrating the adaptability of the general modelling approach to different scheduling environments. The notation used in the model is described as follows.

Table 3. The notation of UCTP model

Set and Indices	
C	Lectures offered
$r \in R$	Room type of different capacities and facilities
$l \in L$	Lecturers
$g \in G$	Student groups
$t \in T$	Time slots available
$d \in D$	Days of the week
$c_b \in C$	Laboratory courses
c_l	Lectures that are taught by lecturer $l, \forall l \in L$
c_g	Lectures that have the same student group $g, \forall g \in G$
T_{lunch}	Time slots for lunch break
T_d	Set of time slots in day $d, \forall d \in D$
H	Set of lectures in pair (C_m, C_n) that needs to be assigned simultaneously in a time slot, $\forall (C_m, C_n) \in C$
I	Set of lectures in pair (C_m, C_n) that needs to be assigned consecutively and in the same day, $\forall (C_m, C_n) \in C$
O	Set of lectures in pair (C_m, C_n) that needs to be assigned on the same day, $\forall (C_m, C_n) \in C$
O'	Set of lectures in pair (C_m, C_n) that should not be assigned on the same day, $\forall (C_m, C_n) \in C$
Parameter	
RC_r	Capacity of room, r
CS_c	Size of course, c
U_{max}	Maximum number of lectures per day scheduled for lecturer, l
$P_{c,t,r}$	Lecturers' preferences on having lecture, c at time slot, t and room, r
$Q_{c,r}$	Lecture, c are assign at room, r
Decision Variable	
$X_{c,t,r}$	Classes, c, assigned to specific time slot, t, and room, r

From the list of requirements in previous section, the constraints can be identified and clearly outlined. These constraints serve as prior guidelines that ensure the generated timetable adheres to institutional policies, academic regulations, and resource limitations. By explicitly defining these set of constraints, the model can generate feasible and practical solutions that align with the university's operational requirements. Hence, the purpose of these constraints is to guide the scheduling process toward creating a timetable that is both efficient, adaptable and realistic.

Table 4. The mathematical equation for UCTP constraints

Constraints	Index Domain	Equation
$\sum_{t}\sum_{r} X_{c,t,r} = 1$	$\forall c$	(1)
$CS_c \cdot X_{c,t,r} \leq RC_r$	$\forall c, \forall t, \forall r$	(2)
$\sum_{c_b \in C}\sum_{t \in T_{un}} X_{c,t,r} = 0$	$\forall r$	(3)
$\sum_{t} X_{c,t,r} = 0$	$\forall (c,r) \in Q_{c,r}$	(4)
$\sum_{c \in C_g}\sum_{r} X_{c,t,r} \leq 1$	$\forall t, \forall g$	(5)
$\sum_{c \in R} X_{c,t,r} \leq 1$	$\forall t, \forall r$	(6)
$\sum_{c \in C_l}\sum_{r} X_{c,t,r} \leq 1$	$\forall t, \forall l$	(7)
$\sum_{c \in C_l}\sum_{t \in T_d}\sum_{r} X_{c,t,r} \leq U_{max}$	$\forall d, \forall l$	(8)
$\sum_{t \in T_d}\sum_{r} (X_{c_m,t,r} - X_{c_n,t,r}) = 0$	$\forall (c_m, c_n) \in O, \forall d$	(9)
$\sum_{t \in T_d}\sum_{r} (X_{c_m,t,r} + X_{c_n,t,r}) \leq 1$	$\forall (c_m, c_n) \in O', \forall d$	(10)
$X_{c_m,t,r} - X_{c_n,t+1,r} = 0$	$\forall (c_m, c_n) \in I, \forall t, \forall r$	(11)
$\sum_{r} (X_{c_m,t,r} - X_{c_n,t,r}) = 0$	$\forall (c_m, c_n) \in H, \forall t$	(12)
$\sum_{t \in T_{lun}} X_{c,t,r} = 0$	$\forall c, \forall r$	(13)

Thus, based on all the listed constraints in (1) to (13), the university course timetable model can be written as follows. The objective of the model is to maximize the overall satisfaction of lecturers' preferences in assigning lectures to time slots and rooms. These preferences are represented by the parameter $P_{c,t,r}$, where integer values range from 1 (least preferred) to 5 (most preferred). The data for the parameter $P_{c,t,r}$ are generated randomly in AIMMS, with all preference levels distributed evenly across the scale. The corresponding preference scale is defined as follows.

- 1: least preferred
- 2: low preference
- 3: moderate preference
- 4: high preference
- 5: most preferred

Therefore, the formulation below combines both the hard constraints (institutional' requirements) and the soft constraint (lecturers' preferences), resulting in a structured Mixed Integer Linear Programming (MILP) model that can be solved using optimization tools.

$$Max\ Z = \sum_{c}\sum_{t}\sum_{r} P_{c,t,r}X_{c,t,r} \tag{14}$$

Subject to:

(1) to (13)

and,

$$X_{c,t,r} \in \{0,1\} \qquad \forall c, \forall r, \forall t$$

The course timetabling problem is divided into two case studies: case study 1 and case study 2. Both case studies use the same primary data and model, with the difference being the specific university requirements and the demands of timetabling users in each case. Next section will cover the elaboration for both case study 1 and case study 2, that includes the computational results for each case, and will analyse the model's performance, respectively.

Case Studies

Case Study 1

The case that uses the same requirements as mentioned in previous section. In this case, all lectures are assigned to suitable time slots from 8.00 AM to 7.00 PM on Sunday to Thursday. Accordingly, the course timetabling model for case study 1 is formulated as presented in third section. The decision variable $X_{c,t,r}$ as defined in Table 3, represents the assignment of courses, *c* to time slots, *t* and rooms, *r*. Thus, $C, T, and\ R$ denote the number of courses, time slots, and rooms, respectively. Lecturers' preferences are represented by the parameter $P_{c,t,r}$, with integer values from 1 (least preferred) to 5 (most preferred). These preference values are generated randomly in AIMMS, with an equal distribution across all preference levels. The model is evaluated using the dataset described in the second section, and AIMMS optimization software is employed to solve the proposed model.

Case Study 2

This case considers the same requirements as mentioned in case study 1, but with additional demands and requests from the lecturers and top management of the university. Some of these requests involve specific compulsory undergraduate courses, namely PAL3000 and BBB2000, which are taken by all students in the programmes. Such demands and requests focus on time slots and rooms and can be listed as follows.

- Lecturers of PAL3000 course requested that the lectures be held at the flat lecture rooms
- Lecturers of BBB2000 course requested the lectures are assigned in the morning sessions
- Previous Deputy Vice-Chancellor (DVC) of Academics requested all lectures and labs are assigned in the morning sessions and completed by 1.00 PM every day

Therefore, this case study will consider the lecture hours from 8.00 AM to 1.00 PM, every day for the assignment of lectures. The lecturers' requests for specific time slots and rooms will be considered while constructing the timetable in this case study. Hence, the course timetabling model for case study 2 can be written as in last section, where the decision variable $X_{c,t,r}$ represents the assignment of course, *c* to time slot, *t* and room, *r*. The only differences between both case studies lie in the considered lecture hours and the inclusion of additional lecturers' and management preferences, while the mathematical structure of the model remains unchanged. The integer values range from 1 (least preferred) to 5 (most preferred) are set for parameter $P_{c,t,r}$ which is the lecturers' preferences on the allocation of lectures to time slots and rooms. The values are distributed at uniformly random. The model is validated with the dataset described in second section. The mathematical tool utilized to solve this model is AIMMS optimization software.

Computational Results

Table 5 provides a comparative summary of the computational results for case study 1 and case study 2, highlighting some differences in solution quality and performance. Case study 1 achieved an optimal solution with 0% gap between the best LP bound and the best solution. 'Best LP Bound' in AIMMS refers to the LP objective value of the best outstanding node, whereas 'Best Solution' refers to the value of the objective function for the best feasible solution discovered thus far. In optimization, the gap here known as optimality gap which measures the relative difference between the best LP bound and the best solution. It is commonly used to assess solution quality. Generally, the optimality gap is calculated as below.

$$Gap\ (\%) = \frac{|Best\ LP\ Bound - Best\ Solution|}{|Best\ LP\ Bound|} \times 100$$

Case study 2 faced unforeseen circumstances that will be further discussed in last section of performance analysis, leading to a solution with a 38.29% gap, but maintained a solution close to 60% of the optimal. This indicates that the model is still able to generate a high-quality timetable under additional constraints and preference requirements. The solution obtained thus far corresponds to the best feasible timetable identified by the solver during the current computation, before it reached the final iteration. However, in the following section, this paper discusses how the model for case study 2 can be adjusted to further improve the solution quality and aim for optimality. The AIMMS progress windows for both case studies are presented in this section by providing further insight into the solver performance and the solutions obtained.

Table 5. The comparison between computational results of case studies

Attributes	Case Study 1	Case Study 2
Solver	AIMMS with CPLEX 12.9	AIMMS with CPLEX 12.9
System Specification	Core i7, 3.40 GHz, 16GB RAM	Core i7, 3.40 GHz, 16GB RAM
Optimal Solution	14,081	10,190
Best LP Bound	14,081	14,091.97
Optimality Gap	0%	38.29%
Execution	Solution obtained with 0% gap	40% relative optimality tolerance
Solution Quality	Optimal solution achieved	60% close to optimal solution
Objective	Maximized preferences with 0% gap	Maximized preferences with 38.29% gap

Performance Analysis

Case Study 1

In case study 1, an optimal solution of 14,081 out of a possible 14,475 was achieved, where 2,622 out of 2,895 lectures (90.6%, as shown in Figure 4) were assigned to the most preferred time slots and rooms. Additionally, 6.4% of lectures were scheduled in preferred time slots, while 2.2%, 0.3%, and 0.4% were allocated to no preference, not preferred, and least preferred time slots, respectively (Figure 4). The timetable in Figure 7 confirms that all constraints listed in (1) to (13) were fully satisfied. (1) and (2) ensured all lectures were assigned to suitable time slots and rooms without exceeding room capacity. (3), (4), and (13) prevented lectures from being scheduled in unavailable time slots or rooms, ensuring no lectures occurred during break hours (1.00 P.M. – 2.00 P.M.). Lab courses were assigned specific lab rooms, and no lectures or labs were scheduled after 7.00 PM, unlike previous university timetables in the year of 2017/2018 due to limited resources. With the mathematical model developed in this study, we were able to prevent assigning any lectures or labs after 7.00 PM compared to the timetable generated by the university.

Both timetables were conflict-free due to (5), (6), and (7), ensuring that each resource (student groups, rooms, and lecturers) was assigned only once per lecture. Constraint (8) limited lecturers to a maximum of five hours per day. No lecturer exceeded their workload, as evidenced in Figure 8. (9) and (11) allowed certain lectures or labs to be scheduled consecutively for two, three, or five hours in the same room, while (10) prevented same-course lectures from being scheduled on the same day. For example, the two-hour STM3201 (G1) lecture was scheduled from 9.00 AM to 11.00 AM on Sunday, with another one-hour lecture on Monday from 6.00 PM to 7.00 PM (12) allowed simultaneous scheduling of courses with multiple student groups but different lecturers, such as BIO3101, which was scheduled for groups G4 and G5 in separate rooms (BK 5-07 and KK 13) at the same time on Tuesday.

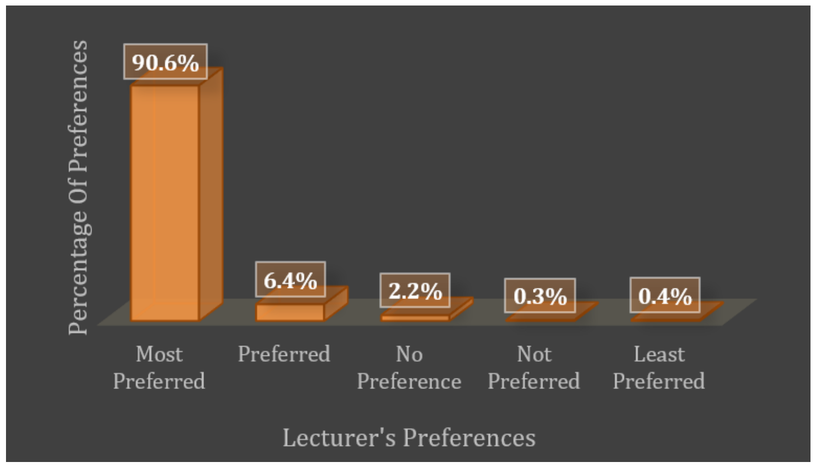

Figure 4. The percentage of the lecturers' preferences for case study 1

Case Study 2

Initially, the model was solved without any adjustments, leading to a solution with a 38.29% gap. The model achieved up to 60% optimality, which demonstrates that it is working effectively as intended. It proves that the model is able to generate a practical timetable based on current demands and preferences. The remaining percentage of optimality could be attained with more sufficient and compatible facilities that are well equipped to handle and support complex data that require longer computational times. In this case, an optimal solution of 10,190 out of a total of 14,475 (if all courses were allocated to the most preferred time slot, with a range of 5 as the maximum) was achieved for the total of lecturers' preferences in the assignment of lectures to time slots and rooms. Figure 5 shows the percentage graph of lecturers' preferences on the allocation of lectures to suitable time slots and rooms for case study 2. It shows that 36.6% and 19.4% of lectures are allocated to the 'most preferred' and 'preferred' time slots and rooms, respectively. The 'no preference', 'not preferred' and 'least preferred' time slots and rooms are respectively 16.5%, 14.4% and 13.2% of all lectures.

As a result, the generated timetable almost satisfies the lecturers' preferences and simultaneously adhere to the model's requirements. Figure 9 and 10 present the examples of timetables generated by the MIP model for a program and a lecturer, respectively. Based on Figure 9, all lectures were allocated to the time slots and rooms without breaching the room capacities due to (1) and (2). The allocation of lectures to unavailable time slots and rooms are avoided with (3), (4) and (13). No lectures are held during the break hours and the labs are assigned to the slots specified in fourth section. The previous DVC's request cannot be fulfilled for all lectures and labs as the resources (time slots and lecturers) are limited. There is a total of 25 time slots for morning sessions per week. However, there are programs that have more than 25 hours of lectures and labs per week. Therefore, it is impossible to allocate all lectures and labs to the morning session only.

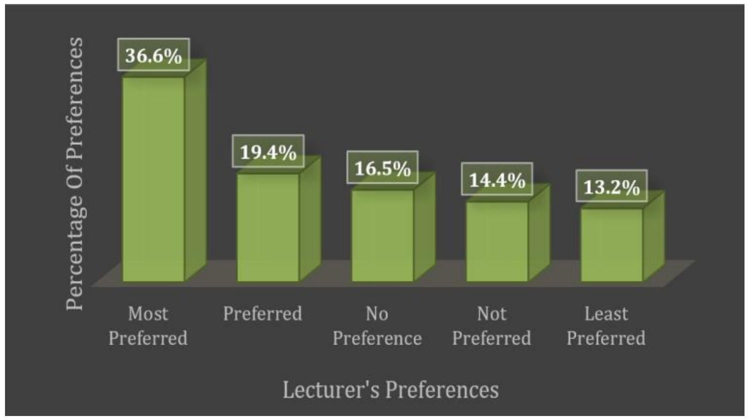

Figure 5. The percentage of the lecturers' preferences for case study 2

Hence, this study introduces adjustments to improve the model. These adjustments ensure a better allocation of lectures to time slots and rooms while still considering lecturers' demands and preferences. To obtain a feasible solution, only program core courses for certain Schools are selected to be assigned on the morning session. The other courses can be assigned to any time slot from 8.00 AM to 7.00 PM. The timetable becomes more compact for both students and lecturers when the teaching period is reduced. As a result, the revised model successfully achieves an optimal solution with 0% gap as shown in Figure 6. As summarized in Figure 6 below, the model consists of 2,106,679 constraints and 4,720,636 variables, of which 4,720,635 are integer variables, indicating a large-scale MILP problem. A total of 40,667,346 nonzero coefficients were involved, reflecting the high level of interaction between variables and constraints in the model. The solver proceeded directly into the MILP phase, performing 478,015 iterations and exploring 3,362 branch-and-bound nodes before convergence.

The model achieved an objective function value of 14,206, with the Best LP Bound equal to the Best Solution, resulting in an optimality gap of 0.00%, which ensures that the obtained solution is both feasible and optimal. The solving time was 2,057,652.86 seconds, with a total computational time of 2,057,708.19 seconds, reflecting the computational complexity associated with the large problem size. During computation, the solver used approximately 6,013.1 MB of memory, demonstrating stable memory utilization for a model of this scale. Overall, these results highlight the practicality of the proposed model and its capability to reach proven optimal solutions despite the large number of variables and constraints involved. Therefore, Figure 6 illustrates the AIMMS progress window after the modifications.

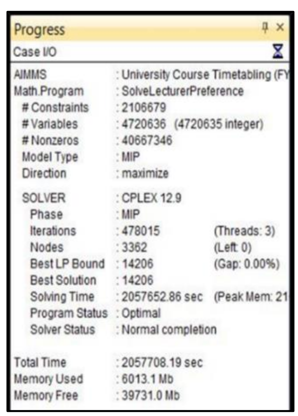

Figure 6. AIMMS progress window after lab period modifications

Furthermore, lecturers and students can use the free time after 1.00 PM for revision or research. Figure 9 shows one of the programs with more than 25 hours of lectures and labs. In this figure, there are no core courses that are assigned after 1.00 PM on any given day. Meanwhile, some of the university core courses, elective courses and labs are assigned after 1.00 PM. Other constraints are also met without any violation. The conflict-free timetable is a result of the (5), (6), and (7). The resources (student groups, rooms and lecturer) are assigned with a lecture one at a time. As can be seen in Figure 10, the lecturer's workload is satisfied with (8). (9) and (11) assign lectures consecutively and on the same day. The assignment of lectures of the same course to the different days is fulfilled with (10). Lectures with student groups of the same program and year of study but have different lecturers are assigned simultaneously by (12). The discussion above shows that all constraints in (1) to (13) are satisfied without any violation even though the relative gap between the 'Best LP Bound' and the 'Best Solution' is 38.29%. To put it another way, a timetable that is 60% close to the optimal solution is generated with all constraints in previous section from (1) to (13) are met. It can be concluded that the relative gap only affects the objective function, i.e. soft constraint of the model.

It causes a large number of lectures not to be assigned to the 'most preferred' and 'preferred' preferences. Assigning all lectures and labs to morning sessions proved challenging due to limited resources like lab rooms and teaching staffs, making it difficult to achieve a 0% relative optimality gap in a short time. A higher-specification and bigger memory size computer could have solved the problem faster, but it was unavailable. To address this, the lab period was modified from the restricted morning slots to 8.00 PM to 7.00 PM daily, giving AIMMS more flexibility in assigning lectures to time slots. The same model can be used to solve the problem, but with some modifications to the lab period. This adjustment enabled the system to achieve a 0% gap, as shown in Figure 6, improving the model's ability to meet lecturer preferences. An optimal solution of 14,206 out of 14,475 was achieved with a 0% gap after modifying the lab period. Figure 9 and 10 provide examples of timetables for a program and a lecturer after the adjustments.

The timetables in Figure 9 and 10 confirm that all constraints in third section of the paper starting from (1) to (13) were met without violations, similar to those in Figure 7 and 8. The previous DVC's request was partially satisfied, with program core courses assigned before 1.00 PM., except for one School. University core courses, electives, and labs were scheduled until 7.00 PM. Despite modifying the lab period, the timetable fulfilled lecturers' preferences while adhering to model constraints. Compared to the 38.29% gap in the previous explanation, the 0% gap resulted in a higher percentage of most preferred allocations, showing that adjusting the lab period improved both feasibility and lecturer satisfaction.

Day	Year	8.00 am	9.00 am	10.00 am	11.00 am	12.00 pm	1.00 pm	2.00 pm	3.00 pm	4.00 pm	5.00 pm	6.00 pm
Sunday	1			CSC3100 (G4) BK5-01	CSC3100 (G4) BK5-01	BBB2000 (G26) BTB4PM			NCC2000 (G1) AU 1-02	NCC2000 (G1) AU 1-02		
	2		STM3201 (G1) KK 3	STM3201 (G1) KK 3					STM3108 (G1) KK 6		FIZ3000 (G2) IBH 13	FIZ3000 (G2) IBH 13
	3							STM3112 (G1) MESB	STM3112 (G1) MESB	STM3303 (G1) Mpro	STM3303 (G1) Mpro	STM3303 (G1) Mpro
	4			STM3115 (G1) KK 4								
Monday	1	BBB2000 (G26) BK5-05	BBB2000 (G26) BK5-05							CSC3100 (G4) MP2	CSC3100 (G4) MP2	CSC3100 (G4) MP2
	2	PAL3000 (G19) IBH11	PAL3000 (G19) IBH11	PAL3000 (G19) IBH 11								STM3201 (G1) KK 1
	3	BBB3103 (G16) BK3-02		STM3113 (G1) BK5-01	STM3113 (G1) BK5-01					STM3112 (G1) MPMasia	STM3112 (G1) MPMasia	STM3112 (G1) MPMasia
	4											
Tuesday	1			BIO3101 (G4) MAFMB BIO3101 (G5) MTASMB	BIO3101 (G4) MAFMB BIO3101 (G5) MTASMB	BIO3101 (G4) MAFMB BIO3101 (G5) MTASMB		BIO3101 (G4) BK 5-07 BIO3101 (G5) KK 13	BIO3101 (G4) BK 5-07 BIO3101 (G5) KK 13			
	2		STM3109 (G1) BK 4-02					STM3108 (G1) MKM	STM3108 (G1) MKM	STM3108 (G1) MKM	STM3108 (G1) IBH 5	STM3108 (G1) IBH 5
	3	STM3303 (G1) KK 12	STM3303 (G1) KK 12		STM3114 (G1) BK 4-01	STM3114 (G1) BK 4-01	Break hour			BBB3103 (G13) BI 2-04	BBB3103 (G13) BI 2-04	
	4										STM3115 (G1) DK 2-01	STM3115 (G1) DK 2-01
Wednesday	1			KIM3100 (G4) KK 3	KIM3100 (G4) KK 3							BIO3101 (G4) KK 15 BIO3101 (G5) IBH 11
	2					FIZ3000 (G2) BK 4-01		STM3102 (G2) KK 3	STM3102 (G2) KK 3			
	3			BBB3103 (G13) BK 3-06	BBB3103 (G12) DK 2-02	BBB3103 (G12) DK 2-02			STM3104 (G2) MAKMAL KOMPUTER PPPPM	STM3104 (G2) MAKMAL KOMPUTER PPPPM	STM3104 (G2) MAKMAL KOMPUTER PPPPM	
	4	STM3107 (G2) MAPM	STM3107 (G2) MAPM	STM3107 (G2) MAPM	STM3107 (G2) MAPM	STM3107 (G2) MAPM			STM3305 (G1) Mpro	STM3305 (G1) Mpro	STM3305 (G1) Mpro	
Thursday	1			KIM3200 (G6) AU 1-02	KIM3200 (G6) AU 1-02			NCC2001 (G1) AU 1-01	NCC2001 (G1) AU 1-01			
	2	STM3109 (G1) MEST	STM3109 (G1) MEST	STM3102 (G2) MMM	STM3102 (G2) MMM	STM3102 (G2) MMM			PAL3000 (G18) BK 3-02	PAL3000 (G18) BK 3-02	PAL3000 (G18) BK 3-02	
	3			STM3104 (G2) KK 3	STM3104 (G2) KK 3	BBB3103 (G12) AU 1-02		STM3112 (G1) MPMasia	STM3112 (G1) MPMasia	STM3112 (G1) MPMasia	BBB3103 (G16) BK 4-01	BBB3103 (G16) BK 4-01
	4			STM3305 (G1) AU 1-01	STM3305 (G1) AU 1-01				STM3107 (G1) AU 1-02	STM3107 (G1) AU 1-02		

Figure 7. Optimized timetable generated by the MIP model in case study 1 for a program

Date	8.00 am	9.00 am	10.00 am	11.00 am	12.00 pm	1.00 pm	2.00 pm	3.00 pm	4.00 pm	5.00 pm	6.00 pm
Sunday			MTK3100 (G1 & G2) MP 2	MTK3100 (G1 & G2) MP 2	MTK3100 (G1 & G2) MP 2		MTK3701 (G2) MESB	MTK3701 (G2) MESB			
Monday											
Tuesday						BREAK HOUR					
Wednesday	MTK3100 (G1) BK 4-01	MTK3100 (G1) BK 4-01									
Thursday							MTK3701 (G2) BK 5-05		MTK3100 (G1) KK 8		

Indicator for the types of lecture:

- Lectures of programme core courses
- Lab works
- Lectures of university core courses

Indicator for the assigned lecture:

- STM3107 (G1) — Course code (Student group)
- MPRO — Room for the assigned lecture

Figure 8. Example of lecturers' timetable for case study 1

Day	Year	8.00 am	9.00 am	10.00 am	11.00 am	12.00 pm	1.00 pm	2.00 pm	3.00 pm	4.00 pm	5.00 pm	6.00 pm
Sunday	1											
	2	FIZ3000 (G2) KK 14	FIZ3000 (G2) KK 14			STM3108 (G1) KK 6				STM3102 (G2) MMM	STM3102 (G2) MMM	STM3102 (G2) MMM
	3			STM3104 (G2) AU 1-02	STM3104 (G2) AU 1-02							
	4	STM3107 (G1) BS	STM3107 (G1) BS	STM3115 (G1) KK 11								
Monday	1	BBB2000 (G26) IBH 13	BBB2000 (G26) IBH 13		KIM3200 (G6) KK 12	KIM3200 (G6) KK 12		NCC2000 (G1) KK 3	NCC2000 (G1) KK 3			
	2	FIZ3000 (G2) KK 19		STM3108 (G1) KK 7	STM3108 (G1) KK 7					STM3108 (G1) MKM	STM3108 (G1) MKM	STM3108 (G1) MKM
	3	BBB3103 (G16) DK 2-02			STM3112 (G1) BK 5-04	STM3112 (G1) BK 5-04						
	4							STM3107 (G2) MAPM	STM3107 (G2) MAPM	STM3107 (G2) MAPM	STM3107 (G2) MAPM	STM3107 (G2) MAPM
Tuesday	1	BIO3101 (G4) BK 5-04 BIO3101 (G5) KK3							BIO3101 (G4) MMIKMB BIO3101 (G5) MAF	BIO3101 (G4) MMIKMB BIO3101 (G5) MAF	BIO3101 (G4) MMIKMB BIO3101 (G5) MAF	
	2	STM3109 (G1) KK 15	STM3109 (G1) KK 15	STM3102 (G2) KK 13	STM3102 (G2) KK 13	STM3201 (G1) KK 11				PAL3000 (G18) BK 5-03	PAL3000 (G18) BK 5-03	PAL3000 (G18) BK 5-03
	3			STM3112 (G1) MPMasia	STM3112 (G1) MPMasia	STM3112 (G1) MPMasia	BREAK HOUR			STM3303 (G1) MPRO	STM3303 (G1) MPRO	STM3303 (G1) MPRO
	4				STM3305 (G1) IBH 6	STM3305 (G1) IBH 6						
Wednesday	1	BBB2000 (G26) IBH 13			CSC3100 (G4) KK 11	CSC3100 (G4) KK 11				CSC3100 (G4) MP 1	CSC3100 (G4) MP 1	CSC3100 (G4) MP 1
	2											
	3	STM3303 (G1) IBH 12	STM3303 (G1) IBH 12	STM3104 (G2) MAKMAL KOMPUTER PPPPM	STM3104 (G2) MAKMAL KOMPUTER PPPPM	STM3104 (G2) MAKMAL KOMPUTER PPPPM			BBB3103 (G13) BK 4 SMS	BBB3103 (G13) BK 4 SMS	BBB3103 (G12) BTA 4 PM	BBB3103 (G12) BTA 4 PM
	4			STM3115 (G1) KK 13	STM3115 (G1) KK 13							
Thursday	1	KIM3100 (G4) DK 2-01	KIM3100 (G4) DK 2-01	BIO3101 (G4) KK 4 BIO3101 (G5) MESB	BIO3101 (G4) KK 4 BIO3101 (G5) MESB						NCC2001 (G1) BK 2-01	NCC2001 (G1) BK 2-01
	2	STM3109 (G1) BK 4-02	STM3201 (G1) KK 14	STM3201 (G1) KK 14						PAL3000 (G19) BI 2-01	PAL3000 (G19) BI 2-01	PAL3000 (G19) BI 2-01
	3	BBB3103 (G13) KK 1	STM3113 (G1) IBH 13	STM3113 (G1) IBH 13	STM3114 (G1) DK 2-03	STM3114 (G1) DK 2-03		STM3112 (G1) MPMasia	STM3112 (G1) MPMasia	STM3112 (G1) MPMasia	BBB3103 (G12) BK 4-06 BBB3103 (G16) KK 7	BBB3103 (G16) KK 7
	4									STM3305 (G1) Mpro	STM3305 (G1) Mpro	STM3305 (G1) Mpro

Figure 9. Optimized timetable generated by the MIP model in case study 2 for a program

Date	8.00 am	9.00 am	10.00 am	11.00 am	12.00 pm	1.00 pm	2.00 pm	3.00 pm	4.00 pm	5.00 pm	6.00 pm
Sunday	MTK3701 (G2) BK 3 SMS										
Monday	MTK3100 (G1) BK 4-01	MTK3100 (G1) BK 4-01									
Tuesday	MTK3100 (G1) BT 5 STM					BREAK HOUR					
Wednesday											
Thursday	MTK3701 (G2) IBH 5	MTK3701 (G2) IBH 5							MTK3100 (G1) MP 3	MTK3100 (G1) MP 3	MTK3100 (G1) MP 3

Figure 10. Example of lecturers' timetable for case study 2

Conclusion

This research investigated the applicability of a general MILP model proposed in [16] to solve the course timetabling problem at an East-Coast Malaysian public university. From the 24 constraints available in the original model, 13 were carefully selected to match the university's operational and academic requirements. Two case studies were conducted: case study 1 addressed standard institutional constraints, while case study 2 incorporated additional requests from lecturers and management. Both case studies were solved using AIMMS with the CPLEX 12.9 solver on a Core i7 computer with 16 GB of RAM. The main contribution of this study lies in the successful adaptation and validation of an existing general MILP model within a real-world university environment, demonstrating its ability to generate conflict-free, compact timetables that satisfy both lecturers' preferences and institutional policies. In contrast to the 2017/2018 timetable, the proposed model eliminated lectures and laboratory sessions scheduled after 7.00 PM, improving timetable practicality and usability for both students and lecturers.

The novelty of this work is reflected in the selective customization of constraints to accommodate institution-specific requirements without reconstructing the original model structure, thereby maintaining the generality of the model while enhancing its applicability in real-world settings. This highlights the flexibility of the model in balancing standard scheduling rules with additional managerial and lecturer-driven demands. From an impact perspective, this study demonstrates that a validated MILP timetabling model can be effectively implemented as a scalable and automated decision-support tool for higher education institutions, reducing manual scheduling effort while improving timetable quality and stakeholder satisfaction. Future research may extend this work by incorporating actual lecturer preferences instead of randomly generated data in AIMMS and integrating lab-specific scheduling constraints to further enhance the flexibility and applicability of the model across diverse university environments.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Acknowledgement

The authors would like to express their sincere gratitude to the Academic Management Centre (AMD) Registration Office of Universiti Malaysia Terengganu for providing valuable insight and support in providing the necessary data.

References

[1] Vangerven, B., Ficker, A. M., Goossens, D. R., Passchyn, W., Spieksma, F. C., & Woeginger, G. J. (2018). Conference scheduling—a personalized approach. *Omega, 81*, 38–47.
[2] Martínez-de-Albéniz, V., & Valdivia, A. (2019). Measuring and exploiting the impact of exhibition scheduling on museum attendance. *Manufacturing & Service Operations Management, 21*(4), 761–779.
[3] Rappos, E., Thiémard, E., Robert, S., & Hêche, J. F. (2022). A mixed-integer programming approach for solving university course timetabling problems. *Journal of Scheduling, 25*(4), 391–404.
[4] Jamaluddin, N. F., & Aizam, N. A. H. (2017). Examination Timetabling Problem: A Case Study*. Indian Journal of Science and Technology, 10*, 31.
[5] Dinh, M. H., Kotary, J., Gouldin, L. P., Yeoh, W., & Fioretto, F. (2024). End-to-End Optimization and Learning of Fair Court Schedules. arXiv preprint arXiv:2410.17415.
[6] Xu, X., Li, C. L., & Xu, Z. (2021). Train timetabling with stop-skipping, passenger flow, and platform choice considerations. Transportation Research Part B: *Methodological, 150*, 52–74.
[7] Qi, J., Chen, T., Zheng, J., & Wang, S. (2023). Port Call Optimization at a Ferry Terminal with Stochastic Servicing Time and Additional Visits. *Journal of Marine Science and Engineering, 11*(9), 1644.
[8] Yan, S. Y., Lu, C. C., & Wu, C. L. (2015). An airline flight scheduling model considering time slot allocation and variable demand. *Journal of the Chinese Institute of Civil and Hydraulic Engineering, 27*(2), 93–104.
[9] Ying, C., & Liebson, M. (2024). An Innovative Approach to Optimize Inbound Delivery Scheduling at Distribution Centers: Application at a Large US Restaurant Chain. *International Journal of Operations Research and Information Systems (IJORIS), 15*(1), 1–21.
[10] Lamiri, M., Xie, X., Dolgui, A., & Grimaud, F. (2008). A stochastic model for operating room planning with elective and emergency demand for surgery. *European Journal of Operational Research, 185*(3), 1026–1037.
[11] Cubillas, J. J., Ramos, M. I., Feito, F. R., & Ureña, T. (2014). An improvement in the appointment scheduling in primary health care centers using data mining. *Journal of medical systems*, *38*(8), 89.

[12] Vakratsas, D., & Naik, P. A. (2007). Essentials of Planning Media Schedules. The SAGE Handbook of Advertising, 333−348.

[13] Long, X., & Zhao, J. (2020). Scheduling problem of movie scenes based on three meta-heuristic algorithms. *IEEE Access, 8*, 59091−59099.

[14] Durán, G., Guajardo, M., & Gutiérrez, F. (2022). Efficient referee assignment in Argentinean professional basketball leagues using operations research methods. *Annals of Operations Research*, 1−19.

[15] Soong, C. J., Ramli, R., & Ibrahim, H. (2011). A hybrid constraint-based programming approach to design a sports tournament scheduling. *European Journal of Scientific Research, 49*(1), 39−48.

[16] Zaulir, Z. M., Aziz, N. L. A., & Aizam, N. A. H. (2022). A general mathematical model for university courses timetabling: Implementation to a public university in Malaysia. *Malaysian Journal of Fundamental and Applied Sciences, 18*(1), 82−94.

[17] Gunawan, A., Ng, K. M., & Poh, K. L. (2006, June). A Mathematical Programming Model for a Timetabling Problem. In CSC (pp. 42−47).

[18] Pereira, V., & Gomes Costa, H. (2016). Linear integer model for the course timetabling problem of a faculty in Rio de Janeiro. *Advances in Operations Research, 2016*(1), 7597062.

[19] Arratia-Martinez, N. M., Maya-Padron, C., & Avila-Torres, P. A. (2021). University course timetabling problem with professor assignment. *Mathematical Problems in Engineering, 2021*(1), 6617177.

[20] Al-Yakoob, S. M., Sherali, H. D., & Al-Jazzaf, M. (2010). A mixed-integer mathematical modeling approach to exam timetabling. *Computational Management Science, 7*, 19−46.

[21] Algethami, H., & Laesanklang, W. (2021). A mathematical model for course timetabling problem with faculty-course assignment constraints. *IEEE Access, 9*, 111666−111682.

[22] Rappos, E., Thiémard, E., Robert, S., & Hêche, J. F. (2022). A mixed-integer programming approach for solving university course timetabling problems. *Journal of Scheduling, 25*(4), 391−404.

[23] Abdellahi, M., & Eledum, H. (2017). The university timetabling problem: modeling and solution using binary integer programming with penalty functions. *International Journal of Applied Mathematics and Statistics, 56*(6), 164−178.

[24] AlHadid, I., Kaabneh, K., Tarawneh, H., & Alhroob, A. (2020). Investigation of simulated annealing components to solve the university course timetabling problem. *Italian Journal of Pure and Applied Mathematics, 44*, 282−290.

[25] Badoni, R. P., Sahoo, J., Srivastava, S., Mann, M., Gupta, D. K., Verma, S., & Karabašević, D. (2023). An exploration and exploitation-based metaheuristic approach for university course timetabling problems. *Axioms, 12*(8), 720.

[26] Arostegui Jr, M. A., Kadipasaoglu, S. N., & Khumawala, B. M. (2006). An empirical comparison of tabu search, simulated annealing, and genetic algorithms for facilities location problems. *International Journal of Production Economics, 103*(2), 742−754.

[27] Chen, M., Tang, X., Song, T., Wu, C., Liu, S., & Peng, X. (2020). A Tabu search algorithm with controlled randomization for constructing feasible university course timetables. *Computers & Operations Research, 123*, 105007.

[28] Fausto, F., Reyna-Orta, A., Cuevas, E., Andrade, Á. G., & Perez-Cisneros, M. (2020). From ants to whales: metaheuristics for all tastes. *Artificial Intelligence Review, 53*, 753−810.

[29] Toaza, B., & Esztergár-Kiss, D. (2023). A review of metaheuristic algorithms for solving TSP-based scheduling optimization problems. *Applied Soft Computing, 148*, 110908.b

[30] Benli, O. S., & Botsali, A. R. (2004). An optimization-based decision support system for a university timetabling problem: An integrated constraint and binary integer programming approach. *Computers and Industrial Engineering*, 1−29.

[31] Aizam, N. A., & Liong, C. Y. (2013). Mathematical modelling of university timetabling: a mathematical programming approach. *International Journal of Applied Mathematics and Statistics, 37*(7), 110−122.

[32] Aizam, N. A. H., & Caccetta, L. (2014). Computational models for timetabling problem. *Numerical Algebra, Control & Optimization, 4*(3), 269.

[33] Aizam, N. A. H., Aziz, N. L. A., & Zaulir, M. Z. (2019). New general university course timetabling model towards real problems: a comparison. *Journal of Advanced Research in Dynamical and Control Systems, 11*(12-Special Issue), 244−257.