Hindawi
Complexity
Volume 2021, Article ID 9940866, 12 pages
https://doi.org/10.1155/2021/9940866

Research Article

Developing a Model for the University Course Timetabling Problem: A Case Study

Mozhgan Mokhtari,[1] Majid Vaziri Sarashk ,[1] Milad Asadpour ,[2,3] Nadia Saeidi ,[1] and Omid Boyer [1]

[1]*Department of Industrial Engineering, Najafabad Branch, Islamic Azad University, Najafabad, Iran*
[2]*Department of Information Systems and Operations Management, Business School, The University of Auckland, Auckland, New Zealand*
[3]*Young Researchers and Elite Club, Najafabad Branch, Islamic Azad University, Najafabad, Iran*

Correspondence should be addressed to Omid Boyer; omidboyer@gmail.com

Received 5 March 2021; Revised 15 November 2021; Accepted 23 November 2021; Published 22 December 2021

Academic Editor: Baogui Xin

Over recent years, timetable programming in academic settings has become particularly challenging due to such factors as the growing number of students, the variety of lectures, the inadequacy of educational facilities in some areas, and the incorporation of teachers and students' preferences into the schedule. Many researchers, therefore, have been formulating the problem of timetabling lectures using different methods. In this research, a multiobjective mixed-integer programming model was developed to provide a timetable for the postgraduate courses at the Industrial Engineering Department of Islamic Azad University, Najafabad Branch (IAUN). The proposed model minimized the violation of the lecturers and educational priorities, the student travel time between classes, and the classes' surplus capacity. To convert the multiobjective model into a single one, the ε-constraint method was adopted, and the model's accuracy and feasibility were examined through a real example solved by the CPLEX solver of GAMS software. The results approved the efficiency of this model in preparing a timetable for university lectures.

1. Introduction

The problems associated with timetabling persist in various sectors such as industry, transportation, and sport. However, timetabling continues to be a complicated task in academia. Educational centers widely differ in terms of the available space and the number of courses, teachers, students, and time slots, making the adoption of a universal schedule virtually impossible [1, 2]. Another challenge facing universities in this regard is creating a timetable that meets staff and students' demands and the existing requirements [3]. To deal with this complexity, many educational institutions apply heuristic methods. Mathematical models, such as integer programming (IP), have recently been performed to solve these problems [4]. The IP problems were developed into the mixed-integer programming model by adding realistic assumptions that make the University Course Timetabling Problems (UCTP) more complicated.

These assumptions combine different decisions such as lecturers and students' preferences, free time, class overlapping, students flow, and the maximum capacity of rooms. The scheduling of classes has a significant effect on students' movements, and this means universities with many students attending courses in a single building are highly likely to encounter the problem of congestion in the aisles [5]. In this respect, the objective functions of timetabling problem in the most relevant studies have focused on the maximization of preferences, the minimization of unregistered courses, time interference, free hours between lectures, and the number of students who fail to apply for courses [2].

This research was motivated by the UCTP at the Industrial Engineering Department (IED) of IAUN. The department has nine classrooms located on the second floor of the Engineering Faculty. There are around 400 postgraduate and 300 undergraduate students majoring in industrial engineering. The department has two chairpersons for post- and undergraduate groups, who provide timetabling programs separately, though they share information about the availability of classrooms and lecturers in each time slot. The postgraduate chair finds it challenging to solve UCTP with three study areas (project management, system optimization, and quality and productivity) because most postgraduate students prefer to take courses on two last days of the week (Wednesday and Thursday Iran). This decision generally results in congestion in the IED.

One possible solution would be to spread courses over the day and week. However, this often leads to free periods in the schedule, thereby causing dissatisfaction among students and teachers. The limited capacity of the classrooms also affects programming despite the chairpersons' attempts to develop the timetable manually by trial and error every semester. Figure 1 illustrates the floor layout of the department.

This study developed a timetabling model to meet the requirements of IED, with three objective functions: minimizing the violation of the teachers and educational priorities, minimizing the travel time for students, and minimizing classrooms' surplus capacity. The model aimed to help the chairperson consider the educational preferences, manage time, and allocate classes more effectively by adding the constraints caused by the department's conditions, including the limited capacity of classrooms and restrictions on the number of groups offered for each lecture.

In summary, the contributions of this study are threefold:

(i) The study applies the mixed-integer programming model to formulate the realistic feature of the timetabling problem, such as the effect of timetabling on the student flow.
(ii) The model has three objectives to satisfy different stakeholders: students, teachers, and the university.
(iii) The feasibility and efficiency of the model have been checked by using the random number and real data.

The rest of the current paper is organized as follows. Section 2 represents a review of the relevant previous studies. In Section 3, the problem will be described, and the proposed model will be formulated. Section 4 will discuss how the model is validated and solved for the random numbers and the case study, followed by an analysis of the results. Finally, the most significant results, along with suggestions for future studies, are discussed in Section 5.

2. Literature Review

Due to the nature of required decisions in scheduling problems such as UCTP, the formulation of this type of mathematical modeling problem often utilizes integer variables. In the following, a comprehensive review of the previous research in the University Course Timetabling Problem is presented.

Formulated objective functions within the literature of UCTP could be summarized in some particular categories, and therefore, we have categorized our reviewed papers based on different objective functions. However, what is challenging among UCTPs is that the problem is completely different from one university to others regarding different constraints and resources. Most of the earlier studies have aimed to provide a university timetable with the minimum cost. For example, Daskalaki et al. [6] developed an IP model of a timetabling problem for the Department of Electrical and Computer Engineering at the University of Patras. The objective function was to minimize the cost to demonstrate the model's capabilities to address the university's timetabling problem, using the MIP solver of CPLEX software. Further, Daskalaki and Birbas [7] proposed a solution approach for the IP model of a university timetabling problem. The model was a cost minimization problem, and the solution was based on a relaxation procedure of certain constraints. These were the constraints that ensured the consecutiveness of the multiperiod sessions assigned to a given course. The applicability of the adopted procedure was investigated by applying real data from a case study. Thepphakorn and Pongcharoen [8] propose a Cuckoo Search-based algorithm for the UCTP of Faculty of Engineering, Naresuan University, with the aim of minimizing the total university operating costs.

Providing a university timetable with particular attention to the preferences of students, teachers, or administrators has been another motivation for the formulation of a UCTP. Ozdemir and Gasimov [3] presented an IP model for the UCTP. The model's objectives were minimizing the average preference level per hour, the average preference level of all instructors, the administration's total preference level, and the total deviation from the upper load limits of the recent instructors. The objectives' weights were calculated using the AHP method, and then the problem was solved using real data from a case study. Gunawan et al. [9] provided a weekly timetable model based on the teachers' preferences. The model's objective function was to maximize the teachers' total preference value of the assignment of courses, days, and time slots. An initial solution was obtained based on the Lagrangian relaxation method; however, this solution was further improved by a Simulated Annealing algorithm. The applicability of the proposed model was examined using real data from a university in Indonesia. Méndez-Díaz et al. [10] considered a timetabling problem arising from a real-world application in a private university in Buenos Aires, *Argentina*. They proposed an integer programming model, which maximizes the global weighted preference (a combination of students' preferences and rank performances) while assigning lessons to the time slots. Afterward, a heuristic algorithm was deployed to solve the model. Jamili et al. [11] proposed a multiobjective integer mathematical model for UCTP. The objectives were to maximize instructors' preferences and the time spent by instructors for teaching, leading to an increase in the available time for research and addressing research affairs of students. The model was coded in GAMS software and solved by the augmented ε-constraint method in the

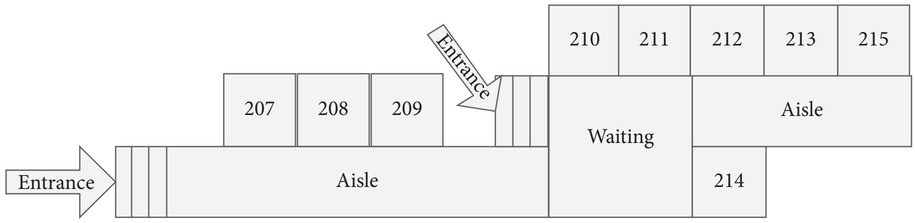

Figure 1: The floor layout of the Industrial Engineering Department of IAUN.

Industrial Engineering and Systems Faculty of a public university in Tehran, Iran. Yasari et al. [12] investigated a UCTP where the registration was implemented in two steps: preregistration and drop/add phases. They developed a two-stage stochastic programming model for this situation, which provided a feasible timetable, maximizing the expected value of satisfaction level among all teachers and students. The performance of the adopted approach was analyzed using random numbers. In the UCTP of Chávez-Bosquez et al. [13], the purpose is to maximize Professors' preferences, and the paper applies a hybrid Tabu Search algorithm to solve the problem. Algethami and Laesanklang [14] propose a multiobjective model for UCTP of Taif University to maximize events assignments and faculty-members preferences satisfaction and minimize student learning days and unassigned events. The model has been solved within IBM ILOG CPLEX software. Colajanni and Daniele [15] formulate an ILP model for UCTP of the University of Catania to maximize teachers' preferences and minimize the daily movements of students among classrooms. The model has been solved within IBM ILOG CPLEX software.

Another group of papers has focused on the minimization of timetable violations. For example, MirHassani [16] formulated an IP model for UCTP to minimize the soft constraint infeasibility and penalize the redundant and nonpreferred times. Azadeh et al. [17] proposed an IP model, intending to minimize the collegians' interferences. The problem was solved by GAMS using random data. The timetabling problem of Vermuyten et al. [5] stated that a timetable should be scheduled based on the teaching preferences of teachers. However, teachers' preferences can be violated by scheduling a lecture at a timeslot when a teacher does not prefer to teach this lecture. The objective functions of the model were the minimization of the violation of teachers' educational preferences and the minimax of the travel time for each series of students. The model was applied to the Faculty of Economics and Business dataset of the KU Leuven Campus Brussels and was solved by using the CPLEX software. Phillips et al. [18] presented an IP model to eliminate violations of an existing timetable while minimizing the disruption to the remainder of the timetable. Real data of the University of Auckland was used to solve the model deploying the Gurobi solver. Bagger et al. [19] formulated an IP model to provide a timetable minimizing a weighted sum of the violations of the soft constraints. This model was validated by solving several real examples from the literature applying the Gurobi solver. In another study, Bagger et al. [20] employed a Dantzig–Wolfe reformulation to solve the model by Column Generation. The objective was to find a feasible timetable while minimizing the soft constraints. In addition, the objective of UCTP studies of Goh et al. [21], Song et al. [22], and Gozali et al. [23] is to minimize violations of soft constraints. In Goh et al. [21], the solution approach is a combined algorithm based on Tabu Search and Simulated Annealing. Song et al. [22] apply a competition-guided multineighborhood local search algorithm to solve their model, while Gozali et al. [23] propose a localized island model genetic algorithm to solve the model. However, in Rezaeipanah et al. [24], the paper maximizes the number of satisfied soft constraints instead of minimizing soft constraints violations. To solve their UCTP, they have presented an Improved Parallel Genetic Algorithm and Local Search.

Meanwhile, in some previous studies, there are capacity limitations on classrooms. In other words, the problem is to schedule courses considering the optimal usage of classrooms. For example, Kaviani et al. [25] presented an IP model for the UCTP with four objectives: minimizing the teacher's idle time, minimizing the surplus capacity of rooms, maximizing the use of the available classrooms, and maximizing teachers' use of the class. The model was solved within LINGO software and using randomly generated data. Phillips et al. [4] presented an IP model for the University of Auckland, which found an efficient partial room assignment and made the best possible use of the available rooms. The objective of the model was the maximization of the number of patterns assigned to the classrooms. Tavakoli et al. [26] formulated a model for the UCTP, where the model considered six objectives: the maximal use of classrooms, lecturers during their attendance at university, the use of a classroom by a lecturer, the assignment of specialized courses to the faculty members, and the quality of the assigned lecturers to courses and minimization of the surplus capacity of rooms. Lemos et al. [27] discussed the problem of room usage optimization by proposing a two-stage IP model. In the first stage, lectures were allocated to the classrooms for the maximum use of classrooms, whereas the second stage minimized the number of transitions from free to occupied (and vice versa) for each classroom. The model was solved using a greedy algorithm and applying real data from Institute Superior Técnico, the Engineering School from Universidade de Lisboa.

Table 1 compares selected papers with the proposed model of this research.

As discussed, the bulk of the recent research has utilized mathematical models with different objective functions for UCPT problems. Nonetheless, most of these models have been formulated as integer programming with binary decision variables. This means the mixed-integer programming model has been paid less attention in the literature, though the continuous variables of MIP models can help consider more realistic assumptions. In this research, a multiobjective mixed-integer programming model was developed for the UCTP, drawing on the model of Vermuyten et al. [5]. It should also be noted that this study considered some particular parameters and constraints in the model to provide a timetable for the IED. These positive points of the model are considering classroom capacity, assignment of teachers based on the expertise, and the number of groups offered for each lecture given the IED's desired circumstances.

3. Materials and Methods

There are several points in the timetabling problem of the IED as follows:

(i) The industrial engineering curriculum entails including a specific number of courses in each semester, which should be scheduled in an organized way.

(ii) The knowledge and experience of a teacher have an effect on the priority of teachers for a lecture.

(iii) Teachers can have a particular number of lectures based on the educational rules in IAUN.

(iv) The congestion and movement of students in aisles disturb other classes. Free hours in the timetable compound this issue. So, the minimization of student flow and also removing free time can alleviate this problem.

(v) Each classroom has different facilities such as a computer and data show. Some classes, therefore, are more suitable for some lectures.

(vi) All model parameters are deterministic, and the problem was scheduled based on the conditions and preferences of the case study.

3.1. Notation. In this section, the required notation for the model formulation is presented in Tables 2–4.

3.2. Model Formulation. A multiobjective mixed-integer programming model with three objective functions is developed to address the IED requirements regarding the mentioned features. The objective functions and the required constraints are explained in this section.

Equations (1) to (3) are objective functions of the proposed MIP model. The first objective function minimizes the violation of the lecturers and educational priorities. The second objective function minimizes the student travel time, and the last objective function minimizes the surplus capacity of classrooms.

$$\text{Min } Z_1 = \sum_{l\epsilon L}\sum_{t\epsilon T}\sum_{c\epsilon C}\sum_{e\epsilon E} c_{\text{lte}} X_{\text{ltce}}. \tag{1}$$

$$\text{Min } Z_2 = \sum_{c\epsilon C}\sum_{d\epsilon\, D}\sum_{t\epsilon T} \text{Tarc}_{\text{cdt}}. \tag{2}$$

$$\text{Min } Z_3 = \sum_{c\epsilon C} cap_c - \sum_{l\epsilon L}\sum_{t\epsilon T}\sum_{c\epsilon C}\sum_{e\epsilon E} \frac{X_{\text{ltce}}\text{sl}_{\text{sl}} n_s}{\text{cap}_c}. \tag{3}$$

Equation (4) states that only one lecture must be presented in a particular time slot and class by a teacher.

$$\sum_{t\epsilon T}\sum_{c\epsilon C}\sum_{e\epsilon E} X_{\text{ltce}}\text{lr}_{\text{le}} = 1 \quad \forall\, l. \tag{4}$$

Equation (5) assures each teacher to conduct only one lecture in a certain time slot and a class.

$$\sum_{l\epsilon L}\sum_{c\epsilon C} X_{\text{ltce}}\text{lr}_{\text{le}} \leq 1 \quad \forall\, t, e. \tag{5}$$

Equation (6) indicates that only one lecture can be held in a classroom in a time slot.

$$\sum_{l\epsilon L}\sum_{e\epsilon E} X_{\text{ltce}} \leq 1 \quad \forall\, t, c. \tag{6}$$

Equation (7) states that a group of students can participate solely in one lecture in a particular time slot.

$$\sum_{c\epsilon C}\sum_{e\epsilon E} X_{\text{ltce}}\text{sl}_{\text{sl}} \leq 1 \quad \forall t, s, l. \tag{7}$$

Equation (8) states that teachers cannot present more than a specific number of lectures (Δ) in one day.

$$\sum_{l\epsilon L}\sum_{t\epsilon T}\sum_{c\epsilon C} X_{\text{ltce}} \leq \Delta_e \quad \forall\, e. \tag{8}$$

Equation (9) demonstrates the relation between X_{ltcr} and U_{tsp}. In this equation, the percentage of students on a path depends on the flow of students between two classes in two consecutive time slots.

$$\begin{gathered} U_{\text{tsp}} \geq a_{\text{lm}}\left(\text{pa}_{\text{cp}} X_{\text{ltce}} + \text{pa}_{\text{dp}} X_{m(t+1)\text{de}} - 1\right) \quad \forall\, (t\epsilon\{1,..,|T-1|\}, p, e, \\ (c, d\epsilon C),\ (l, m\epsilon L, l \neq m). \end{gathered} \tag{9}$$

Table 1: Comparison of selected papers with the proposed approach.

Reference number	Type of formulation		Objective function(s)									Solution approach	Case study
			Max			Min							
	Integer programming	Mixed-integer programming	Assigning courses	Classroom usage	Preferences of instructor	Classroom surplus capacity	Travel time	Movements between classrooms	Preferences violation	Timetable disruption	Teaching time		
[4]	*			*								Gurobi IP solver	*
[5]	*	*					*		*			CPLEX software	*
[10]	*				*						*	Augmented ε -constraint method	
[14]	*			*						*		Gurobi IP solver	*
[18]	*		*	*		*						LINGO software	
[19]	*			*				*				Greedy algorithm	*
Present research		*				*	*		*			**Epsilon-constraint method**	*

Table 2: Sets of the model.

Sets	Description
L, M	Set of lectures
E	Set of teachers
S	Set of students groups based on areas of study
C, D	Set of all classes
P	Set of all paths in the building
T	Set of available time slots

Table 3: Parameters of the model.

Parameters	Description
c_{lte}	Penalty cost when lecture l is scheduled for teacher e in time slot t
n_s	The number of students in group s
$f_{\max}$	Maximum allowed student flow
a_{lm}	Percentage of students moving between lectures l and m
pa_{cp}	If classroom c is on the path, p equals 1 and 0 otherwise
Δ_e	Teacher e can present a certain number of lectures
area_{cd}	Area between two classes c and d
dis_{cd}	Distance between two classes c and d
G_l	The maximum number of lectures l in a semester
$\nu_{\max}$	Maximum walking speed
α	Scale parameter
lr_{le}	It equals 1 if lecture l is taught by teacher e and 0 otherwise
sl_{sl}	It equals 1 if lecture l is suggested for group s and 0 otherwise

Table 4: Decision variables of the model.

Decision variables	Description
X_{ltce}	It equals 1 if lecture l is scheduled in time slot t by teacher e in classroom c and 0 otherwise
F_{cdt}	Total number of students who move between classes c and d in period t
U_{tsp}	Percentage of group s students has been moved by using path p in period t
Tarc_{cdt}	The travel time between classrooms c and d in period t

Equation (10) states the total student flow between classes c and d at time t.

$$F_{\text{cdt}} = \sum_{p\epsilon P}\sum_{s\epsilon S} n_s U_{\text{tsp}} \quad \forall t,\ (c, d\epsilon C). \tag{10}$$

Equation (11) ensures that this flow should not be greater than the maximum allowed flow.

$$F_{\text{cdt}} \le f_{\max} \quad \forall t,\ (c, d\varepsilon\ C). \tag{11}$$

Equation (12) determines the travel time from class c to class d at time slot t, which varies depending on the total number of students, the distance of two classrooms, the area of the aisle, and the maximum speed of movement.

$$\text{Tarc}_{\text{cdt}} = \left[\left(\frac{\text{dis}_{\text{cd}}}{\alpha}\right)\left(\frac{F_{\text{cdt}}}{\text{area}_{\text{cd}}}\right)\right] + \frac{\text{dis}_{\text{cd}}}{\nu_{\max}} \quad \forall t,\ (c, d\varepsilon\ C). \tag{12}$$

Equation (13) states that the number of lectures in a semester cannot be more than the predetermined number specified by the department's chair.

$$\sum_{t\varepsilon T}\sum_{c\varepsilon C}\sum_{e\varepsilon E} X_{\text{ltce}} \le G_l \quad \forall l. \tag{13}$$

Finally, the decision variables' domains are defined by equations (14)–(16).

$$X_{\text{ltce}}\varepsilon\{0, 1\}. \tag{14}$$

$$U_{\text{tsp}}\varepsilon[0, 1]. \tag{15}$$

$$F_{\text{cdt}} \ge 0, \text{Tarc}_{\text{cdt}} \ge 0. \tag{16}$$

3.3. Solution Approach. Multiobjective problems include more than one objective function, particularly conflicting objectives. The multiobjective mathematical model area has been widely employed for decades because most real-world problems have various objectives. Many methods and approaches have been developed to tackle multiobjective problems [27].

The ε-constraint method is one of the most efficient methods which can be applied. Accordingly, one of the objective functions is optimized, and other objectives are added to the constraints. The steps of this method are as follows:

(1) The payoff table is calculated for all objectives

(2) One objective is selected to be optimized, and other objectives are considered as constraints

(3) The ε values account for the constrained objectives function

(4) Efficient solutions (Pareto front) to the problem are achieved by the main objective optimization and the epsilon's parametric variation

(5) The Pareto solutions are reported [28, 29]

Figure 2 represents the steps of the ε-constraint method.

In the present study, the ε-constraint method has been deployed to solve the proposed model.

4. Experiments

In order to validate the proposed model, a random problem was first generated and solved using the CPLEX solver of GAMS software on a laptop with Intel Core i5, 2.5 GHz, and 4 GB of RAM.

4.1. Validating Model by Random Data. This example considered eight lectures in three days, four classrooms, four lecturers, and six paths between classrooms. There were four time slots per day, which means there were a total

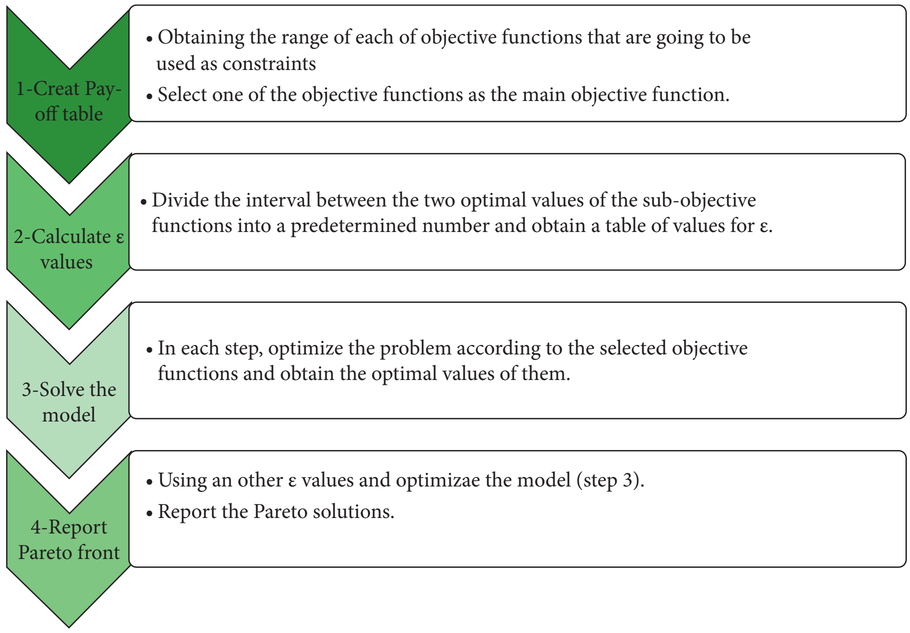

Figure 2: The steps of the ε-constraint method.

of 12 time slots. The floor layout of the classroom's location and paths is shown in Figure 3, and the most important input data of the random problem are presented in Tables 5–8.

Table 5 shows the capacity of each classroom (cap_c). The number of students in each group (n_s) has been presented in Table 6.

Table 7 includes the lectures offered for each group of students (sl_{sl}) and the lectures taught by each teacher (lr_{lr}).

Table 8 shows the paths that connect the classrooms based on Figure 3.

The outputs of the model solved by GAMS software in Table 9 demonstrate the efficiency of the model to create a timetable.

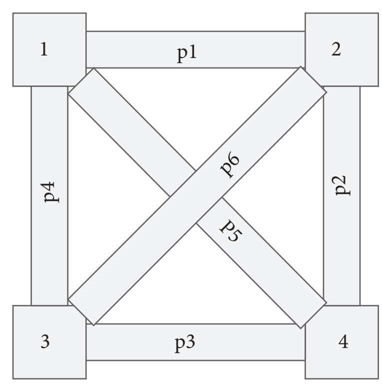

Figure 3: Location of classrooms and paths.

Table 5: Capacity of each classroom.

Classroom code	Capacity
1	50
2	50
3	40
4	40

Table 6: The number of students in each group.

Group code	Number of students
1	15
2	20
3	30

4.2. Applied Model by Real Data. This section will discuss a real example of the IED at IAUN for postgraduate students for the first semester of 2019–2020. It should be mentioned that the IED is located in the Engineering Faculty and offers three different areas of study for postgraduate, including project management, system optimization, and quality and productivity.

This real example considers 14 lectures, eight teachers (denoted by E1 to E8), two days per week, nine classrooms, four time slots on Wednesday, and two time slots on Thursday. The limitation of time slots is due to the availability of the classrooms and preventing overlap with the undergraduate classes. The input data for this instance are presented in Tables 10–16.

Table 10 represents available postgraduate lectures of the IED and teachers' areas of interest.

Table 11 shows the capacity of each classroom (cap_c). For instance, the capacity of classroom number 207 is 30 students, and its code is 1.

The number of students in each group (n_s) is presented in Table 12. For example, the number of students in the project management group (program) with group code S1 is 25.

Table 7: Lectures offered for each group of students that each teacher teaches them.

Students group	Lecture							
	L1	L2	L3	L4	L5	L6	L7	L8
S1	1	0	0	1	1	0	0	1
S2	0	1	0	1	0	1	1	0
S3	1	0	1	0	1	1	0	1
Teachers	Lecture							
E1	1	1	0	0	1	0	1	0
E2	1	1	1	1	0	1	1	1
E3	0	1	0	1	1	1	0	1
E4	0	0	1	1	0	1	1	1

Table 8: All paths that connect classrooms.

Path	Classroom															
	C1 C1	C1 C2	C1 C3	C1 C4	C2 C1	C2 C2	C2 C3	C2 C4	C3 C1	C3 C2	C3 C3	C3 C4	C4 C1	C4 C2	C4 C3	C4 C4
P1	0	1	0	1	1	0	1	0	0	1	0	0	1	0	0	0
P2	0	0	1	0	0	0	1	0	1	1	0	1	0	0	1	0
P3	0	0	1	0	0	0	0	1	1	0	0	0	0	1	0	0
P4	0	0	1	1	0	0	0	1	1	0	0	0	1	1	0	0
P5	0	0	1	0	0	0	0	1	1	0	0	1	0	1	1	0
P6	0	1	0	1	1	0	1	0	0	1	0	1	0	0	1	0

Table 9: Timetable of the random example.

Day	Time			
	8 am–10:30 am	10:30 am–13 pm	13 pm–15:30 pm	15:30 pm–16 pm
Tuesday	Lecture 3, classroom 3, and teacher 2	Lecture 7, classroom 4, and teacher 4	—	—
Wednesday	—	Lecture 1, classroom 2, and teacher 1	Lecture 8, classroom 1, and teacher 4	Lecture 4, classroom 2, and teacher 3
Thursday	Lecture 5, classroom 1, and teacher 1	Lecture 6, classroom 1, and teacher 2	Lecture 2, classroom 4, and teacher 2	—

Table 10: Available postgraduate lectures.

Name of lecture	Code of lecture	Code of teachers
Project management information systems	L1	E1 and E2
Project planning and scheduling	L2	E2 and E8
Standards of project management	L3	E2, E5, and E8
Procurement of project	L4	E3 and E8
Design of experiments	L5	E4 and E6
Quality and productivity	L6	E3 and E7
Excellence and quality	L7	E3 and E7
Total quality management	L8	E3 and E7
Integer programming	L9	E5, E6, and E8
Nonlinear programming	L10	E5, E6, and E8
Queuing theory	L11	E4 and E6
Reliability theory	L12	E4
Decision-making methods	L13	E3 and E5
Financial management	L14	E1

Table 13 demonstrates the lectures offered for each group of students (sl_{sl}). As can be seen, if lecture l is offered for a group (program) s, the value is 1 and 0 otherwise.

The area ($area_{cd}$) between the two classrooms is shown in Table 14. For example, the area between classrooms no. 1 and no. 2 is 24 m^2.

Table 11: Capacity of each classroom.

Classroom number	Classroom code	Capacity
207	1	30
208	2	30
209	3	30
210	4	70
211	5	30
212	6	30
213	7	30
214	8	50
215	9	50

Table 12: The number of students in each group.

Group (program) name	Group code	Number of students
Project management	S1	25
System optimization	S2	25
Quality and productivity	S3	25

Table 13: Suitable lectures for each group of students.

Students group	Lectures													
	L1	L2	L3	L4	L5	L6	L7	L8	L9	L10	L11	L12	L13	L14
S1	1	1	1	1									1	1
S2					1	1	1	1				1	1	1
S3				1	1				1	1	1	1	1	1

Table 14: Area between two classrooms.

Area	Classroom								
	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	0	24	96	102	120	126	144	150	168
C2	24	0	24	30	48	54	72	78	96
C3	96	24	0	6	24	30	48	54	72
C4	102	30	6	0	24	30	48	54	72
C5	120	48	24	24	0	6	24	30	48
C6	126	54	30	30	6	0	24	30	48
C7	144	72	48	48	24	24	0	6	24
C8	150	78	54	54	30	30	6	0	24
C9	168	96	72	72	48	48	24	24	0

The distance (dis_{cd}) between two classrooms is illustrated in Table 15. For example, the distance between classrooms no. 1 and no. 2 is 4 m.

By considering the real data of the IED, (G_l) is equal to 1, the number of lessons presented by one professor is four (Δ), the maximum speed is assumed to be 10 ($\nu_{\max}$), and the scaling parameter is 20.

Then, three objectives are optimized separately to investigate the feasibility and the efficiency of the proposed model for the timetabling problem. Table 16 shows each objective function's values and the allocation of a lecture to a teacher, classroom, and time slot.

As can be seen from Table 16, lecture one is taught by teacher one in time slot six in classroom nine when the first objective has been optimized.

The proposed model is a multiobjective model, so the ε-constraint method is used to convert the model to a single objective model. For this reason, three objective functions are optimized to calculate the payoff table (Table 17).

Then, the first objective was optimized, and the rest were placed in the constraints by six different values of ε to show conflicting objectives function and reach the Pareto solutions. Table 18 shows Pareto solutions based on different six ε values.

It is evident from Figure 4 and Table 18 that the classroom's surplus capacity is increasing to cover the educational priorities as the first objective function, which means the model has been decided to use more classrooms to increase educational priorities.

Table 15: Distance between two classrooms.

Distance	Classroom								
	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	0	4	16	17	20	21	24	25	28
C2	4	0	4	5	8	9	12	13	16
C3	16	4	0	1	4	5	8	9	12
C4	17	5	1	0	4	5	8	9	12
C5	20	8	4	4	0	1	4	5	8
C6	21	9	5	5	1	0	4	5	8
C7	24	12	8	8	4	4	0	1	4
C8	25	13	9	9	5	5	1	0	4
C9	28	16	12	12	8	8	4	4	0

Table 16: Outcomes of the optimized model.

Objective function	Value	Allocating lectures to teacher, class, and time slot					
		L1.T6.C9.E1	L2.T2.C9.E2	L3.T5.C9.E8	L4.T1.C6.E8	L5.T6.C5.E4	L6.T3.C8.E6
$\mathbf{z}_1^*$	15	L7.T6.C6.E7	L8.T3.C6.E3	L9.T5.C8.E6	L10.T2.C6.E5	L11.T6.C2.E6	L12.T5.C6.E4
		L13.T5.C6.E4	L14.T5.C6.E4				
		L1.T1.C1.E1	L2.T1.C2.E2	L3.T1.C3.E8	L4.T1.C4.E3	L5.T1.C5.E4	L6.T1.C6.E7
$\mathbf{z}_2^*$	456	L7.T2.C1.E7	L8.T2.C2.E3	L9.T1.C7.E5	L10.T1.C8.E6	L11.T2.C3.E6	L12.T2.C4.E4
		L13.T2.C5.E5	L14.T2.C6.E1				
		L1.T6.C7.E1	L2.T3.C7.E2	L3.T4.C5.E1	L4.T2.C1.E3	L5.T5.C1.E4	L6.T5.C7.E3
$\mathbf{z}_3^*$	315	L7.T2.C2.E7	L8.T4.C6.E3	L9.T6.C5.E8	L10.T4.C2.E6	L11.T3.C6.E6	L12.T4.C3.E4
		L13.T2.C6.E5	L14.T5.C3.E1				

Table 17: Payoff table for three objective functions.

Objective function	Z1	Z2	Z3
$\mathbf{z}_1^*$	15	63	146
$\mathbf{z}_2^*$	501.6	456	726.15
$\mathbf{z}_3^*$	366.66	336.268	315

Table 18: Pareto solutions of objective functions. Additionally, Figure 4 draws a comparison of the values of objective functions Z1 and Z3 as an example to prove the conflict between the two objectives.

Objective function	ε0	ε1	ε2	ε3	ε4	ε5
Z1	15	35	45	65	85	95
Z2	546	516	531	531.3	501	456.15
Z3	336.2	330	327.7	322.5	317.5	315

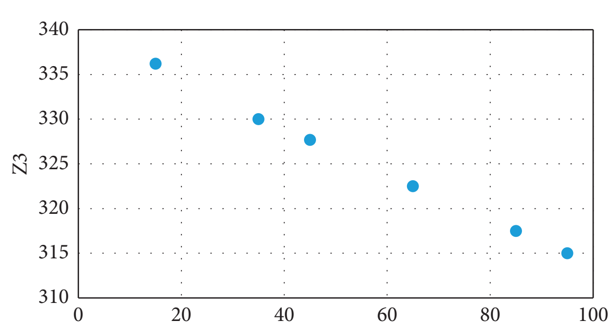

Figure 4: Pareto solutions of Z_1 and Z_3.

Ultimately, Table 19 compares the conventional university lecture timetable systems and the outcomes of the mathematical model for the Department of Industrial Engineering of IAUN. The results indicate the amount of educational priorities objective in the conventional method stands at 17, whereas by means of the mathematical model, this figure arrives at 15, which indicates an improvement of approximately 13% in the quality. Another significant

Table 19: The proposed timetable for the case study.

Lecture	The conventional method Day/time slots/classroom/teacher	The mathematical method Day/time slots/classroom/teacher
Total penalty	17	15
Project planning and scheduling	Wednesday/8 am–10:30 am/209/E8	Wednesday/10:30 am–13 pm/215/E2
Standards of project management	Wednesday/10:30 am–13 pm/208/E2	Thursday/8 am–10:30 am/215/E8
Procurement of project	Wednesday/13 pm–15:30 pm/214/E3	Wednesday/8 am–10:30 am/212/E8
Design of experiments	Thursday/8 am–10:30 am/213/E4	Thursday/10:30 am–13 pm/211/E4
Quality and productivity	Thursday/10:30 am–13 pm/214/E3	Thursday/10:30 am–13 pm/210/E3
Excellence and quality	Thursday/10:30 am–13 pm/211/E7	Thursday10:30 am–13 pm/212/E7
Total quality management	Thursday/8 am–10:30 am/211/E7	Wednesday/13 pm–15:30 pm/212/E3
Integer programming	Wednesday/8 am–10:30 am/207/E6	Thursday/8 am–10:30 am/214/E6
Nonlinear programming	Thursday/8 am–10:30 am/210/E5	Wednesday/10:30 am–13 pm/212/E5
Queuing theory	Thursday/8 am–10:30 am/207/E6	Thursday/10:30 am–13 pm/208/E6
Reliability theory	Thursday/10:30 am–13 pm/213/E4	Thursday/8 am–10:30 am/212/E4
Decision-making methods	Wednesday/15:30 pm–18 pm/214/E3	Thursday/8 am–10:30 am/208/E3
Financial management	Wednesday/10:30 am–13 pm/215/E1	Thursday/8 am–10:30 am/207/E1

change resulting from the mathematical model is the run time. The previous method was based on the programmer's experience, and it demands a great deal of time to modify the timetable.

5. Conclusion

This study provided multiobjective mixed-integer programming to prepare a timetable for postgraduate students at the Industrial Engineering Department of IAUN. The model has three objective functions: minimizing the violation of the lecturers and educational priorities, minimizing students' travel time, and minimizing classrooms' surplus capacity. The study also investigated the related constraints created by classrooms, days, time slots, and the expertise of teachers.

The model was applied to schedule all postgraduate lectures according to the data from the first semester of 2019–2020. The results approved the proposed model's applicability and practicality in providing a case study timetable considering the limitations and preferences of the case study. The multiobjective model was transformed into a single objective model using the ε-constraint method and solved by GAMS software, CPLEX solver. The parametric variation of ε resulted in the Pareto optimal solutions, which indicated a trade-off between objective functions.

Researchers in future studies can apply the proposed model in this study for scheduling lectures in other universities and educational centers. However, creating software capable of scheduling lectures is one of the other exciting directions for future research. Further research should also focus on developing heuristic or metaheuristic techniques that can solve large-scale lecture timetabling problems.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

References

[1] A. Schaerf, "A survey of automated timetabling," *Artificial Intelligence Review*, vol. 13, no. 2, pp. 87–127, 1999.

[2] S. A. MirHassani and F. Habibi, "Solution approaches to the course timetabling problem," *Artificial Intelligence Review*, vol. 39, no. 2, pp. 133–149, 2013.

[3] M. S. Ozdemir and R. N. Gasimov, "The analytic hierarchy process and multiobjective 0-1 faculty course assignment," *European Journal of Operational Research*, vol. 157, no. 2, pp. 398–408, 2004.

[4] A. E. Phillips, H. Waterer, M. Ehrgott, and D. M. Ryan, "Integer programming methods for large-scale practical classroom assignment problems," *Computers & Operations Research*, vol. 53, pp. 42–53, 2015.

[5] H. Vermuyten, S. Lemmens, I. Marques, and J. Beliën, "Developing compact course timetables with optimized student flows," *European Journal of Operational Research*, vol. 251, no. 2, pp. 651–661, 2016.

[6] S. Daskalaki, T. Birbas, and E. Housos, "An integer programming formulation for a case study in university timetabling," *European Journal of Operational Research*, vol. 153, no. 1, pp. 117–135, 2004.

[7] S. Daskalaki and T. Birbas, "Efficient solutions for a university timetabling problem through integer programming," *European Journal of Operational Research*, vol. 160, no. 1, pp. 106–120, 2005.

[8] T. Thepphakorn and P. Pongcharoen, "Performance improvement strategies on Cuckoo Search algorithms for solving the university course timetabling problem," *Expert Systems with Applications*, vol. 161, Article ID 113732, 2020.

[9] A. Gunawan, K. M. Ng, and K. L. Poh, "A hybridized Lagrangian relaxation and simulated annealing method for the course timetabling problem," *Computers & Operations Research*, vol. 39, no. 12, pp. 3074–3088, 2012.

[10] I. Méndez-Díaz, P. Zabala, and J. J. Miranda-Bront, "An ILP based heuristic for a generalization of the post-enrollment course timetabling problem," *Computers & Operations Research*, vol. 76, pp. 195–207, 2016.

[11] A. Jamili, M. Hamid, H. Gharoun, and R. Khoshnoudi, "Developing a comprehensive and multi-objective mathematical model for university course timetabling problem: a real case study," in *Proceedings of the International Conference on Industrial Engineering and Operations Management*, Paris, France, July 2018.

[12] P. Yasari, M. Ranjbar, N. Jamili, and M.-H. Shaelaie, "A two-stage stochastic programming approach for a multi-objective course timetabling problem with courses cancelation risk," *Computers & Industrial Engineering*, vol. 130, pp. 650–660, 2019.

[13] O. Chávez-Bosquez, J. Hernández-Torruco, B. Hernández-Ocaña, and J. Canul-Reich, "Modeling and solving a Latin American university course timetabling problem instance," *Mathematics*, vol. 8, no. 10, p. 1833, 2020.

[14] H. Algethami and W. Laesanklang, "A mathematical model for course timetabling problem with faculty-course assignment constraints," *IEEE Access*, vol. 9, pp. 111666–111682, 2021.

[15] G. Colajanni and P. Daniele, "A new model for curriculum-based university course timetabling," *Optimization Letters*, vol. 15, no. 5, pp. 1601–1616, 2021.

[16] S. A. MirHassani, "A computational approach to enhancing course timetabling with integer programming," *Applied Mathematics and Computation*, vol. 175, no. 1, pp. 814–822, 2006.

[17] A. Azadeh, H. Gholizadeh, and M. Jeihoonian, "A multi-objective optimisation model for university course timetabling problem using a mixed integer dynamic non-linear programming," *International Journal of Services and Operations Management*, vol. 15, no. 4, pp. 467–481, 2013.

[18] A. E. Phillips, C. G. Walker, M. Ehrgott, and D. M. Ryan, "Integer programming for minimal perturbation problems in university course timetabling," *Annals of Operations Research*, vol. 252, no. 2, pp. 283–304, 2017.

[19] N.-C. F. Bagger, G. Desaulniers, and J. Desrosiers, "Daily course pattern formulation and valid inequalities for the curriculum-based course timetabling problem," *Journal of Scheduling*, vol. 22, no. 2, pp. 155–172, 2019.

[20] N.-C. F. Bagger, M. Sørensen, and T. R. Stidsen, "Dantzig-Wolfe decomposition of the daily course pattern formulation for curriculum-based course timetabling," *European Journal of Operational Research*, vol. 272, no. 2, pp. 430–446, 2019.

[21] S. L. Goh, G. Kendall, N. R. Sabar, and S. Abdullah, "An effective hybrid local search approach for the post enrolment course timetabling problem," *Opsearch*, vol. 57, no. 4, pp. 1131–1163, 2020.

[22] T. Song, M. Chen, Y. Xu, D. Wang, X. Song, and X. Tang, "Competition-guided multi-neighborhood local search algorithm for the university course timetabling problem," *Applied Soft Computing*, vol. 110, Article ID 107624, 2021.

[23] A. A. Gozali, B. Kurniawan, W. Weng, and S. Fujimura, "Solving university course timetabling problem using localized island model genetic algorithm with dual dynamic migration policy," *IEEJ Transactions on Electrical and Electronic Engineering*, vol. 15, no. 3, pp. 389–400, 2020.

[24] A. Rezaeipanah, S. S. Matoori, and G. Ahmadi, "A hybrid algorithm for the university course timetabling problem using the improved parallel genetic algorithm and local search," *Applied Intelligence*, vol. 51, no. 1, pp. 467–492, 2021.

[25] M. Kaviani, H. Shirouyehzad, and S. M. Sajadi, "A mathematical model for university course timetabling problems by considering multi functions," *International Journal of Modelling in Operations Management*, vol. 3, no. 3/4, pp. 282–295, 2013.

[26] M. M. Tavakoli, H. Shirouyehzad, F. H. Lotfi, and S. E. Najafi, "Proposing a new multi objective mathematical model for university course timetabling problem regarding optimisation of the quality of lecturers," *International Journal of Modelling in Operations Management*, vol. 7, no. 1, pp. 75–94, 2018.

[27] A. Lemos, F. S. Melo, P. T. Monteiro, and I. Lynce, "Room usage optimization in timetabling: a case study at Universidade de Lisboa," *Operations Research Perspectives*, vol. 6, Article ID 100092, 2019.

[28] K. Deb and K. Deb, "Multi-objective optimization," in *Search Methodologies*, pp. 403–449, Springer, Boston, MA, USA, 2014.

[29] M. Ehrgott and X. Gandibleux, "Multiobjective combinatorial optimization - theory, methodology, and applications," in *Multiple Criteria Optimization: State of the Art Annotated Bibliographic Surveys*, pp. 369–444, Springer, New York, NY, USA, 2003.