Course timetabling in medical universities given physicians' educational and clinical tasks

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Abstract

The physician assignment and course timetabling problem at medical universities is a generalized version of the academic timetabling problem. This problem entails assigning courses, educational and clinical tasks to physician faculty members over a semester or academic year. The problem of timetabling academic courses and scheduling physicians in a hospital has been investigated independently in previous studies in this field. These two fields of research are brought together in this article through the presentation of a multi-objective mixed-integer linear programming (MILP) model. The proposed model is based on two optimization criteria: minimizing workload imbalance and maximizing physician preferences. The model is applied to a case study involving the assignment of physicians to courses, educational and clinical tasks at Kurdistan University of Medical Sciences' Department of Infectious Diseases. Pareto solutions are obtained using an enhanced version of the augmented epsilon constraint implemented in the GAMS optimization software; one is selected as the most desirable solution using the TOPSIS method. The proposed model is generic and could be adapted for use in other departments or medical schools.

Keywords: Course Timetabling, Physician Assignment, Medical Universities, Multi-objective Optimization, Augmented Epsilon-Constraint Method

1. Introduction

Scheduling is a decision-making problem in which limited resources such as workers, equipment, and tools are allocated to tasks over time in order to optimize one or more objective functions. Scheduling has been researched and studied for many years as one of the well-known combinatorial optimization problems. Numerous studies have been conducted in this field of optimization in a variety of fields, including manufacturing [1], transportation [2,3], healthcare [4,5], sports [6], and education [7]. [8]. Inefficient scheduling of a system results in the irrational use of available resources and, as a result, an increase in costs. The university course timetabling problem (UCTTP) is a critical area of scheduling that aims to allocate events (including students, teachers, and courses) to predefined timeslots and classes, as well as to create an appropriate schedule for students and professors while meeting technical constraints. UCTTP is an NP-hard problem [9], and numerous exact and heuristic algorithms have been developed to solve it.

Schaerf [10] classified timetabling problems into three main categories. (1) School scheduling is the process of creating a weekly schedule for all classes in a school, ensuring that no teacher is assigned to more than one class at any given time. (2) Course scheduling, which sets up a weekly schedule for all course sessions, is designed to minimize for participating students the overlap of different courses taught by different professors. (3) Examination timetabling, which includes exam planning for a collection of university courses, aims to avoid concurrent examinations with similar students and distribute exams as evenly as possible. Babaei et al. (2015) classified approaches to UCTTP resolution into four categories. 1) Graph coloring theory, linear or integer programming (LP/IP), and constraint satisfaction programming (CSP) as examples of OR methods, 2) Swarm intelligence and metaheuristic algorithms, 3) novel intelligent methods like hybrid algorithms, fuzzy algorithms, and clustering algorithms, and 4) multiagent systems

Another scheduling area, on the other hand, was mentioned as being related to healthcare. Service staff scheduling is a well-known application of timetabling in which workers are assigned to timeslots. One such issue is shift scheduling in hospitals. Physicians and nurses are scheduled daily in three 8-hour shifts, with each ward assigned a specific number of doctors and nurses. Three types of physician scheduling problems exist: staffing, rostering, and re-planning. The staffing issue entails making strategic decisions about the workforce's size and composition, as well as the rotation of residents throughout the clinic. Rostering is the process of creating a rotational roster and assigning shifts for a specified time period. It typically lasts between a few weeks and several months at the tactical and operational offline levels. If the planning level is pre-operational, it is referred to as "offline planning." Treatment selection, nurse rostering, and appointment scheduling are all examples of offline operational planning. The problem of re-planning is done on a short-term time horizon at the online level, where decisions are made in response to unforeseen events such as employee absenteeism and demand fluctuations. Online operational planning records responses to unforeseen events and workflows, such as determining the severity of an illness and preparing for emergencies [11].

The article is structured as follows: To begin, the following section conducts a review of the scheduling literature, with an emphasis on scheduling in health care, and conducts a research gap analysis. The third section discusses the mathematical model and the solution method in detail. Section 4 solves and analyzes the timetabling problem at Kurdistan University of Medical Sciences as a real-world application of the proposed model. The final section contains conclusions, managerial insights, and recommendations for future research.

2. Literature review

The problem of teacher assignment to school courses was initially addressed by Tillett [12] using a mixed-integer linear programming (MILP) model. The proposed MILP model aims to maximize teachers' preferences for courses, given their merit in the principal's allocation. Preference has been treated as a soft constraint in this model. Selim (1982) proposed an algorithm for allocating teachers to courses that took into account teacher availability, inconvenient times for courses, and faculty requirements for courses. Tripathy [13] proposed a model for UCTTP with the goal of minimizing the total cost of overlapping courses over time. Since teachers tend to teach fewer distinct topics in their areas of expertise, Hultberg and Cardoso [14] presented a basic model for allocating teachers to courses to minimize the average number of distinct subjects taught. Dimpoulou and Miliotis [15] developed an integer programming model to allocate courses to time slots and classrooms. The solution obtained from the proposed model has been used as the input for the examination timetabling. In the proposed integrated course-examination timetabling, the availability of classrooms, students' flexibility in the choice of courses, and teachers' preferences have been considered. Socha et al. [16] considered an academic course timetabling problem with three hard and two soft constraints. The objective function of the problem is to minimize the violation of the soft constraints in feasible solutions. Yang and Jat [17] introduced a genetic algorithm with a guided search strategy and a local search technique for the university course timetabling problem presented by Socha et al. [16]. Daskalaki et al. [18] developed an integer programming model for the university scheduling problem. The objective function is to minimize two cost-terms; the first is the costs of allocating courses over timeslots and days, and the second is the assignment cost, addressing the preferences for teaching periods, days of the week, and classrooms assigned to courses. Rezaeipanah et al. [19] presented a hybrid method for course scheduling that is based on an improved parallel genetic algorithm and local search. While hard constraints such as class capacity and course overlapping are imposed in the constraints in this problem, the objective function attempts to maximize the number of satisfied soft constraints such as the number of courses per day.

The majority of the research on course timetabling is single-objective in nature, with the objective being to minimize violations of soft constraints. However, some research has addressed contradicting criteria in multi-objective models. Multi-objective decision-making (MODM) is a subclass of multi-criteria decision-making (MCDM) that entails optimizing two or more conflicting objective functions concurrently while taking a variety of technical constraints into consideration. Due to the inconsistency or incompatibility of objectives, it is impossible to achieve an optimal solution in multi-objective optimization that optimizes all functions simultaneously because a solution that improves one objective may degrade the others. In this case, the most desired solutions are said to be non-dominated, efficient, non-inferior, or Pareto optimal [20]. Domenech and Lusa [21] proposed a MILP model designed to balance teachers' workloads and maximize their preferences for the problem of teacher-course allocation, employed at the Barcelona School of Management and Engineering at the Polytechnic University of Catalonia. For UCTTP with a long horizon, Immonen and Putkonen [22] considered two criteria: teacher preferences and fair workload distribution. The proposed approach was used to optimize teaching planning in the Department of Mechanical Engineering at the University of Finland. Jamili et al. [23] developed a multi-objective mathematical model for allocating courses and time slots. They used the augmented epsilon-constraint method to solve their model. Lindahl et al. [24] proposed three bi-objective mixed-integer models using an epsilon constraint algorithm to solve them. Da Cunha et al. [25] developed a nonlinear integer programming model for the teacher assignment problem that takes full-time, part-time, or hourly teachers into account to maximize profit for private higher-education institutions. Yasari et al. [26] developed a two-stage stochastic programming model for the university course timetabling problem, in which registration occurs in two phases: preregistration and drop/add.

Due to the fact that scheduling decisions in the field of healthcare systems are multi-criteria in nature, the majority of research in this field has utilized multi-objective models. Again, among the few uni-objective studies in this field, several recent studies are discussed, followed by a discussion of multi-objective ones. Zaerpour et al. [27] developed a MIP model to assign time slots to departments with the goal of maximizing the minimum service level to address the doctor-clinic assignment problem at the tactical level. Due to the limited capacity of hospitals and the changing preferences of individuals to get services at home, several companies have chosen to provide medical services at home, a critical area of health care that is referred to as home health care. Castaño and Velasco [28] presented a mathematical programming model for the scheduling of medical students in a Colombian healthcare facility. The objective is to balance the number of students assigned to various services throughout the semester.

Bard et al. [29] developed a mixed-integer programming (MIP) model for the problem of scheduling residents to perform different clinical tasks on the blocks. As a multi-objective model, theirs sought to minimize the imbalance in the number of clinic sessions attended by each resident over the course of the year, to minimize the number of times a resident receives a night float block immediately before or after an intensive care unit block, and to minimize the maximum deviation from the average number of patients seen in the clinic during a month. Ağralı et al. [30] developed a MIP model for a Belgian health care organization that considers employee-specific skills, minimum rest time, maximum overtime, flexible employment contracts, and employee equity. Outpatient clinics are organized into departments, each of which is staffed by a number of physicians. In some clinics, diagnostic tests are performed on patients to determine which clinics they should be assigned to. Hong et al. [31] addressed the problem of assigning medical residents to shifts with differing characteristics, requirements, and capabilities. Rather than cost minimization or profit maximization, the proposed model's objective function is to optimize equity, including total shift, night shift, and covered optional shift equities. Entezari and Mahootchi [32] developed a MILP model to manage daily staff routing and service scheduling in home healthcare systems. Five objective functions are considered in this study: the total time traveled by all staff members, then total tardiness in providing services to patients, the total overtime worked by staff members, the total violation of continuity of care, and the violation of staff time windows. Hosseinpour et al. [33] presented a multi-objective mathematical model for assigning patients to nurses and determining how nurses are routed under uncertainty. In their model, they also took into account nurses' skills and patient preferences. Akbarzadeh and Manhut [34] examined the scheduling problem for medical students, in which students are assigned to multiple disciplines and hospitals in order to receive an adequate education. The proposed model aims to maximize students' preferences for the disciplines and hospitals they wish to study while also ensuring academic equality among students.

Physicians at medical universities have a variety of educational and clinical responsibilities, including text review, morning rounds, clinic shifts, courses, and on-call shifts. Due to the breadth of services and the extent to which teachers contribute to their provision, the issue addressed in this paper is unique in comparison to previous research. Each ward in a teaching hospital is staffed by several physicians responsible for teaching and guiding courses and other tasks involving student groups. Historically, physicians have been assigned to these tasks manually, which may cause some people to be dissatisfied with the timetable provided and may also make providing a timetable more difficult in large-size problems. The purpose of this paper is to model the physician faculty scheduling problem in medical universities. We discuss scheduling in medical universities first and then present a bi-objective MILP model based on the assumptions and constraints. The case of the Department of Infectious Diseases at Kurdistan University of Medical Sciences is presented as an illustration of the proposed model. The model is solved using an improved version of the augmented epsilon-constraint method.

3. Problem definition and mathematical model

Students attend four stages of education at universities of medical sciences. To begin, they enroll in foundational science courses offered by their faculty (for example, physiology, biochemistry, histology, and medical physics). This step focuses on developing an understanding of the body's structure, biological pathogens, and health fundamentals. Students next undergo a physiopathology period designed to educate them about physiological fundamentals, familiarize them with illness causes and contributing variables, and teach them how to identify diseases analytically. In the third step, students undertake a clinical training phase during which they study diseases in a hospital setting and monitor the status of hospitalized patients. This stage aims to diagnose diseases from a clinical and laboratory standpoint, gain the ability to apply thought and independence, reach a quick conclusion to deal with the patient reasonably well, and plan prevention and treatment operations. The clinical internship is the fourth stage, to develop skills and strengthening decision-making, increasing self-confidence, supplementing development through the intern's encounter with health issues, and delegating responsibility to health care. Teachers teach students in the hospital during the third and fourth stages.

Kurdistan University of Medical Sciences was established in 1986 as the educational and research complex of the Kurdistan Regional Health Organization. It was renamed Kurdistan University of Medical Sciences in 1992, and it now includes medical and paramedical disciplines. This study is based on a case study of timetabling for the Department of Infectious Diseases, one of the most important departments in the Faculty of Medicine, regarding the number of physicians, courses, and educational and clinical tasks. Prior to the start of the academic year, a monthly schedule of courses and educational and clinical responsibilities for the upcoming semester should be planned. The problem of assigning infectious medicine professors to courses and educational and clinical tasks is intended to balance physicians' workloads and preferences.

Physician faculty members provide clinical education to students, conduct patient visits, and participate in other hospital-related activities, in addition to teaching in university classrooms. Each ward of a teaching hospital has a number of physicians responsible for teaching and guiding courses and other activities for student groups. In such hospitals, physicians are assigned to specific wards, and students rotate in groups for various training in the wards during their clinical internship. In some wards, training takes place on a monthly basis; in others, it takes two or three months. Here, each student's stay in a hospital ward lasts one month. The educational and clinical responsibilities of physicians are broadly classified into several categories, including text review, morning rounds, clinic shifts, courses, and on-call shifts. Physicians introduce the theory to students during the text review and ask them to present it in class. During the morning round, students report to the physician on their previous 24-hour shift and the patients' biographies. Each morning round has a predetermined number of physicians, and one day per week is designated as the common morning round for all physicians. Because the text review and morning round are held concurrently each day, each physician may attend only one of them. The following stage is the working round, which all physicians attend. Following that, students enter a training round where physicians explain the causes of various illnesses and how to diagnose and treat them. During the same time period, some physicians are also available in the hospital's specialized clinic for patient visits. Due to the synchronization of training rounds and clinic shifts, each physician can attend only one of them. In the current system, a physician provides only one course per day.

Each week consists of seven workdays in this type of full-time scheduling. Due to the fact that different tasks are performed on different days, each task is considered on a subset of workdays. For instance, there are subsets of workdays for courses, clinic shifts, and training rounds from Saturday to Wednesday. Tuesdays are reserved for all physicians' morning rounds, and thus the text review is not conducted on this day. Additionally, a physician must be on-call on all weekdays, so workdays encompass the entire week. Each physician is required to spend a minimum number of hours per week on educational and clinical tasks, which include the following: (1) clinic shifts, (2) training rounds, (3) morning rounds, and (4) on-call shifts. The amount of time a physician works on a weekly basis is determined by his or her academic rank and organizational position at the university. When a physician is assigned to a task during a specified time slot, the physician's working time is reduced by the amount of time spent on that task. Each teacher has a portfolio of courses to teach, which means that each teacher is capable of teaching only a limited number of courses. Additionally, physicians can schedule their time (the hours and days of the week during which they may be present or prefer to be present) according to their preferences, allowing them to engage in other personal and occupational activities. Physicians have three academic levels in the proposed case study: assistant professor, associate professor, and professor (full professor). Each month, the ward's workload exceeds what all physicians are required to do, necessitating the provision of additional services and, of course, overtime compensation. This section presents the mathematical model of the problem based on the explanations provided. To this end, notations are introduced first.

Input Elements

I	Set of physicians (i is the index for physicians)
J	Set of courses (j is the index for courses)
K	Set of text reviews (k is the index for text reviews)
L	Set of clinical tasks (l is the index for clinical tasks)
D	Set of workdays (d is the index for workdays)
CST	Subset of workdays including clinic shifts, courses, and training rounds
MT	Subset of workdays including morning rounds and texts reviews
Max_i	Array for maximum monthly working hours for physician i
O_i	Array for working times of physician i
S_{ij}	Array which set to 1 if physician i can teach course j and to 0 otherwise
C_j	Array for the number of teaching hours for course j
B_k	Array for the number of teaching hours for text review k

A_l Array for the duration of task l

G_i Array for the preference coefficient of physician i

P_{idl} Array for the preference of physician i for task l on day d

P'_{ikd} Array for the preference of physician i for text review k on day d

P''_{ijd} Array for the preference of physician i for course j on day d

Decision variables

X_{ijd} A binary variable that is set to 1 if physician i teaches course j on day d and to 0 otherwise

Z_{ikd} A binary variable that is set to 1 if physician i holds text review k on day d and to 0 otherwise

Y_{idl} A binary variable that is set to 1 if physician i is assigned to task l on day d and to 0 otherwise

δ_i The overtime for physician i

To obtain a more concise form of the model, index l is defined. It takes values 1 to 4, respectively, for clinic visits (1), training rounds (2), morning rounds (3), and on-call shifts (4). Based on the assumptions made and the notations introduced, the problem is modeled as follows.

$$\min Z_1 = \sum_{i\in I} \frac{\delta_i}{O_i} \tag{1}$$

$$\max Z_2 = \sum_{l\in L, l\le 2} \sum_{i\in I} \sum_{d\in CST} G_i P_{idl} Y_{idl} + \sum_{l\in L, 3\le l\le 4} \sum_{i\in I} \sum_{d\in MT} G_i P_{idl} Y_{idl} + \sum_{i\in I} \sum_{k\in K} \sum_{d\in MT} G_i P'_{ikd} Z_{ikd} + \sum_{i\in I} \sum_{j\in J} \sum_{d\in CST} G_i P''_{ijd} X_{ijd} \tag{2}$$

Subject to:

$$\sum_{i\in I} \sum_{d\in MT} Z_{ikd} = 1 \quad , \forall k \in K \tag{3}$$

$$\sum_{i\in I} \sum_{k\in K} Z_{ikd} \le 1 \quad , \forall d \in MT \tag{4}$$

$$\sum_{i\in I} Y_{id3} = 2 \quad , \forall d \in MT \tag{5}$$

$$\sum_{i\in I} Y_{idl} = 1 \quad , \forall d \in CST \ , l = 1,2 \tag{6}$$

$$\sum_{i\in I} \sum_{d\in CST} X_{ijd} = 1 \quad , \forall j \in J \tag{7}$$

$$\sum_{i\in I}\sum_{j\in J} X_{ijd} \le 1 \quad , \forall d \in CST \tag{8}$$

$$\sum_{i\in I} Y_{id4} = 1 \quad , \forall d \in D \tag{9}$$

$$\sum_{l\in L\ ,l\le 2}\sum_{d\in CST} Y_{idl}A_l + \sum_{l\in L\ ,3\le l\le 4}\sum_{d\in MT} Y_{idl}A_l + \sum_{k\in K}\sum_{d\in MT} Z_{ikd}B_k + \sum_{j\in J}\sum_{d\in CST} X_{ijd}C_j \ge O_i \quad , \forall i \in I \tag{10}$$

$$\sum_{l\in L\ ,l\le 2}\sum_{d\in CST} Y_{idl}A_l + \sum_{l\in L\ ,3\le l\le 4}\sum_{d\in MT} Y_{idl}A_l + \sum_{k\in K}\sum_{d\in MT} Z_{ikd}B_k + \sum_{j\in J}\sum_{d\in CST} X_{ijd}C_j \le Max_i \quad , \forall i \in I \tag{11}$$

$$\sum_{l\in L\ ,l\le 2}\sum_{d\in CST} Y_{idl}A_l + \sum_{l\in L\ ,3\le l\le 4}\sum_{d\in MT} Y_{idl}A_l + \sum_{k\in K}\sum_{d\in MT} Z_{ikd}B_k + \sum_{j\in J}\sum_{d\in CST} X_{ijd}C_j - O_i = \delta_i \quad , \forall i \in I \tag{12}$$

$$\sum_{d\in CST} X_{ijd} \le S_{ij} \quad , \forall i \in I\ , \forall\, j \in J \tag{13}$$

$$\sum_{k\in K} Z_{ikd} + Y_{id3} = 1 \quad , \forall i \in I\ , \forall d \in MT \tag{14}$$

$$\sum_{l\in L\ ,l\le 2} Y_{idl} \le 1 \quad , \forall i \in I, \forall d \in CST \tag{15}$$

$$\delta_i \ge 0 \quad , \forall i \in I \tag{16}$$

$$X_{ijd}, Y_{idl}\ , Z_{ikd} \in \{0,1\} \quad , \forall i \in I, \forall\, j \in J, \forall k \in K, \forall d \in D, \forall l \in L \tag{17}$$

The proposed model incorporates two optimization criteria presented as two objective functions: workload balance and physician preference maximization. Equation (1) is related to the first criterion and seeks to minimize the total ratio of physicians' overtime hours to their work hours. The higher the academic rank of the physician, the fewer working hours the physician has, and thus the greater the value of this ratio. Additionally, because the pay rate is directly related to the academic rank of the physician, this objective function considers the cost of tuition fees indirectly. For the second criterion, physicians' preferences for task assignments are maximized according to their academic rank using Equation (2). Physician preferences for (1) clinic shifts and training rounds, (2) morning rounds and on-call shifts, (3) text reviews, and (4) courses are represented by four segments of this objective function. According to similar research, there is a limit to the number of teachers assigned to each course, which has been established for each text review based on Constraint (3). Each day is allotted a maximum of one text review under constraint (4). Constraint (5) ensures proper physician-morning assignment, with two physicians assigned to each morning round due to the requirement of two physicians per morning round. Constraint (6) establishes the assignment of physicians to training and morning rounds, with each round requiring only one physician. Constraint (7) ensures physician-course assignment by stating that only one physician should be assigned to each course. Constraint (8) ensures that only one course is assigned to each day. The on-call physician is a physician who can be contacted and summoned to the medical center during waiting hours (after office hours, weekends, and holidays) based on his or her roster. Clearly, the time period during which an on-call physician will be available for consultation should be planned. Constraint (9) ensures that appropriate physician-on-call shift assignments are made to ensure that each day has exactly one physician on call. Constraints (10) and (11) specify that a physician's total monthly hours must fall between his or her normal working hours and the maximum monthly working hours. Each physician is required to devote a minimum number of hours per week to educational and clinical activities, and his or her weekly work schedule is determined by his or her academic rank and organizational position at the university. Constraint (12) establishes the amount of overtime paid to each physician. Due to the fact that the number of working hours and the number of duties assigned to teachers are not exactly equal, each teacher is required to pay more than his or her obligation to provide services. As a result, a cap on each teacher's overtime must be established. 13) Ensures that physicians are assigned to courses that are included in their portfolios. Constraint (14) requires each physician to perform either text review or morning rounds on a daily basis. Constraint (15) similarly ensures that each physician is assigned either a training round or a clinic shift each day. Constraints (16) and (17) determine the domains of the decision variables.

The proposed model is composed of $id\left(j+l+k\right)$ decision variables and $k+5d+j+i\left(2d+j\right)$ constraints, yielding a bi-objective mixed-integer linear programming problem (MILP). The presence of binary decision variables in the proposed model results in a discrete solution space and NP-hard problem. However, due to the small number of variables in each set in real-world situations, it is possible to solve the model precisely in order to obtain all efficient solutions in an acceptable amount of time. The following section describes the method for solving the proposed model using the augmented epsilon constraint method. After obtaining a complete set of efficient solutions, the TOPSIS method is used to select the most desirable solution.

4. Solution method

Several approaches to solving multi-objective mathematical models have been proposed, the most well-known of which is the epsilon-constraint method, which produces an exact set of efficient solutions under some simple conditions. The structure of this method is briefly explained below. Consider a model with two objective functions as follows.

Program (1)

$$\min f_1\left(\boldsymbol{X}\right) \;\&\; \max f_2\left(\boldsymbol{X}\right)$$

Subject to: $\boldsymbol{X} \in \boldsymbol{S}$

where $\boldsymbol{X}$ is the vector of decision variables and $\boldsymbol{S}$ is the feasible region. The first step in the epsilon constraint method is to create a pay-off table. The pay-off table in bi-objective models has two rows and two columns, as illustrated in Table (1).

Program (2) is solved to obtain the values for the first row.

Program (2)

$\min f_1(\boldsymbol{X})$

Subject to: $\boldsymbol{X} \in \boldsymbol{S}$

If X_1 denotes the optimal solution to this program, then $f_1^* = f_1(X_1)$ and $f_{12} = f_2(X_1)$. Program (3) is solved in a similar manner to obtain the values for the second row of the pay-off table.

Program (3)

$\min f_2(\boldsymbol{X})$

Subject to: $\boldsymbol{X} \in \boldsymbol{S}$

If X_2 denotes the optimal solution to this program, then $f_{21} = f_1(X_2)$ and $f_2^* = f_2(X_2)$. Each row of the pay-off table represents one of the efficient frontier's extreme points. The efficient frontier in bi-objective models is a (not necessarily straight) line segment connecting the two points in the pay-off table. The following steps of the epsilon constraint method involve a repetitive procedure in which other efficient solutions are obtained by moving from one of the two endpoints of the efficient frontier to the other. The epsilon-constraint method has some weaknesses, one of which is the possibility of producing weakly efficient solutions. Mavrotas [35] developed an improved version of the augmented epsilon-constraint method (Mavrotas [36]), dubbed AUGMECON2, to obtain the complete set of Pareto solutions. AUGMECON2 converts all constraints to equalities via the use of slack or surplus variables. These variables are all treated as new terms in the objective function (with a lower priority in the lexicographic method), compelling the model to generate efficient solutions.

None of the solutions obtained using the AUGMECON2 method are dominant over the others. Numerous multi-attribute decision-making (MADM) techniques can be used to determine the most desirable solution to implement. This article makes use of the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method, which will be described briefly below: The TOPSIS method, developed by Yoon and Hwang [37], is used to rank and compare efficient solutions and select one of them by taking into account quality indicators that cannot be entered into the model. That is, the decision-makers are presented with the values of the objective functions obtained for the efficient solutions, they perform the necessary weighting and scoring using the specified indicators, and finally, one of the efficient points is chosen for implementation. The TOPSIS method employs a decision matrix with columns for alternatives (efficient solutions) and rows for criteria. The higher-ranking alternative should be the one that is the closest to the positive ideal solution and the furthest from the negative ideal solution. The TOPSIS method is comprised of the following six steps:

Step 1- Quantify and scale the decision matrix $A=[A_{ij}]$ based on *n* criteria and *m* alternatives.

Step 2- Utilize the following relationship to standardize the decision matrix:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}},\ i=1,\ldots,m\ ,\ j=1,..,n$$

Step 3 - Determine the positive ideal solution and the negative ideal solution as follows:

$$V_j^+ = \left\{ \left(\max_i \left(V_{ij} \right) \mid j \in j^+ \right), \left(\min_i \left(V_{ij} \right) \mid j \in j^- \right) \right\},\ j=1,\ldots,n$$

$$V_j^- = \left\{ \left(\min_i \left(V_{ij} \right) \mid j \in j^+ \right), \left(\max_i \left(V_{ij} \right) \mid j \in j^- \right) \right\},\ j=1,\ldots,n$$

Step 4- Calculate the distance from the positive ideal and negative ideal solution:

$$d_i^+ = \sqrt{\sum_{j=1}^{n} \left(V_{ij} - V_j^+ \right)^2}$$

$$d_i^- = \sqrt{\sum_{j=1}^{n} \left(V_{ij} - V_j^+ \right)^2}$$

Step 5 – Determine the relative closeness (CL^*) coefficient of each alternative to the ideal solution:

$$CL_i = \frac{d_i^-}{d_i^- + d_i^+}$$

Step 6- Ranking the alternatives: any alternative with a larger CL is better.

5. Implementation and sensitive analysis

The MILP model developed in Section 3 is used here for course timetabling at Kurdistan University of Medical Sciences' Department of Infectious Diseases. The department has seven doctors, including five assistant professors and two associate professors. According to educational regulations, the weekly work hours for assistant professors, associate professors, and professors are 16, 14, and 12 hours, respectively, and the preference coefficient is 1/6, 1/3, and 1/2, respectively. Each day of on-call and each round of basics is considered one working hour, and each morning round, training round, course teaching, or clinic shift is considered two working hours. If the physician is unavailable, the value of an assignment preference is set to 0, 1 if the physician is available, and 3 if the physician prefers the assignment. The pay-off table is obtained using the parameters listed above and is shown in Table (2).

Figure (1) depicts the entire set of Pareto solutions obtained by solving the proposed model with the CPLEX solver from the GAMS software. A PC with a 2.9 GB Core i7 CPU and 8GB of RAM was used to run the software.

Figures (2) and (3) depict each physician's overtime hours (the first objective function), and preference met (the second objective function) for all Pareto solutions. As can be seen, one physician's preference is greater than the others. This is because she has a strong preference for a set of educational and clinical tasks that other physicians despise, which results in her working the most overtime. The decision-makers must strike a balance between the workloads of physicians and their preferences. The opinions of professors and the head of the infectious disease department were solicited in order to arrive at the most desirable efficient solution. These comments are analyzed using the TOPSIS method, and the best weights for the objective functions are 0.33 and 0.67, respectively. According to these weights, the most efficient solution has first and second objective function values of 470 and 9429, respectively.

5.1. Sensitivity analysis

To conduct a sensitivity analysis of the model, two parameters are considered: physicians' maximum monthly working hours and the physician's preference coefficient. Each parameter is altered and examined independently within a permissible range while the other parameters remain constant. The Pareto solutions for four distinct scenarios of maximum monthly working hours (based case, +10%, +20%, +30%, and +40%) have been determined, and the resulting Pareto frontier is depicted in Figure (4). According to this figure, increasing the maximum monthly working hours results in a more equitable distribution of workload and an improvement in the first objective function. Because a 10% reduction in maximum monthly working hours does not result in an optimal solution for the model, reduction cases for this parameter are not considered.

Two scenarios are considered in addition to the base scenario in order to determine the sensitivity of the Pareto frontier to changes in the physician's preference coefficient. As previously stated, the preference coefficients for assistant professors, associate professors, and professors were 0.17, 0.33, and 0.50, respectively, with a difference of 0.17 between the coefficients of consecutive ranks. In the first scenario, the difference and variance of the preference coefficient parameter are reduced, and values of 0.24, 0.33, and 0.42 with differences of 0.09 are considered. In the second scenario, as the parameter's variance increases, values of 0.08, 0.33, and 0.58 with consecutive differences of 0.25 are considered. By comparing the Pareto frontiers in Figure (5) for these two scenarios to the original scenario, it is concluded that decreasing the difference in preference coefficients for academic degrees results in an increase in the amount of preferences satisfied.

6. Conclusions and directions for future research

In this paper, a multi-objective MILP model was proposed for solving the problem of timetabling courses and educational and clinical tasks in medical universities. The proposed model balanced physicians' workloads and takes into account their preferences for assignment to courses, clinic shifts, training rounds, morning rounds, on-call shifts, and text reviews. This was done given constraints on the problem sets, including the normal working time and the maximum allowed overtime hours of the physicians, their ranks, their course portfolios, and the number of physicians in each task. Besides, a case study was performed for timetabling for the Department of Infectious Diseases of Kurdistan University of Medical Sciences, an important department of this university, regarding the number of physicians, courses, and educational and clinical tasks. The proposed model was solved using AUGMECON2 in the GAMS optimization software. Two parameters are used to conduct a sensitivity analysis on the model: physicians' maximum monthly working hours and the physician's preference coefficient.

According to the results of the paper, the following can be considered as appealing areas for future research. In this study, physicians were considered full-time, while part-time physicians and teachers can also be employed. This research attempted to distribute overtime among full-time physicians equitably, but it is unpleasant in the real world for overtime practitioners to be obliged beyond their normal working time. Thus, if the part-time workforce is considered, physicians' satisfaction is likely to increase. This has economic benefits as well as the more favorable results it obtains for physicians. Moreover, a specific day in each week (Tuesdays) was considered in our work as the common morning throughout the hospital, with all faculty members in the hospital wards having a predetermined date. However, some groups may prefer to have mornings on other days and therefore different timetables, so all the wards can plan together to make the best decision in that regard.

References

1. Mousavipoor, S., Farughi, H., AhmadiZar, F. "A novel bi-objective model for a job shop scheduling problem with consideration of Fuzzy parameters, modified learning effects and

multiple preventive maintenance activities", Scientia Iranica, (), pp. -. doi: 10.24200/sci.2021.54614.3839 (2021).

2. Rabbani, M., Sadeghsa, S., Vaez-Alaei, M., & Farrokhi-Asl, H. "Robust and sustainable full-shipload routing and scheduling problem considering variable speed: A real case study", *Scientia Iranica*, 26(3), pp. 1881-1897 (2019).

3. Ataeian, S., Solimanpur, M., Amiripour, S., Shankar, R. "Synchronized timetables for bus rapid transit networks in small and large cities", Scientia Iranica, 28(1), pp. 477-491. doi: 10.24200/sci.2019.51501.2220 (2021).

4. Babaei, H., Karimpour, J., & Hadidi, A. "A survey of approaches for university course timetabling problem", *Computers & Industrial Engineering*, 86, pp. 43-59 (2015).

4. Behmanesh, R., Zandieh, M., Hadji Molana, S. "The surgical case scheduling problem with fuzzy duration time: An ant system algorithm", *Scientia Iranica*, 26(3), pp. 1824-1841. doi: 10.24200/sci.2018.20602 (2019).

5. Yazdi, M., Zandieh, M., Haleh, H., Pasandideh, S. "Efficient scheduling of emergency surgeries by adjusting the schedule of elective surgeries" *Scientia Iranica*, (), pp. -. doi: 10.24200/sci.2021.53630.3339 (2021).

6. Van Bulck, D., Goossens, D., Schönberger, J., & Guajardo, M. "RobinX: A three-field classification and unified data format for round-robin sports timetabling", *European Journal of Operational Research*, 280(2), pp. 568-580 (2020).

7. Kayanda, A., Busagala, L., Tedre, M., & Oyelere, S. "Towards the Development of Timetabling Software for improving Decision-Making in Tanzanian Higher Education Context", In *2020 15th Iberian Conference on Information Systems and Technologies (CISTI)*, IEEE , pp. 1-6, (2020).

8. Leung, J. Y. (Ed.). "*Handbook of scheduling: algorithms, models, and performance analysis*", CRC Press (2004).

9. Garey, M. R. "Computers and intractability: A guide to the theory of np-completeness", *Revista Da Escola De Enfermagem Da USP*, 44(2), p. 340 (1979).

10. Schaerf, A. "A survey of automated timetabling", *Artificial intelligence review*, 13(2), pp. 87-127 (1999).

11. Erhard, M., Schoenfelder, J., Fügener, A., & Brunner, J. O. "State of the art in physician scheduling", *European Journal of Operational Research*, 265(1), pp. 1-18 (2018).

12. Tillett, P. I. "An operations research approach to the assignment of teachers to courses", *Socio-Economic Planning Sciences*, 9(3-4), pp. 101-104 (1975).

13. Tripathy, A. "Computerised decision aid for timetabling—a case analysis", *Discrete applied mathematics*, 35(3), pp. 313-323 (1992).

14. Hultberg, T. H., & Cardoso, D. M. "The teacher assignment problem: A special case of the fixed charge transportation problem", *European Journal of Operational Research*, 101(3), pp. 463-473 (1997).

15. Dimpoulou, M., & Miliotis, P. "Implementation of a university course and examination timetabling system", *European Journal of Operational Research*, 130(1), pp. 202-213 (2001).

16. Socha, K., Knowles, J., & Sampels, M. "A max-min ant system for the university course timetabling problem", Springer, Berlin, Heidelberg, In *International Workshop on Ant Algorithms* , pp. 1-13 (2002).

17. Yang, S., & Jat, S. N. "Genetic algorithms with guided and local search strategies for university course timetabling", *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 41(1), pp. 93-106 (2011).

18. Daskalaki, S., Birbas, T., & Housos, E. “An integer programming formulation for a case study in university timetabling”, *European Journal of Operational Research,* 153(1), pp. 117-135 (2004).

19. Rezaeipanah, A., Matoori, S. S., & Ahmadi, G. “A hybrid algorithm for the university course timetabling problem using the improved parallel genetic algorithm and local search”, *Applied Intelligence*, 51(1), pp. 467-492 (2021).

20. Deb, K. “Multi-objective optimization”, In *Search methodologies* ,Springer, Boston, MA, pp. 403-449 (2014).

21. Domenech, B., & Lusa, A. “A MILP model for the teacher assignment problem considering teachers' preferences”, *European Journal of Operational Research*, 249(3), pp. 1153-1160 (2016).

22. Immonen, E., & Putkonen, A. “An heuristic genetic algorithm for strategic university tuition planning and workload balancing”, *International Journal of Management Science and Engineering Management*, 13(2), pp. 118-128 (2018).

23. Jamili, A., Hamid, M., Gharoun, H., & Khoshnoudi, R. “Developing a comprehensive and multi-objective mathematical model for university course timetabling problem: a real case study”, In *Conference: proceedings of the international conference on industrial engineering and operations management, Paris, France* , p. 2108 (2018).

24. Lindahl, M., Mason, A. J., Stidsen, T., & Sørensen, M. “A strategic view of University timetabling”, *European Journal of Operational Research,* 266(1), pp. 35-45 (2018).

25. da Cunha Jr, J. J., & de Souza, M. C. “A linearized model for academic staff assignment in a Brazilian university focusing on performance gain in quality indicators”, *International Journal of Production Economics*, 197, pp. 43-51 (2018).

26. Yasari, P., Ranjbar, M., Jamili, N., & Shaelaie, M. H. “A two-stage stochastic programming approach for a multi-objective course timetabling problem with courses cancelation risk”, *Computers & Industrial Engineering*, 130, pp. 650-660 (2019).

27. Zaerpour, F., Bischak, D. P., & Menezes, M. B. “Coordinated lab-clinics: A tactical assignment problem in healthcare”, *European Journal of Operational Research*, 263(1), pp. 283-294 (2017).

28. Castaño, F., & Velasco, N. “Exact and heuristic approaches for the automated design of medical trainees rotation schedules”, *Omega*, 97, p. 102107 (2020).

29. Bard, J. F., Shu, Z., Morrice, D. J., & Leykum, L. K. “Constructing block schedules for internal medicine residents”, *IISE Transactions on Healthcare Systems Engineering*, *7*(1), pp. 1-14 (2017).

30. Ağralı, S., Taşkın, Z. C., & Ünal, A. T. “Employee scheduling in service industries with flexible employee availability and demand”, *Omega*, 66, pp. 159-169 (2017).

31. Hong, Y. C., Cohn, A., Gorga, S., O'Brien, E., Pozehl, W., & Zank, J. “Using Optimization Techniques and Multidisciplinary Collaboration to Solve a Challenging Real-World Residency Scheduling Problem”, *INFORMS Journal on Applied Analytics*, 49(3), pp. 201-212 (2019).

31. Selim, S. M. “An algorithm for constructing a university faculty timetable”, *Computers & Education*, 6(4), pp. 323-332 (1982).

32. Entezari, Z., Mahootchi, M. “Developing a mathematical model for staff routing and scheduling in home health care industries: Genetic Algorithm based solution scheme”, Scientia Iranica, (), pp. -. doi: 10.24200/sci.2020.54116.3600 (2020).

33. Hosseinpour-Sarkarizi, A., Davari-Ardakani, H., Izadbakhsh, H. “Home Health Care Routing and Scheduling Problem under Uncertainty Considering Patient Preferences and Service Desirability”, Scientia Iranica, (),pp. -. doi: 10.24200/sci.2020.54313.3694 (2020).

34. Akbarzadeh, B., & Maenhout, B. “An exact branch-and-price approach for the medical student scheduling problem”, *Computers & Operations Research*, 129, p. 105209 (2021).

35. Mavrotas, G., & Florios, K. "An improved version of the augmented ε-constraint method (AUGMECON2) for finding the exact pareto set in multi-objective integer programming problems", *Applied Mathematics and Computation*, 219(18), pp. 9652-9669 (2013).

36. Mavrotas, G. "Effective implementation of the ε-constraint method in multi-objective mathematical programming problems", *Applied mathematics and computation*, 213(2), pp. 455-465 (2009).

37. Hwang, C. L., & Yoon, K. "Multiple Attribute Decision Making: Methods and Applications", Springer Verlag. New York (1981).

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Table (1) General structure for pay-off table in bi-objective models

	$\min f_1(\boldsymbol{X})$	$\max f_2(\boldsymbol{X})$
$f_1(\boldsymbol{X})$	f_1^*	f_{12}
$f_2(\boldsymbol{X})$	f_{21}	f_2^*

Table 2: Pay-off table for the case study

	$\min f_1(\boldsymbol{X})$	$\max f_2(\boldsymbol{X})$
$f_1(\boldsymbol{X})$	470	6713
$f_2(\boldsymbol{X})$	497	9429

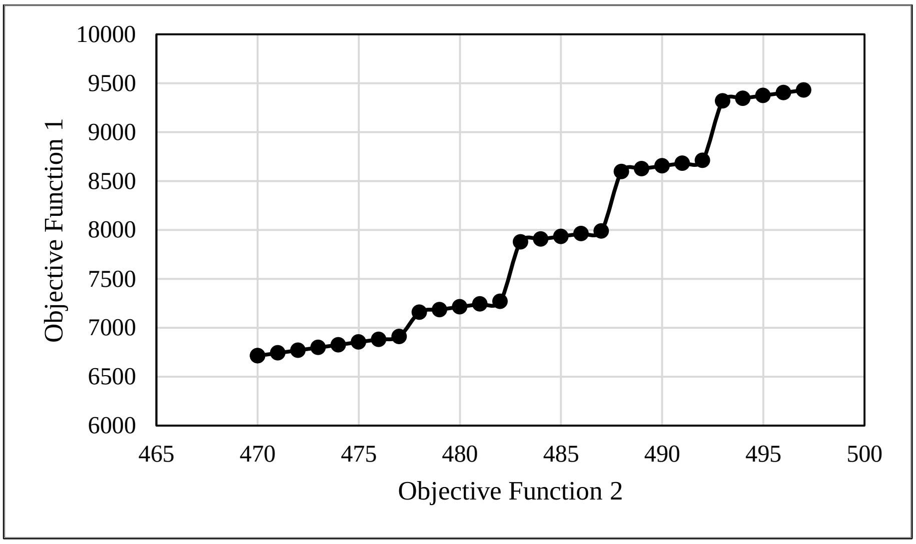

Figure 1: Pareto solution set derived using AUGMECON2

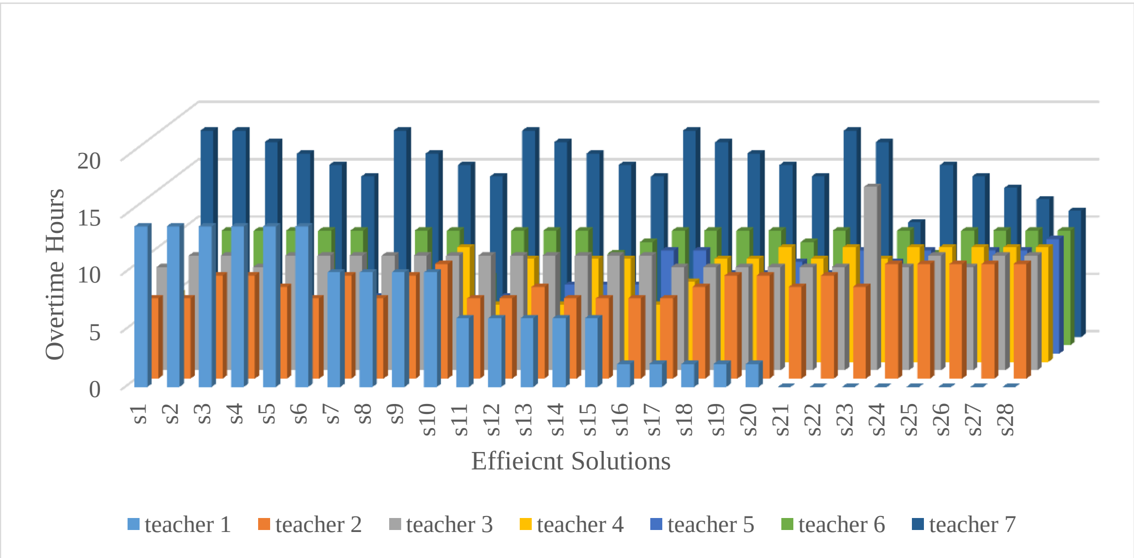

Figure 2: Physicians' overtime hours in efficient solutions

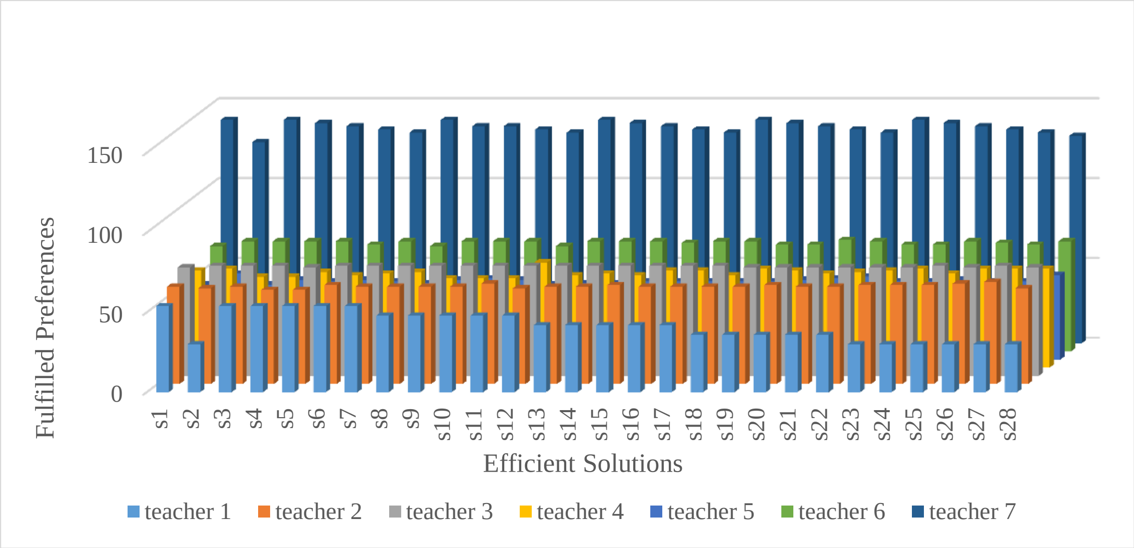

Figure 3: Physicians' fulfilled preferences in efficient solutions

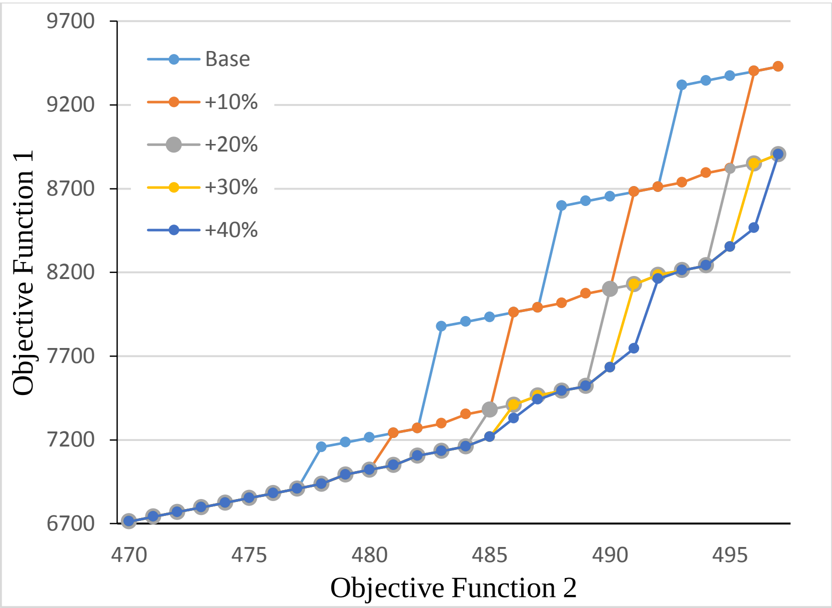

Figure 4: Pareto solutions with different values of the maximum monthly working hours

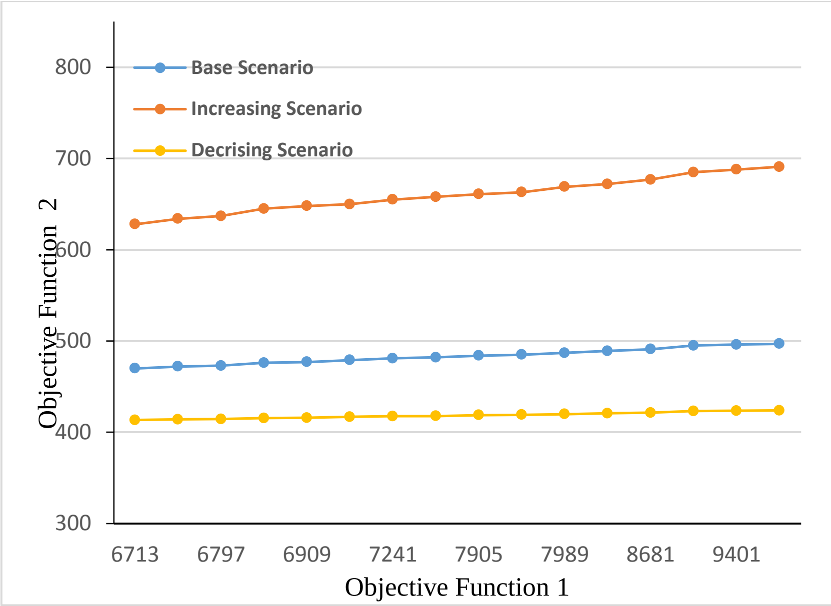

Figure 5: Pareto solutions with different values of the preference coefficient of a physician according to her/his academic rank