Multiobjective Course Scheduling with Mathematical Programming and Analytic Network Process

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Abstract. This paper provides an approach to solve the faculty-course-time slot assignment problem. Two interactive steps are defined based on multi objective mathematical programming models with special emphasis on participant preferences. First, the course-time slot assignment problem is solved followed by the assignment of faculty to courses. An Analytic Network Process model is used to weight the different objectives of the problem. A real case application is included by comparing the outcome with the current solution.

Keywords. Zero-One Multiobjective Programming, Faculty-Course-Time Slot Assignment Problem, Timetabling**.** The Analytic Network Process.

1. Introduction

The school timetabling problem can be defined as a scheduling of a certain number of meetings, attended by certain group of students and a teacher (or teachers) over a period of time, in conformity with the availability of resources (e.g. rooms, teaching aids etc.) and fulfilling certain additional requirements.

This research focuses on faculty-course-time slot (FCT) assignment problem. The FCT problem is a special case of the more general school timetabling problem which in turn is a special case of the problem of matching people, places, time slots, and facilities that is the general timetabling problem.

There is great deal of research done on educational timetabling problem. Al-Yakoob and Sherali (2006) develop a mixed-integer programming approach to a class timetabling problem. MirHassani (2006) considers a computational approach to enhancing course timetabling with integer programming. Özdemir and Gasimov (2003) solve multiobjective 0-1 faculty course assignment problem.

Large amounts of data, a diversity of teaching methods and ever increasing requirements in curricula makes this kind of scheduling hard. The problem may vary from one country to another or even from school to school in the same country. One more requirement is the 0-1 discreteness of the variables that multiplies the complexity of how to go about solving the assignment problem. Usually the approach has been to find any acceptable solution instead of the optimum one. No method is yet available to handle the problem in all its complexity.

Heuristic searches have had a reasonable amount of success. Santiago et all. (2005) proposed a two-phase heuristic evolutionary algorithm for personalizing course timetables and applied the algorithm to a Spanish University. Carrasco and Rato (2001) use Genetic Algorithm for class-teacher timetabling problem. Ueda et all. (2001) consider time slot-room assignments in a university by using genetic algorithms. Head and Shaban (2007) deal with the simultaneous course student timetabling by using a heuristic approach. Arntzen (2005) used the tabu search method for a university timetabling problem.

One of the important considerations in educational timetabling problems is the participant preference, taken into account by some researchers. Harwood and Lawless (1975) used goal programming to examine the conflicting goals in the faculty course assignment problem. Bloomfield and McSharry (1979) considered the faculty preferences in a two-stage heuristic approach. Schniederjans and Kim (1987) described an application of a zero-one goal programming approach to allocate teaching staff to specific courses based on departmental needs and the personal preferences of departmental faculty. Badri (1996) proposed a two stage optimization model to maximize faculty-course preferences in assigning faculty members to courses and then maximize faculty time preferences in allocating courses to time blocks.

The study described here involves assignment of courses to time slots and faculties to the courses with particular emphasis on preference. We extend a previously developed two-phased approach (Kara, Özdemir, 1997) to its multiobjective case and applied to solve FCT problem.

2. A Two Phased Approach on the Solution of Multiobjective FCT Problem -an Application

Among all dimensions considered, the size of educational timetabling problem makes it the hardest to solve. This study focuses on three of the main concepts of the problem: a faculty, course and time slots. A two step approach proposed for solving to solve such a problem. The first assigns courses to time slots by considering hard constraints of the problem. The objective function is to maximize an evaluation function which reflects the pedagogical appropriateness of the course-time slot assignments. In the second step, the instructors are assigned to the courses by providing the course-time slot assignments. By doing that, their preferences related to the time slots of the scheduled courses, are indirectly included in the course assignments. In addition, administrative tendencies on faculty-course assignments and weekly upper course limits are considered as objectives. This multiobjective structure is solved by using a weighted sum scalarization method. An Analytic Network Process model is used to weight the objectives. In the next section, we explain the details of the two step process. Solution of a real case is given to illustrate both steps by comparing the outcome with the assignment being currently made.

2.1 Course-time slot assignment

The mathematical model of the course-time slot assignment problem is constructed as follows: Two consecutive lecture hours are considered as a time slot. Model parameters are as follows:

$I = \{i: i=1,2,\ldots m\}$ courses

$T = \{j: j=1,2,\ldots l\}$ time slots

m: number of courses

w_i: weight of course i with respect to its difficulty to understand

c_i: weight of course i with respect to its number of students

h_i: number of weekly time slots of course i

l: number of teaching time slots in a week

n_t: weighting for time slot t

f: number of teaching time slots in a day

Z_p: set of available teaching time slots on day p

d: number of teaching days in a week

e: number of classes

I_s: number of different courses for class s

E_s: daily upper limit (in time slots) for class s

Decision variables

$$x_{it} = \{1, \text{ if course } i \text{ is assigned to time slot } t, \quad 0, \text{ otherwise}$$

Constraints

Each course must be assigned to at most one time slot in a day

$$\sum_{t \in Z_p} x_{it} \leq 1 \qquad \forall (i,p) \qquad p = 1,\ldots,d \quad (1)$$

Two courses of the same class can not be assigned to the same time slot.

$$\sum_{i \in I_s} x_{it} \leq 1 \qquad \forall (s,t) \qquad (2)$$

Each course must be assigned to the required number of time slots in a week.

$$\sum_{t} x_{it} = h_i \qquad \forall i \in I \qquad (3)$$

Daily load of each class has an upper limit.

$$\sum_{\forall i \in I_s} \sum_{t \in T_p} x_{it} \leq E_s \qquad \forall (s, p) \qquad (4)$$

The objective function consists several of different considerations

$$Min \sum_{i} \sum_{t} w_i \, n_t \, c_i x_{it} \qquad (5)$$

The model is used to solve the particular case of an educational institution that has 54 instructors and 49 different courses. We define each specific group of students as a class that has to take a predefined set of courses. Different classes may a course in common in their curricula. The courses are grouped into 13 groups. There is a set of instructor for each course group to teach the courses only in that group. All groups are mutually exclusive so an instructor can not teach a course from another group. The study is based on one of these course groups, Art and Social Science. There are 8 courses as TDE3, TDE4, ED1, ED2, TD2, ED, TET2 and EDMET. For this group, there are also 8 instructors who teach these courses. As we explained above, the same course (for instance TDE3) may necessarily be assigned to different classes (for instance to 4G and 4L). So, 43 course-class pairs are needed an instructor assignment. Table 1 shows these pairs with a code.

Table 1
Course-class pairs with the codes

Course -class pair	The code	Course-class pair	The code	Course-class pair	The code
4G TDE3	01	4F ED1	16	9D ED	31
4L TDE3	02	4G ED1	17	9E ED	32
4D TDE3	03	4D ED1	18	9F ED	33
6A TDE3	04	4K ED1	19	9G ED	34
4E TDE4	05	4H ED2	20	9H ED	35
4F TDE4	06	6D ED2	21	9I ED	36
4H TDE4	07	4M EDMET	22	9K ED	37
4K TDE4	08	4M TD2	23	9L ED	38
4B TDE4	09	6B TET2	24	9M ED	39
4M TDE4	10	6E TET2	25	9N ED	40
4A TDE4	11	6D TET2	26	9O ED	41
4C TDE4	12	6C TET2	27	9P ED	42
4N TDE4	13	9A ED	28	9R ED	43
4L TDE4	14	9B ED	29		
6A TDE4	15	9C ED	30		

Courses differ in their level of difficulty. They are categorized as easy to understand, reasonable and as difficult and assigned the weights as 1,2 and 3, respectively. The course weights are indicated in Table 2. During lecturing, the level of understanding of the students changes according to the day and also the time of day. It usually reaches a maximum point before noon and declines in the afternoon. It again reaches a maximum point in the late afternoon. From this perspective, the days of the week also have different weights. Usually there is a lower performance in the beginning and the last days of the week, and it fits a normal distribution as it has a maximum point in the middle of the week (Anagün, 1990). In the light of the above, the days and the time slots that are under consideration are weighed as in Table 3.

Table 2
Course weights

Course difficulty	a_i	Courses in this group
difficult	3	TDE3, TDE4, ED1, ED2
reasonable	2	TD2, ED
easy to understand	1	TET2, EDMET

Table 3
Day and time slot weights

Day	weight	Time slot	weight
Monday	0.5	1, 2	2
Tuesday	0.7	3, 4	4
Wednesday	1	5, 6	3
Thursday	0.7	7, 8	1
Friday	0.5		

Table 4
Block numbers corresponding to day- time slot pairs

Day ⇨ / Time slot ⇩	Monday	Tuesday	Wednesday	Thursday	Friday
			Block Numbers		
1-2	1	5	9	13	17
3-4	2	6	10	14	18
5-6	3	7	11	15	19
7-8	4	8	12	16	20

Each block is numbered as given in Table 4. By using Table 3, a weight for each block is calculated. Due to space limitation, we only explain the weight for in first block corresponds Monday 1-2, as an example:

The weight for Monday* time slot (1-2) weight = 0,5*2 = 1

The mathematical model of the course-time slot assignment problem for the given set of data is solved by using Lindo 6.0 software. The value of the objective function is calculated to be 910.3 for the current assignment. On the other hand, it is equal to 1237.4 for the proposed schedule in our model. To keep the paper within reasonable length, some parameter sets, the current and proposed assignments are not given here, in detail.

2.2 Faculty-course assignment

The model involves assigning instructors to courses. The instructors are grouped as tenured and new faculty. This introduces different upper limits on their weekly loads. We indicate course-class pairs with course for the rest of the paper. Model parameters are as follows:

$I = \{i: i=1,2,\ldots.n\}$ courses
$J = \{j: i=1,2,\ldots.m\}$ instructors
h_i : number of hours required to teach ith course
u_j: upper limits of the jth instructor's weekly load
t_{ij}: preference level of the ith course by the jth instructor (t_{ij} = 1,2,3,4,5 and 6, if the instructor likes to give the course less and less in increasing order of the value, 100 indicates that the course is undesirable for the instructor to teach)
a_{ij} : administrative preference level for the assignment of ith course to the jth instructor (a_{ij} the same with the definition of t_{ij}).

<u>Decision variables</u>

$$y_{ij} = \{1, \text{if instructor } j \text{ is assigned to course } i, \quad 0, \text{ otherwise}$$

<u>Constraints</u>
Each course must be assigned to only one instructor.

$$\sum_{j \in J} y_{ij} = 1 \qquad \forall i \in I$$

An instructor can not teach more than his upper weekly limits in hours.

$$\sum_{i} y_{ij} h_i \leq u_j \qquad \forall j \in J$$

Objective functions:

Minimize, for each of the instructors, the average preference level, L_j, per hour thought

$$\frac{\sum_{i} y_{ij} t_{ij} h_i}{\sum_{i} h_i y_{ij}} \qquad \forall\, j$$

Minimize the administrations total preference level on instructor-course assignments.

$$\sum_{i \in I} \sum_{j \in J} y_{ij} a_{ij}$$

Minimize the total deviation from the upper load- limits of the instructors.

$$\sum_{j \in J} (u_j - \sum_{i \in I} y_{ij} h_i)$$

The last objective is defined as a goal constraint. Later, we show how the total deviations from the goal are minimized in the objective function. Before discussing the multi objective structure of the problem, we say a few more words about the first objective function.

In previous studies, people considered faculty preferences via objective function, and in most, either sum of the preferences or sum of the deviations from the preferences are optimized by using decision models. However, with respect to the overall performance of the system, these approaches may have some drawbacks as demonstrated by the following example.

Assume we are given three feasible solutions for the faculty-course assignment problem where, as in Table 5, 1 means the most desirable course and 6 the least desirable. The instructor preference levels (t_{ij}'s) for $y_{ij} \geq 0$, the sum of the preferences and the differences among the instructor preference levels are given in the following table.

Table 5
Preference levels obtained for three feasible solutions

	Solution 1	Solution 2	Solution 3
Instructor 1	1	2	3
Instructor 2	5	4	3
Sum of the preferences	6	6	6
Difference	4	2	0

In solution 1, instructor 1 is assigned to a course that is mostly desired by him whereas the second instructor is assigned to his fifth preference. The value of the objective function in this solution is obtained as 6. Similarly, the objective function values are obtained as 6 for both Solution 2 and Solution 3. With respect to this kind of objective function based on the total preference levels of the solution, all three solutions are considered to be the same. However, in reality, the satisfaction levels of the individuals have gaps that affect the overall performance of the system. Especially in the first case, the second instructor is assigned to a course that is not very desirable for him while the first instructor is assigned to his most preferred course. On the other hand, in Solution 3, both instructors have been assigned to their third preferences and their satisfaction levels are not different. So, instead of using an assignment procedure that results in the maximum satisfaction for an instructor while yielding a very low satisfaction for another as in Solution 1, an assignment as in Solution 3 is more acceptable. A different approach based on the deviations of individual preferences must be used. In order to get Solution 3, with such an approach mentioned above, we set a min max objective function as follows:

$$min\left\{\max_j t_{ij} : y_{ij} \geq 0\right\}$$

By doing this, we will get {5,4,3} as the maximum dissatisfaction levels of each feasible solution given in Table 5. Then min {5,4,3}=3 will indicate the best solution as Solution 3 to optimize the overall satisfaction in a more acceptable way.

As a result, the additivity assumption on preferences does not hold on the assignments. Moreover when an instructor gives more than one course and the number of hours of the courses are different -as with our problem- it is possible to extend the process along similar lines. In our case, each instructor teaches a different number of courses, and the courses have different weekly hours. Thus we compute for each instructor weighted mean of the preferences per hour. Then we define the first objective of the problem as minimizing the maximum average preference level obtained for any feasible solution, as follows:

$$\min \max_j \left(\frac{\sum_i y_{ij} t_{ij} h_i}{\sum_i h_i y_{ij}} \right)$$

The preference function involves a fraction, besides we use a a min max structure for which linearity does not hold. Next we make the following transformation.

$$y_1 \geq (\sum_i y_{ij} t_{ij} h_i) \text{-} (\sum_i h_i y_{ij}) \quad \forall j$$

$$min\ y_1$$

For the third objective we define a goal constraint, and the deviational variables are minimized in the objective function.

$$\sum_i y_{ij} h_i + d_j^- - d_j^+ = u_j \qquad \forall j \in J$$

By incorporating other two objectives, and defining w_i's are the weights of the objectives, the objective function takes form:

$$\min\ (w_1 y_1 + w_2 \sum_{i \in I} \sum_{j \in J} y_{ij} a_{ij} + w_3 \sum_{j \in J} (d_j^- + d_j^+)\ )$$

With this kind of weighted sum, the scalarization approach does not guarantee all pareto-optimal solutions due to the fact that the convexity conditions do not hold. And this is because of the 0-1 decision variables that problem has. On the other hand, weighted sum scalarization does guarantee to find at least one pareto optimal solution and there are studies in the literature that solve the problem with scalarization anyway. (Chang et all. 2000, Demirtaş and Üstün, 2008 (in press)).

This problem turns out to be a multi objective one by bringing other questions: How to establish the weights of importance for different objectives? An Analytic Network Process model is used to weigh different objectives of the problem. To construct an ANP structure, the parties influenced by the problem's stakeholders as well as those they have an influence on need to be added as clusters. Here instructors and the administration are the parties that affect each another. A cluster for courses is defined in order to take into account the considerations for the courses. And finally the objectives of the problem are listed in a separate cluster named alternatives since the purpose is to get their relative priorities. Figure 1 shows a software screen view from the ANP structure of the problem when the mode to see the connections is selected for *state of belonging* criterion. The elements bordered as dark are the ones that affect the selected criterion. So it is seen that *state of belonging* is influenced by the weekly loads of instructors, number of the students of courses, hard constrains and the overall performance of the system. There are many dependencies and feedbacks among criteria and objectives as in this example. These kind of dependencies can not be considered in an Analytic Hierarchy Process (AHP) model which assumes the criteria to be independent. But this does not mean that ANP should always be used.

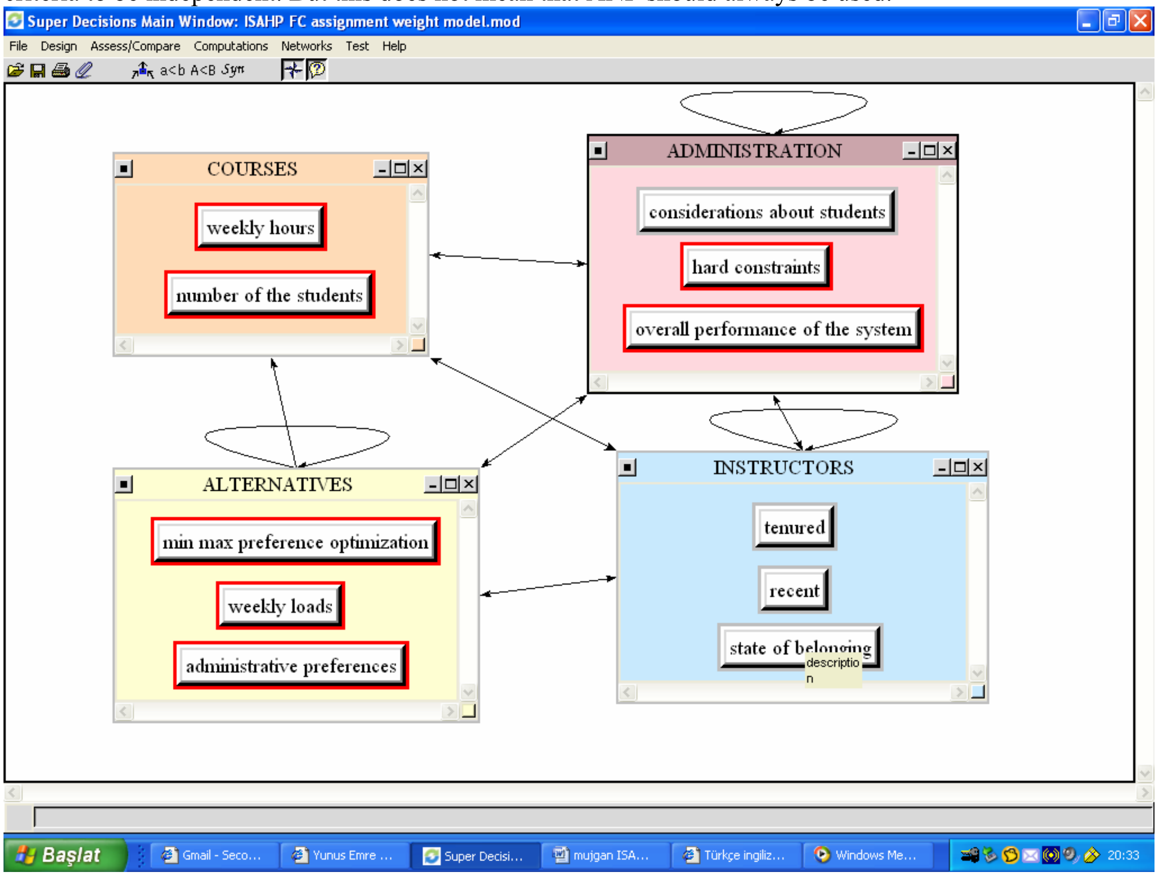

Figure 1 The ANP model of the weighting problem -a sample screen view of the connections

By considering the connections made by the decision maker, required paired comparisons are performed. Table 6 gives the synthesized values as the objective function weighs of the problem.

Table 6
ANP outcome

Objectives	min max inst. prefer.	min. admin. Preferences.	min. load deviations.
w_i	0.39	0.32	0.29

Table 7 gives the upper bounds on weekly loads of the instructors.

Table 7
Upper Bounds (in hours) on Weekly Loads for Instructors

j	1	2	3	4	5	6	7	8
u_j	27	11	25	19	26	14	26	21

The multi objective faculty-course assignment problem is solved by Lingo 6.0 as the second step of the approach. To keep the paper in a reasonable length, we only give the computational details for instructors to compare the average satisfaction levels of them for both proposed and current assignments, as in Table 8 and Table 9, respectively.

Table 8
Proposed faculty course assignment and the corresponding average preference levels of the instructors

Instructor number	Proposed courses	Nnumber of hours required to teach the course	Corresponding preference value	Average preference level (per hour)	Instructor number	Proposed courses	Nnumber of hours required to teach the course	Corresponding preference	Average preference level (per hour)
01	9F ED 9H ED 9I ED 9M ED 9O ED 9D ED 4G TDE3	(4) (4) (4) (4) (4) (4) (3)	1 1 2 5 2 5 3	2.7	05	4M TDE4 4M EDMT 4D ED1 6D ED2 6A TDE3 9B ED	(3) (4) (6) (6) (3) (4)	1 1 5 2 5 3	2.92
02	4F TDE4 6B TET2 6D TET2	(3) (4) (4)	3 5 1	3	06	4K TDE4 4H TDE4 9A ED 9L ED	(3) (3) (4) (4)	1 1 3 6	3
03	4K ED1 4H ED2 4B TDE4 4C TDE4 6A TDE4 6E TET2	(4) (6) (3) (3) (3) (4)	3 1 3 3 5 4	2.91	07	4D TDE3 4E TDE4 4F ED1 4G ED1 9E ED	(3) (3) (6) (4) (4)	1 4 3 2 3	2.65
04	9C ED 9N ED 4M TD2 4N TDE4 6C TET2	(4) (4) (3) (4) (4)	3 4 3 3 2	3	08	4L TDE3 4A TDE4 4L TDE4 9K ED 9P ED 9R ED	(3) (3) (3) (4) (4) (4)	4 1 1 5 3 3	2.95

As an example, the average preference level for the first instructor in Table 8 is calculated as follows:
$y_{\text{[illegible]}} = 1, y_{\text{[illegible]}} = 1, y_{\text{[illegible]}} = 1, y_{\text{[illegible]}} = 1, y_{\text{[illegible]}} = 1, y_{\text{[illegible]}} = 1, y_{\text{[illegible]}} = 1$
which correspond the courses 4G TDE3, 9D ED, 9F ED, 9H ED, 9I ED, 9M ED, 9O ED.

$$\frac{(y_{\text{[illegible]}} * 3 * 3 + y_{\text{[illegible]}} * 5 * 4 + y_{\text{[illegible]}} * 1 * 4 + y_{\text{[illegible]}} * 1 * 4 + y_{\text{[illegible]}} * 2 * 4 + y_{\text{[illegible]}} * 5 * 4 + y_{\text{[illegible]}} * 2 * 4)}{(3 + 4 + 4 + 4 + 4 + 4 + 4)}$$

$$= \frac{73}{27} = 2.7$$

The numbers used to reflect the preferences are 1,2,3,4,5, 6 and 100 for an undesirable assignment. This means that any average preference level greater than six implies at least one unpreferred course assigned to the instructor. It is clear in Table 9 that Instructors 3,5,7 and 8 are currently assigned courses they do not prefer to teach. Especially none of the courses assigned to 7th instructor are preferred by him. Table 8 and 9 confirm that the proposed assignment contrasts strongly with the current situation. In the proposed assignment, none of the assigned courses is considered very unpleasant to the instructors. Not so in current practice.

Table 9
Current faculty course assignment and the corresponding average preference levels of the instructors

Instructor number	Current courses	Nnumber of hours required to teach the course	Current preference value	Average preference level	Instructor number	Current courses	Number of hours required to teach the course	Current preference value	Average preference level
01	9G ED	(4)	1	2.83	05	4C TDE4	(3)	1	**67.19**
	9F ED	(4)	1			4N TDE4	(3)	100*	
	9H ED	(4)	1			4L TDE4	(3)	100*	
	9I ED	(4)	2			4M TD2	(4)	2	
	6B TET2	(4)	6			9M ED	(4)	100*	
	6C TET2	(4)	6			9K ED	(4)	100*	
02	4K ED (4)	(4)	4	2.66	06	4G TDE3	(3)	4	2.28
	6E TET2	(4)	3			4D TDE3	(3)	2	
	6C TET2	(4)	1			4L TDE3	(3)	2	
						4E TDE4	(3)	3	
						4F TDE4	(3)	3	
						4H TDE4	(3)	1	
						4K TDE4	(3)	1	
03	4H ED2	(6)	1	**42.31**	07	6A TDE3	(3)	100*	**100**
	6D ED2	(6)	100*			6A TDE 4	(3)	100*	
	4D ED1	(6)	100*			9L ED	(4)	100*	
	4G ED1	(4)	1			9B ED	(4)	100*	
	4M EDMT	(4)	2			9O ED	(4)	100*	
	4B TDE4	(3)	3			9A ED	(4)	100*	
04	9C ED	(4)	3	2.25	08	9P ED	(4)	3	**16.95**
	9E ED	(4)	1			9R ED	(4)	3	
	9D ED	(4)	1			4M TDE4	(3)	100*	
	9N ED	(4)	4			4A TDE4	(3)	1	
						4F ED1	(6)	2	

In Table 10 we summarize the values of the objective functions for both assignments. The proposed assignment far improves the optimum value.

Table 10
Objective function values

Objectives	$w_{1=0.39}$ f_1	$w_{2=0.32}$ f_2	$w_{3=0.29}$ f_3	Overall value
Current assignment	100	105	29	81,01
Proposed assignment	3	113	8	39,65

3. Conclusion

A two phased approach has been implemented to solve course-time slot assignment first, and then to the course-instructor assignment problem.

In the course-time slot schedule as the outcome of the first phase, instructors are asked to give their preferences on the courses they would like to teach. Three objectives related to the instructor's average satisfaction levels, administrative preference levels and finally the deviations from the upper teaching loads of the instructors are defined. Since the objectives do not have the same importance, an Analytic Network Process model is used to weigh them. Demonstrated in Table 10, the total dissatisfaction on the objectives declines from 81,01 to 39,65. In the proposed solution none of the parties comes out very dissatisfied on any of the assignments. Dissatisfactions for faculty members 3,5,7 and 8 remarkably decline to 2.95 at the worst case. The total deviations from the upper weekly teaching loads of the instructors are decreased from 29 to 8. Finally, the value for total administrative preference on instructor course assignments is increased from 105 to 113 which is the only undesirable outcome that we do not consider to be significant.

One might say that the approach may contribute to the happiness of the people involved.

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