Multi-Objective examination Timetabling Problem: Modeling and resolution using a based ε-constraint method

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Abstract:
In this work we aim to deal with the Multi-objective Examination Timetabling MOETP, in which we firstly propose a mathematical formulation containing three objectives: the minimization of the number of conflicts where students have to pass two exams in adjacent periods, the second objective represents the minimization of the necessary number of timeslots to pass all exams, the third objective is: the minimization of the number of students' enrollments when exams do not satisfy temporal relation-ships immediately before/after. Secondly we propose to adapt a based ε-constraint method to solve the multi-objective examination timetabling problem. Our proposed approach was experimentally tested on a set of randomly generated data.

Key words:
Multi-objective optimization, Examination timetabling problem, ε-constraint method.

1. Introduction

University timetabling problems belong to the larger family of general timetabling problem, the main objective of the problem is to assign a set of entities (lectures, exams, meeting …) to a set resources (timeslots, rooms, …). We distinguish two categories of the University timetabling problems: examination timetabling problem ETP and courses timetabling problem CTP. In this work we are interested by the ETP.

University Examination Timetabling Problem ETP deals with assigning a set of exams to a given number of timeslots. The principal hard constraints of this process are avoiding students' clashes (i.e. Each student cannot write more than one exam in the same timeslot, certain exams must be affected at the same time, certain exams must respect the precedence constraint, Some exams must be written only in a subset of the available timeslots, no student must write more than n examinations in any m consecutive periods and rooms' capacities must not be exceeded at any timeslot). However, a number of particular regulations, which depend on the institution, are also to be taken into account in the exam timetabling problems [1,2,3,4].

Other constraints are soft (maximization of the number of timeslots between two consecutive exams, Spread conflicting exams as even as possible for each student [5, 7, 6, 8, 9, 10, 11], Minimize the number of timeslots needed [12,13], Minimize the number of students setting two exams in a room on the same day [8, 14], Minimize the number of students setting two exams overnight [8, 15], Minimize the number of students setting two adjacent exams the same day [16, 17], Minimize the number of times that room capacities are exceeded, Minimize the number of conflicts where students have exams in adjacent days, Minimize the number of conflicts where students have exams in overnight adjacent periods, Minimize the number of times that students have exams that are not scheduled in period of proper duration, Minimize the number of students having exams that are not scheduled before/after another specified exams, minimize the number students having exams that are not scheduled immediately before/after another specified exams).

Examination timetabling problems can be formulated as a multiobjective problem where objectives measure the violations of the soft constraints. The Multiobjective optimization [18, 19, 20] is concerned with the minimization of a vector of objectives F(x) that can be the subject of a number of constraints or bounds. The conventional challenge of multiobjective optimization is assessment of the quality of solutions. Formally, one solution can be considered to be better than another only in the case when the values of all its criteria outperform those of the second ones: i.e. the first solution "dominates" the second one. All solutions which are not dominated by any other one, can be considered to be optimal. However, only one solution from this non-dominated set (often called the "Pareto front") can become the final result. To obtain it, the decision maker must express his/her preferences.

However, several authors (for example [21, 22, 23]) have studied the multiobjective university timetabling problem.

2. Literature review

The most popular approach applied to the multiobjective examination timetabling problem is the weighted sum

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aggregation of all criteria into one cost function and application of some single-objective metaheuristic [24, 1]. However, this method has a critical step which was the translation of user preferences into the weights of criteria, indeed, this step requires experience on the part of the user. Another inconvenient of this method is that the results produced by its application are usually substantially scattered.

E. Burke and al. in [21] have presented a multicreteria approach in british universities. The autors aim in their paper to formulate the university examination timetabling problems as a multicriteria decision problem. They consider many criteria which concern room capacities, the proximity of the exams for the students, the order and locations of events, etc. Such that each criteria have a level of importance in different situations and for different institutions.

The authors propose a new multicriteria approach to solve the problem. This approach is divided into two phases. The first phase aims to find high-quality timetables with respect of each objective separately. In the second phase, the goal is to find a compromised solution with respect to all the criteria simultaneously, this is done by carrying out a trade-offs between criteria values.

This approach consists of considering a point that optimizes all criteria (ideal point). But as known, such a solution does not exist. The heuristic search of the criteria space starts from the timetables obtained in the first phase in order to find a solution that is as close as possible to this ideal point with respect to a certain defined distance measure.

In [22], M.P. Carrasco and al. proposed a multiobjective genetic algorithm for the Class/Teacher timetabling problem, considering two distinct objectives. Thus, the authors described their proposed genetic multiobjective approach which represents each timetabling solution with a matrix-type chromosome and is characterized by special crossover and mutation consisting to act over a secondary population and a fixed-dimension main population of chromosomes. Favorable results were obtained through an application of the proposed approach to a real instance taken from a university establishment in Portugal.

J.M. Thompson and al., aim in their work to resolve a Multi-Objective University Examination Scheduling in [23]. Their proposed approach was based on a lexicographic ordering of criteria which are divided into groups and the search is conducted in several phases by each group.

3. Mathematical formulation

To formulate the problem mathematically we have to hold up all the necessary notations as follows:

- N is the number of exams
- T is the total number of timeslots
- The matrix $E = (E_{ij})_{N\times N}$ where each element is the number of students that have to take both exams i and j.
- The matrix $M=(M_{hk})_{T\times T}$ defined as:

$$M_{hk} = \begin{cases} 1 & \text{if timeslot h have a precedence or succession relation whith timeslot k} \\ 0 & \text{otherwise} \end{cases}$$

(Example for T=5)

$$M = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \end{pmatrix}$$

- The preference matrix $P=(P_{ij})_{N\times N}$ defined as:

$$P_{ij} = \begin{cases} E_{ij} & \text{if exam i havea preferenceto be planedbefore exam j} \\ 0 & \text{otherwise} \end{cases}$$

- The decision variables are :

$$x_{ih} = \begin{cases} 1 & \text{if the exam i is affected to the timeslot h} \\ 0 & \text{otherwise} \end{cases}$$

$$y_h = \begin{cases} 1 & \text{if the timeslot h is active} \\ 0 & \text{otherwise} \end{cases}$$

Our proposed MOETP formulation is as follows:

$$Min \ \{ f_1 ; f_2 ; f_3 \}$$

$$f1 = \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{h=1}^{T} \sum_{k=1}^{T} E_{ij} \, x_{ih} \, x_{jk} \, M_{hk}$$

$$f2 = \sum_{h=1}^{T} 2^k y_h$$

$$f3 = \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{h=1}^{T} \sum_{k=1}^{T} P_{ij} \, x_{ih} \, x_{jk} \, (1 - M_{hk})$$

The three objective functions defined by (f_1), (f_2) and (f_3) represent respectively: the number of conflicts, where students have exams in adjacent periods on the same day, the necessary number of timeslots to pass all exams and the number of students having exams that are not scheduled immediately before/after another specified exams, Subject to:

$$\sum_{h=1}^{T} x_{ih} = 1 \qquad \forall\, i = 1,\dots,N \qquad (1)$$

$$\sum_{h=1}^{T} E_{ij} x_{ih} x_{jh} = 0 \qquad \forall\, i, j = 1,\dots,N \;\; i \neq j \quad (2)$$

$$\sum_{i=1}^{N} x_{ih} \geq y_h \qquad \forall\ h = 1,\ldots,\ T \qquad (3)$$

$$\sum_{i=1}^{N} x_{ih}(1-y_h) = 0 \qquad \forall\ h = 1,\ldots,\ T \qquad (4)$$

$$x_{ih} \in \{1,0\} \qquad \forall i = 1,\ldots,N, \forall h = 1,\ldots,T \quad (5)$$

$$y_h \in \{1,0\} \qquad \forall\ h = 1,\ldots,\ T \qquad (6)$$

Constraints (1) ensure that each exam must be assigned to one and only one timeslot, constraints (2) avoid that each student writes more than one exam in the same period. Constraints (3) and (4) ensure that a timeslot is active if and only if at least one exam is assigned to this timeslot.

4. Resolution of the MOETP

4.1 Multi-objective optimization

Multiobjective optimization is concerned with the minimization of a vector of objectives F(x) that can be the subject of a number of constraints or bounds [20].

$$\begin{cases} \text{Minimize } F(x) \\ \quad \text{subject to} \\ \qquad g(x) \leq 0 \\ \qquad h(x) = 0 \end{cases}$$

When a multi-objective optimization problem is solved, a multitude of solutions are obtained. Only a limited number of these solutions will be interesting. There must be a dominance relation between these solutions and the other solutions, in the following sense:

Definition: the dominance relation
A vector x_1 dominates another vector x_2 if: x_1 is at least as good as x_2 in all the objectives, and x_1 is strictly better than x_2 in at least one objective.

$$\begin{cases} \forall\, i \in \{1,\ldots,n\}\ f_i(x_1) \leq f_i(x_2) \\ \exists\, i_0 \in \{1,\ldots,n\}\ f_{i_0}(x_1) \prec f_{i_0}(x_2) \end{cases}$$

Solutions that dominate others but do not dominate their self are called optimal solutions in the Pareto sense (or non-dominated solutions).

Definition: weak Pareto optimum
A point x* is said to be a weak Pareto optimum or a weak efficient solution for the multi-objective problem if and only if there is no $x \in S$ such that $f_i(x) < f_i(x^*)$ for all $i \in \{1,\ldots, n\}$.

Definition: strict Pareto optimum
A point x* is said to be a strict Pareto optimum or a strict efficient solution for the multi-objective problem if and only if there is no $x \in S$ such that $f_i(x) \leq f_i(x^*)$ for all $i \in \{1,\ldots,n\}$, with at least one strict inequality.

Definition: Pareto front
The image of the Pareto optimums set, i.e., the image of all the efficient solutions, is called Pareto front or Pareto curve or surface. The shape of the Pareto front indicates the nature of the trade-off between the different objective functions.
In many cases, pareto front cannot be computed efficiently. Even if it is theoretically possible to find all these points exactly, they are often of exponential size;
A comprehensive survey of the methods aiming to define the pareto front, presented in the literature in the last 33 years, from 1975, [25]. The survey analyzes separately the cases of two objective functions, and the case with a number of objective functions strictly greater than two. Another interesting survey on these techniques related to multiple objective integer programming can be found by Ehrgott, M. and al. in [26, 32], where he discusses different scalarization techniques. In [27], T'Kind and al. presented the multiobjective optimization approaches in a part of their book "Multicriteria scheduling".

4.2 Approach of resolution: ε-constraint Method

The ε-constraint method proposed by Chankong and Haimes in 1983 [28] consists to transform a multi-objective optimization problem into a mono-objective optimization problem comprising some additional constraints. So, the decision maker chooses one objective out of n to be minimized; the remaining objectives are constrained to be less than or equal to a given target values. The approach is briefly as follows:

- We choose an objective function to optimize first;
- An initial constraint vector is selected;
- The problem is transformed by maintaining the priority objective and by transforming the other objectives into inequality constraints.

We suppose that the priority objective function is f_1.
We choose a vector of constraints ε_i, $i \in \{2, \ldots, k\}$;
$\varepsilon_i \geq 0$.

$$\begin{cases} \text{Minimize } f_1(x) \\ \quad \text{avec} \\ \qquad f_2(x) \leq \varepsilon_2 \\ \\ \\ \qquad f_k(x) \leq \varepsilon_k \\ \qquad g(x) \leq 0 \\ \qquad h(x) = 0 \end{cases}$$

This formulation of the ε-constraints method can be derived by a more general result by Miettinen's theorem in 1999 [29] :

Miettinen theorem :

If an objective k and a vector $\varepsilon = (\varepsilon_1,\ldots,\varepsilon_{k-1}, \varepsilon_{k+1},\ldots,\varepsilon_n) \in IR^{n-1}$ exist, such that x* is an optimal solution to the following problem Pε:

$$\begin{cases} \min f_k(x) \\ f_i(x) \le \varepsilon_i, \forall i \in \{1,\ldots,n\} \setminus \{k\} \\ x \in S \end{cases}$$

We say that the solution x* is a weak Pareto optimum.
This theorem derives from a more general theorem [30] :

Yu theorem :

x* is a strict Pareto optimum if and only if for each objective k, with k = 1,...,n, there exists a vector $\varepsilon = (\varepsilon_1,\ldots,\varepsilon_{k-1}, \varepsilon_{k+1},\ldots,\varepsilon_n) \in IR^{n-1}$ such that f(x*) is the unique objective vector corresponding to the optimal solution to problem Pε.

The Miettinen theorem is an easy implementable version of the result by Yu (1974). Indeed, the uniqueness constraint represents one of the difficulties of the result of Yu theorem. The weaker result by Miettinen allows one to use a necessary condition to calculate weak Pareto optima independently from the uniqueness of the optimal solutions. However, if the set S and the objectives are convex this result becomes a necessary and sufficient condition for weak Pareto optima.
In 1986, Steurer [31] proposed that the decision maker can vary the upper bounds εi to obtain weak Pareto optima. Clearly, this is also a drawback of this method, i.e., the decision maker has to choose appropriate upper bounds for the constraints. Moreover, the method is not particularly efficient if the number of the objective functions is greater than two. For these reasons, Erghott in 2005 [32], proposed two modifications to improve this method, with particular attention to the computational difficulties that the method generates.
One advantage of the ε -constraints method is that it is able to achieve efficient points in a non-convex Pareto curve. As shown by Marler and Arora, 2004 in [33], if the solution to the ε-constraint method is unique then it is efficient.

4.3 ε-constraint method adaptation

The ε-constraint method can be applied to any three objective optimization problem with two conflicting objectives at least. The examination timetabling problem treated in this paper is a three-objective combinatorial optimization problem as shown in the mathematical formulation section. The three objective functions defined by (f_1), (f_3) et (f_2) represent respectively: Number of conflicts, where students have exams in adjacent periods on the same day, Number of students having exams that are not scheduled immediately before/after another specified exams, the necessary number of timeslots to pass all exams. Thus we confirm that the two conflicting objectives are f_1 and f_3. One issue with this approach is that it is necessary to preselect which objective to minimize and the ε_j values.
Our proposed based ε -constraint approach, consists to choose as objective function to optimize, the objective f_2, which aims to minimize the necessary number of timeslots to pass all exams. Since function objectives f_1 and f_3 are contradictory, indeed, f_1 represents de minimization of the number of conflicts, where students have exams in adjacent periods on the same day and f_3 represents the number of students having exams that are not scheduled immediately before/after another specified exams.
So we define our constrained single-objective problem $P(\varepsilon_1, \varepsilon_3)$ as follows :

$$Min \sum_{h=1}^{T} 2^k y_h$$

Subject to:

$$\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{h=1}^{T}\sum_{k=1}^{T} E_{ij}\, x_{ih}\, x_{jk}\, M_{hk} \le \varepsilon_1 \qquad (1)$$

$$\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{h=1}^{T}\sum_{k=1}^{T} P_{ij}\, x_{ih}\, x_{jk}\, (1 - M_{hk}) \le \varepsilon_3 \qquad (2)$$

$$\sum_{h=1}^{T} x_{ih} = 1 \qquad \forall i = 1,\ldots, N \qquad (3)$$

$$\sum_{h=1}^{T} E_{ij} x_{ih} x_{jh} = 0 \qquad \forall i, j = 1,\ldots, N \quad i \ne j \quad (4)$$

$$\sum_{i=1}^{N} x_{ih} \ge y_h \qquad \forall h = 1,\ldots, T \qquad (5)$$

$$\sum_{i=1}^{N} x_{ih} (1 - y_h) = 0 \qquad \forall h = 1,\ldots, T \qquad (6)$$

$$x_{ih} \in \{1, 0\} \qquad \forall i = 1,\ldots, N, \forall h = 1,\ldots, T \quad (7)$$

$$y_h \in \{1, 0\} \qquad \forall h = 1,\ldots, T \qquad (8)$$

The proposed approach is based on a gradual variation of parameters ε_1 and ε_3 (increment ε_1 and decrement ε_3).

Our approach is based in the following steps:

- Assign to parameter ε1 the different values that can be taken by objective f_1, starting from the minimum value f1min and ending with the maximum value f1max.

- For each value f_{1k} in the discrete interval [f1min, f1max], assign ε_3 the maximum value that can take the objective function f_3. Then we decrement by one, the value of ε_3 while the resulting of the problem $P(\varepsilon_1 = f_{1k}, \varepsilon_3)$ is feasible.
- Increment the value of f_{1k} and reiterate the steps.

Each resulted feasible couple $(\varepsilon_1^*, \varepsilon_3^*)$ of the resolved problem $P(\varepsilon_1, \varepsilon_3)$, generates an optimal solution that we note $x^* = opt(f_1, \varepsilon_1^*, \varepsilon_3^*)$.

1.1. Experimental results :

This section aims to represent the results of our based ε-constraints method adaptation. For that, we use a randomly generated set of examination timetabling problem ETP. For the random generation of data, we have inspired from the set of the 13 real-world examination timetabling problems introduced by Carter, Laporte and Lee in 1996 [13] from three Canadian high schools, five Canadian universities, one American university, one British university and one university in Saudi Arabia and which can be downloaded from:
ftp://ftp.mie.utoronto.ca/pub/carter/testprob/.
Each instance is characterised by five values:

- The number of examinations
- The number of students: is the number of students in each instance.
- The number of enrolment
- The number of timeslots
- The density of conflict: To indicate the density of the conflicting exams in each of the instances,

The proposed approach was implemented with java, and the models are solved with CPLEX 12.2. Our experiments were performed on a HP Probook 4540s with an Intel® Core™ i3-3110 CPU running at 2.4 GHz with a RAM 4,00 Go.

Table1 represent the results obtained for some of the randomly generated instances :

Table 1: Results obtained using ε-constraint approach

instance	*Extracted instance*	*S**	*CPU time (sec)*	*Gap (%)*
Cars91	5e_3t	f1=16	38	0%
		f2= 7		
		f3=13		
Cars91	6e_4t	f1=6	41	0%
		f2= 13		
		f3=30		
Hec92	6e_5t	f1=14	51	0%
		f2=7		
		f3=26		
Hec92	7e_4t	f1=32	32	2%
		f2=7		
		f3=25		
Yor83	7e_5t	f1=30	41	2%
		f2=7		
		f3=29		
Yor83	8e_7t	f1=44	43	2%
		f2=83		
		f3=34		

The column S* represent a solution of the exact Pareto front for the instances: 5e_3t, 6e_4t and 6e_5t, and an approximate Pareto front for the other instances. Thus, we have imposed a non-null tolerance on the relative gap (computed by CPLEX solver) for solving problem $P(\varepsilon_1, \varepsilon_3)$, all that in objective to reduce computing times. We define this gap by the relative gap between the best upper bound (a feasible solution value) and the best lower bound (the linear relaxation value of the best node remaining).
The proposed approach seems unable to be adapted for the big instances in terms of resolution time.

Conclusion and perspectives:

In this work we aimed to treat a MOETP, Firstly we proposed a mathematical formulation considering three objectives. Then we proposed a based ε-constraint which is an exact approach, we have tested our approach for a set of small randomly generated instances. The proposed approach works well for these instances, but seems unable to resolve the big ones. Our perspective is to propose a based surrogate Worth Trade-off method (SWT) to resolve the big instances which is an approximate approach.

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