A survey of the state of the art of Educational Timetabling Problems

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***Abstract*— An Educational Timetabling Problem (ETP) consists of assigning meetings or exams between teachers and students, considering a list of hard or soft requirements. ETPs are very challenging assignments classified as NP hard problems. Given the complexity of the problem, this paper aims to provide a comprehensive review of the relevant literature in the field, identifying trends in solution techniques and approaches. For this purpose, the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) protocol was used. The search yielded 55 results; 12 articles were excluded at the screening stage after being analyzed based on their titles and abstracts, and 17 others were excluded after further analysis. The remaining 26 articles were included in the research. The analyses of solution techniques and approaches to optimize ETPs reveal that meta-heuristic-based methods are the authors' most popular choice. It was observed that, despite their popularity, meta-heuristics are rarely implemented in isolation. The analysis of the chosen initialization strategy shows that most authors start with feasible initial solutions and develop a mechanism to generate them, integrated with the main algorithm.**

Keywords—Educational Timetabling Problems, optimization, solution techniques.

I. INTRODUCTION

An Educational Timetabling Problem (ETP) consists of assigning meetings or exams between teachers and students, considering a list of different hard or soft requirements. Hard constraints have to be satisfied to generate a feasible timetable. Soft constraints are not mandatory, but if a minimum number of violated soft requirements is obtained, then the timetable is said to be optimal [1].

Traditionally, Educational timetabling can be classified into university and (high) school timetabling. Problems (HSTP). University timetabling is further divided into the University Course Timetabling Problem (UCTP or UCTTP) and the University Examination Timetabling Problem (UETP or UETTP) [2]. However, new formulations are being introduced in the literature to provide a more accurate representation of different varieties of the problem, as particular rules of educational institutions worldwide make the problem highly variable.

Although it has been studied in the literature since the 1960s, introduced by Gotlieb [3] and having a thriving research community, with notable biannual conference series such as Practice and Theory of Automated Timetabling dedicated to timetabling practices and their applications [4], the timetabling problem is still addressed by manual scheduling procedures by a majority of universities [5].

According to Muklason et al. in [6], manual scheduling still causes recurring problems when making a schedule. These problems include the large amount of time invested in it, less flexibility to sudden changes, and poor consideration of students' needs. Those issues indicate the need for automation in such tasks. However, it is a very challenging assignment classified as an NP-hard problem, which means that the amount of computation required to find solutions increases exponentially with problem size [7].

Given the complexity of the problem, this paper has the main goal of providing a review of the relevant literature in the field, searching for trends in the solution techniques and approaches, as well as in the problem formulations. To categorize the solution techniques found in the state of the art, the categories selected for classification were: meta-heuristics, exact optimization methods, hyper-heuristic approaches, and matheuristic approaches.

It is also of interest in this research to analyze the initialization strategies used by authors, separating them according to the feasibility of the initial solutions and the kind of mechanism used to generate them. The categories of initial solutions identified are: unfeasible, feasible, and good quality, and they are usually generated through a solver or algorithm.

The main contributions of this paper are:

1. Presenting a general overview of the ETPs through a Systematic Review of Literature;

2. Categorization of the solution techniques and approaches selected by the authors to address ETPs, organized in chronological order.

3. Introducing a novel categorization for the initialization strategy based on the viability of the initial solutions;

II. SURVEY METHODOLOGY

This article performs a literature review on recent approaches to the optimization of ETPs. For this purpose, the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) protocol was used. The search term "Educational Timetabling Problem" was used in the IEEE Xplore, ACM digital library, and Science Direct databases. The following queries were used: consider only publications from 2014 onwards. The search on August 23, 2024, yielded 55 results. All articles found were published in English, although this was not a criterion used in the search.

After the search, all results found were analyzed through their titles and abstracts (screened). Those that dealt with a type of problem that did not belong to any ETP variant were discarded, with 12 articles being excluded at this stage. The remaining articles were retrieved and assessed for eligibility. At this point 17, articles were excluded because of the following criteria: systematic review of literature: 7 articles, study of problem formulation: 7 articles, case study: 1 article, study of algorithm selection strategy: 1 article, and development of an application for generating automated schedules: 1 article.

In common, all articles excluded have the fact that they did not study an optimization strategy. The 26 remaining articles were included in the research. Table I presents the country of origin for each study, and the content analysis indicates that Brazil stands out with the highest number of contributions. Table II displays the distribution of publications by year. The data reveal a declining trend over time, which becomes more evident when visualized in Fig. 1.

The next section presents the previous surveys found in the search. Section IV describes and categorizes the approaches chosen by the authors to optimize a type of ETP. Section V describes the initialization strategy found in each paper and presents a new categorization based on the viability of initial solutions.

III. PREVIOUS SURVEYS

The search performed as described in section II returned seven previous surveys. The references and scope of each of them are described in Table III. We observed that the results differ from each other and from the present research in several aspects.

Babaei, Karimpour and Hadidi [8], Yang, Ayob, and Nazri [9], and Abdipoor et al. [2] developed their surveys focused on the UCTP. However, Yang, Ayob, and Nazri utilized a practical case to study satisfaction factors for the elaboration of a timetable, while the other two papers are differentiated for their scopes, as Abdipoor et al. focus on meta-heuristic approaches, and Babaei, Karimpour and Hadidi (2015) do not make any kind of limitation.

The researches by Johnes [10] and Drake et al. [11] have very different objectives from the others and is not even restricted to the field of ETPs. The first lists Operational

TABLE I COUNTRY OF ORIGIN PER PUBLICATION

Country	Nº of publications	Country	Nº of publications
Australia	1	Indonesia	2
Brazil	7	United Kingdom	3
China	2	Greece	1
Egypt	1	Portugal	2
Mexico	2	Thailand	1
Tunisia	2	Malaysia	2

Research techniques to solve specific topics in education, and the second reviews the literature on selection hyperheuristics. Tan et al. [12] were the only authors among the survey authors found who analyzed optimization methodologies, specifically for HSTP.

The focus of the research by Ceschia, Di Gaspero and Schaerf [13], as well as that of the present research, is the general field of ETPs. However, the researches differ from each other in the focus as we study optimization strategies and the authors analyze problem formulations, benchmarks, and state-of-the-art results. In addition, in the present work, we are introducing a new categorization of initialization strategies based on the viability of the solutions.

IV. SOLUTION TECHNIQUES AND APPROACHES

To categorize the solution techniques found in the state of the art, we based ourselves on the categories proposed by Tan et al. [14]. The authors classify existing algorithms into: mathematical optimization algorithms, meta-heuristic algorithms, graph coloring algorithms, matheuristic approaches, hyper-heuristic approaches, and hybrid approaches.

Instead of using a category of mathematical optimization algorithms, we chose the term exact optimization methods that are not synonymous, but the latter is a category of the former and is sufficient for the purposes of this work. According to the results found, the categories selected for classification were, then: metaheuristics, exact optimization methods, hyper-heuristic approaches, and matheuristic approaches.

Graph coloring and hybrid approaches were not considered necessary categories since within the universe of the analyzed studies, those that used graph coloring did so as part of another approach. The hybrid approach defined by the authors involves a combination of the strengths of two or more metaheuristics. In these cases, we consider that a meta-heuristic category already covers the method that uses this type of strategy.

In the following sections, a brief description of the solution techniques found in the state of the art will be provided according to the category in which it is classified. Table III summarizes the findings of this section.

TABLE II DISTRIBUTION OF PUBLICATIONS BY YEAR

Year	Nº of Publications
2014	5
2015	5
2016	3
2017	4
2018	2
2019	1
2020	3
2021	2
2022	1

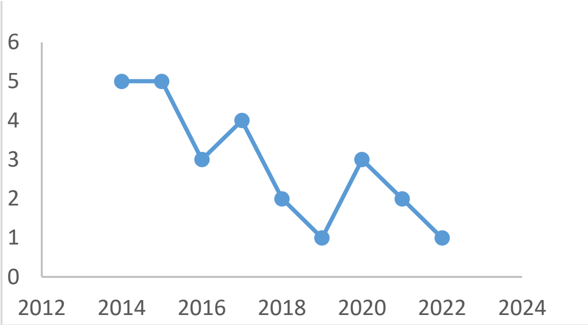

Fig. 1. Evolution of the number of publications by year

A. *Metaheuristics*

As the metaheuristics category had the greatest number of occurrences, it was considered important to detail the findings further. In order to do so, the results were then classified according to the method employed. Table IV shows all the methods of metaheuristics found and summarizes the reference in which each one of them was used. The results indicate that the most popular methods are Variable Neighborhood Search (VNS), Iterated Local Search (ILS), Tabu Search (TS), and Simulated Annealing (SA).

Dorneles, Araújo, and Buriol [15] combined the Fix and optimize (F&O) method with the Variable Neighborhood Descent (VND) meta-heuristic to compose an optimization strategy to solve the Class-Teacher Timetabling Problem with Compactness Requirements (CTTPCR), where each neighborhood is formed by a decomposition type τ and a number k. The type of decomposition varies between class, teacher, and day, and in each case, one of these elements is selected to have a k number of free elements to be optimized, while the rest are fixed.

Elloumi et al. [16] demonstrated two size reduction schemes for the classroom assignment problem, a component of the UETP. The two procedures provide a partial solution to the problem, and the remainder of the exams that remain unallocated to classrooms will be handled using the VNS meta-heuristic adapted by the authors through the proposition of neighborhood structures and Local Search (LS) heuristics.

Fong et al. [17] created the method called Artificial Bee Colony hybridized with Imperialist Nelder-Mead Great Deluge. The objective of the proposed approach is to improve the global exploration power of ABC and enhance the local exploration capacity to adjust the search region of each solution.

Fonseca and Santos. [18] show the application of three variations of the VNS metaheuristic to the HSTP. The authors define the neighborhoods used in the VNS. One of the variations used, called skewed variable neighborhood search, was presented by the authors of the paper through the introduction of a relaxed solution acceptance rule through which it becomes possible to accept a new solution that is worse than the current solution if the distance between them is large enough to trigger the relaxed condition.

Alves, Oliveira and Rocha Neto. [19] used the Genetic Algorithm (GA) to solve two instances of ETPs for multiple courses. To solve the problem, the proposed algorithm solves the schedules of one course at a time, providing partial solutions that change the parameters to be used by the algorithm in solving the schedules of the next courses,

TABLE III CLASSIFICATION PER FAMILIES OF METAHEURISTICS

Meta-heuristic	**Reference**	**Total**
Variable Neighborhood Descent	[15]	1
Variable Neighborhood Search	[16],[17],[18],[24],[6]	4
Artificial Bee Colony	[17]	1
Imperialist competitive algorithm	[17]	1
Great Deluge	[17]	1
Iterated Local Search	[24],[27],[1],[31]	4
Genetic Algorithm	[19],[22]	3
Ruin and Recreation	[20]	1
Particle Swarm Optimization	[21]	1
Cat Swarm Optimization	[25]	1
Threshold Acceptance Local	[26]	1
Late Acceptance Strategy	[27]	1
Tabu Search	[27],[6],[29],[1]	4
Simulated Annealing	[27],[28],[1],[31]	4
Cuckoo Search	[30]	1
Hill Climbing	[23]	1

considering that the same teachers teach different courses. The order in which the courses are selected is determined by the complexity of the schedule, that is, courses with a greater number of pairs (teacher, curricular component) are selected first.

Li et al. [20] created the algorithm called Stochastic Evolutionary Ruin and Recreate, based on the principles of Ruin and Recreate (R&R) incorporated into evolutionary features. Its general idea is to divide a solution into its components and assign a score to each component through an evaluation function that works in dynamic environments. The scores determine the chances of the components surviving in the current solution. Therefore, in each iteration, some components are evaluated as not worth keeping.

TABLE IV CLASSIFICATION OF THE RESULTS ACCORDING TO THE SOLUTION TECHNIQUE

Reference	Solution Technique				Problem
	Meta-Heuristic	Hyper-heuristic	Matheuristic	Mathematical Optimization	
[15]	x				CTTPCR
[16]	x				UETP
[17]	x				UCTP
[18]	x				HSTP
[34]		x			UCTP
[35]		x			HSTP
[19]	x				UCTP
[20]	x				UETP
[21]	x				MSP
[22]	x				UCTP
[38]			x		HSTP
[36]		x			UCTP
[23]	x				UCTP
[37]		x			UETP
[24]	x				HSTP
[25]	x				HSTP
[26]	x				UETP
[27]	x				HSTP
[28]	x				UETP
[6]	x				UCTP
[29]	x				UCTP
[1]	x				HSTP
[30]	x				UCTP
[31]	x				UCTP
[32]	x				UCTP
[33]				x	MCTP
Total	**20**	**4**	**1**	**1**	

Salem and Hassine [21] proposed a PSO-based approach to solve the Meeting Scheduling Problem (MSP). According to the authors, ETPs can be understood as variants of this type of problem. The velocity operator is obtained as demonstrated by (1):

$$V = c_1.\left(pbest_{i,t} - present_{i,t}\right) + c_2.\left(gbest_{i,t} - present_{i,t}\right) \quad (1)$$

The difference between two particles is given by the meetings present in one particle (with better performance) that do not occur at the same time in the other particle (with worse performance). To obtain a new particle $X_{i,t+1}$, the result of equation 1 must be added to a particle $X_{i,t}$.

The procedure is done by replacing the time and/or location of the meetings in the current position $X_{i.t}$ with the times/rooms of the meetings, as in the best position.

Abdelhalim and Khayat [22] used GA to develop a model for solving a UCTP. The model introduced a new recombination operator called "utilization crossover" that focuses on the utilization rate of classrooms, trying to reduce the number of under/overutilized events (with occupancy rates lower than 75% and higher than 100%, respectively) and increase the number of well-utilized events on a chromosome.

Mauritsius et al. [23] developed a method for solving ETPs based on the use of heuristics. The method has two stages: the first is intended to construct an initial schedule that does not necessarily need to be feasible. In this stage, two heuristics are used: Largest Degree First (LD), Largest Weighted Degree First (LWD), and Least Saturation Degree First (LSD). The first is used to choose the events assigned to the resources, and the second is used in case of a tie. In the second stage, new LSD heuristics will be used to make the schedule feasible.

Saviniec and Constantino [24] proposed five soft computing algorithms to address HSTP. The main idea behind the algorithms is the hybridization of the ILS and VNS metaheuristics with two neighborhood operators created by the authors to explore the structure of the problem. The two operators are called matching (MT) and torque (TQ), and the five algorithms are different combinations between the metaheuristics and the use and order of the operators: ILS-TQ, ILS-MT-TQ, ILS-TQ-MT, VNS-MT-TQ, and VNS-TQ-MT.

Skoullis, Tessapoulos and Beligiannis [25] proposed a hybrid algorithm based on Cat Swarm Optimization (CSO) that consists of two separate basic parts, which are executed sequentially: The main process, which is the basic CSO-based algorithm, and a local search refinement procedure, applied right after the main process, in an attempt to improve the quality of the resulting schedule about the number of idle hours that each teacher has available between their teaching hours.

Leite et al. [26] developed a cellular evolutionary algorithm with threshold acceptance metaheuristics and local search. The cellular evolutionary algorithm generates the offspring population. For the local search step, the threshold acceptance metaheuristic is used, where neighboring individuals generated from a feasible solution are accepted as the new current solution, even if they perform worse than the old current solution, as long as the difference between the performances of the two is less than a pre-established threshold.

Saviniec, Santos and Costa [27] used parallel metaheuristic models to propose two resolution methods for HSTP. The first method is based on central memory and operates as follows: a group of metaheuristics is executed concurrently while possibly cooperating through the exchange of current solutions made through the central memory that maintains a set of elite solutions.

Leite, Melício and Rosa. [28] built an algorithm for solving ETPs based on the SA metaheuristic. The method developed is called Fast Simulated Annealing (FastSA) and was built with the intention of producing a more efficient version of SA, accelerating the search process by reducing the number of solutions fitness evaluations.

Muklason, Iranti and Marom [6] applied a VNS algorithm hybridized with TS to UCTP. The algorithm is cited by the authors in previous works applied to solving other types of problems and works as follows: VNS is applied, and after the LS phase, the new solutions produced will be evaluated. If the new solution is better than the current one, it will replace the current solution, otherwise, it will become part of a list of unwanted moves.

Chen et al. [29] added controlled randomization to the TS methodology together with an acceptance threshold mechanism, to build the tabu search method with controlled randomization. In the method, during the search for environments, a solution worse than the current solution X can be accepted in a controlled manner according to a threshold τ.

Saviniec et al. [1] resorted to column generation for the resolution of a new extensive formulation for the HSTP. The solution model proposed is cooperative parallel. The method uses a team of metaheuristics to build and improve solutions, as explained in this section in [27]. The model described above was modified to incorporate new agents based on column generation. These agents use partial solutions obtained by column generation to obtain lower bounds for the problem and extend them to complete solutions using an original method that is based on a (F&O) heuristic.

Thepphakorn and Pongcharoen [30] developed the Cuckoo Search (CS) metaheuristic to solve the UCTP. The authors analyzed the success of three different strategies: a parameter setting approach (static and adaptive), an approach based on movement strategies (Lévy flights and Gaussian random walk), and a hybridization approach with local search (insertion operator and exchange operator).

Song et al. [31] proposed an LS algorithm with multiple neighborhoods based on SA. The authors introduced six neighborhood operators, three of which are basic and three specific to the UCTP problem, and the union of all neighborhoods provides the search space considered by the algorithm. The combination of neighborhoods is done through an innovative mechanism proposed by the authors that promises to balance the quality of the solutions and the computational cost of obtaining them.

Tung Ngo et al. [32] used GA to solve the UCTP. The authors modified the method by adding a repair process that is applied to both the initial solutions and the solutions after going through the recombination and mutation stages to ensure that the constraints are respected.

B. Exact Methods of Optimization

A Branch and Check algorithm for solving the Multiphase Course Timetabling Problem (MCTP) was presented by Esmaeilbeigi et al. [33]. The problem must first be relaxed and then solved by a solver. Each time a feasible solution of the relaxed formulation is obtained, it is checked whether it is possible to convert this solution into a feasible solution for the non-relaxed problem. If not, the infeasible solution is removed.

Whenever an integer feasible solution of the relaxed formulation is found, this integer solution is checked and is only accepted as feasible if the integer solution can be converted into a feasible solution for the non-relaxed problem. If not, one or more violated constraints are identified and added to remove this infeasible solution from the relaxed formulation. As a result, any optimal solution reported by the solver leads to an optimal feasible solution for the MCTP.

C. Hyper-heuristics

A hyperheuristic methodology based on ILS that combines several move operators was proposed by Soria-Alcaraz et al. [34] to solve the UCTP. The operators are low-level heuristics and are used within the ILS process to cause disturbances in the current solutions and are selected through a mechanism that takes into account a vector of probabilities and also a score attributed to each of the heuristics according to their performance.

Ahmed Özcan and Kheiri [35] studied and compared the performance of 15 hyperheuristics formed by the combinations of five selection methods and three acceptance methods, all listed from a literature review developed by the authors. The 15 hyperheuristics are used to select and combine 9 low-level heuristics to address 18 instances of HSTP.

Soria-Alcaraz et al. [36] developed a hyper-heuristic approach combining add and delete operations within an ILS methodology to solve UCTPs and UETP. The add and delete operations can be used to construct a new solution from a previously existing feasible solution, in which events will be removed from the timetable and reinserted into other valid periods. The adding and deleting procedure is done through a list that keeps track of the add and delete operations performed and their order.

Muklason et al. [37] developed an approach to solve ETPs incorporating the concept of fairness from the students' perspective. The model consists of three phases: In phase 1, initial feasible solutions are constructed. In phases 2 and 3, a hyper-heuristic selection is employed, incorporating reinforcement learning and the GD algorithm as heuristic selection and move acceptance components, respectively. Fourteen low-level heuristics commonly used in the literature for exam scheduling problems were used.

D. Matheuristics

Fonseca, Santos and Carrano [38] proposed a hybrid method using a variant of the VNS metaheuristic and a matheuristic to provide the refinement of the best solution obtained by the VNS. In the matheuristic approach, a heuristic works at a macro level, controlling LS procedures. These local searches are integer programming models, in which a subset of variables is fixed to the current values in the current solution, and the remaining variables of the model can be freely modified by the IP solver.

V. Initialization Strategies

Due to the large number of constraints in ETPs, finding feasible initial solutions is often a challenging process. For this reason, initialization processes are commonly addressed in the literature. To organize the strategies found during the analysis of the selected works, we introduced a categorization for the process of generating initial solutions. The categories of initial solutions identified are: unfeasible, feasible, and good quality.

When none or only a fraction of the hard constraints are to be taken into account during initialization or when the procedure for constructing the initial solutions is not capable of guaranteeing their viability, the chosen strategy is to create unfeasible initial solutions. In this case, since there is no mechanism to guarantee the viability of the solutions, it is necessary to develop a step that verifies whether the solutions have already become feasible before the algorithm meets the termination criteria.

The strategy of creating feasible initial solutions requires that the hard constraints be respected, but without worrying about the soft constraints. By disregarding the soft constraints to initialize the particles, the authors make it easier for the algorithm to find initial solutions, which can reduce computational time. However, since the quality of the solutions is directly linked to the number of soft constraints they can satisfy, this can compromise the optimality of the final solutions.

Good quality initial solutions are generated taking into account both soft and hard constraints. This strategy is important since good quality initial solutions increase the probability of directing the search to better regions of the search space and further help in the convergence to better solutions.

In addition, the authors still differ in their initialization strategy regarding the way to generate the solutions; some choose to use solvers, and others develop an initialization mechanism within the algorithm. Table V summarizes all the procedures described in this section.

VI. Conclusion

This paper presents an overview of the solutions techniques and approaches employed in the optimization of ETPs. The analyses of solution techniques and approaches to optimize ETPs reveal that meta-heuristic-based methods are the most popular choice by authors. It was observed that despite their popularity, meta-heuristics are hardly implemented in an isolated manner, and that it is very common to use of auxiliary heuristics and the hybridization between meta-heuristics. Other approaches are also considered by authors in smaller proportions, like hyper-heuristics, matheuristics, and exact methods.

Through the analysis of the results found in the literature, new questions were brought to our consideration, like the analysis of the initialization strategy chosen. It shows that most authors prefer to start with feasible initial solutions and develop a mechanism to generate them integrated with the main algorithm. Only one author chose the strategy of starting with initial solutions that consider both hard and soft

TABLE IV CATEGORIZATION OF THE RESULTS ACCORDING TO THE INITIALIZATION STRATEGY

Reference	Initialization Estrategy			Mecanismum	
	Unfeasible	Feasible	High Quality	Algorithm	solver
[15]		x			x
[16]	x			x	
[17]		x		x	
[18]		x			x
[34]				x	
[35]					x
[19]		-		-	
[20]		-		-	
[21]		x			x
[22]			x	x	
[38]		-			x
[36]		x		x	
[23]	x			x	
[37]		x		x	
[24]	x			x	
[25]	x			x	
[26]		x		x	
[27]	x			x	
[28]		x		x	
[6]		x		x	
[29]	x			x	
[1]		x		x	
[30]		x		x	
[31]		x		x	
[32]	x			x	
[33]		x		x	

constraints. To start with unfeasible solutions is also a popular choice, whether they are random solutions or solutions that consider only a fraction of the hard constraints.

We believe that this kind of detailed analysis can be beneficial to researchers who want to explore the development of algorithms to optimize ETPs. For future research, we believe that there is potential to closely look into the optimization strategies in order to find out how authors maintain the feasibility of the initial solutions or how they ensure that unfeasible initial solutions become feasible before the termination criteria are met.

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