Área Departamental de Engenharia de Electrónica e Telecomunicações e de Computadores

Examination Timetabling Automation using Hybrid Meta-heuristics

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Relatório Final

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Resumo

Nos últimos anos o tema de criação de horários tem sido alvo de muito estudo. Em muitos locais, a criação de horários ainda é feita manualmente, o que leva à criação de um horário que normalmente tem falhas ao qual se fosse criado por uma máquina, poderia obter-se melhores resultados.

A criação de horários não é uma tarefa fácil, mesmo para uma máquina. Por exemplo, horários escolares necessitam de seguir certas regras para que seja possível a criação de um horário válido. Mas como o espaço de estados (soluções) válidas é tão vasto, é impossível criar um algoritmo que faça *brute force* e assim obter a melhor solução possível, considerando as regras fornecidas. Daí a utilização de heurísticas que varrem de uma forma guiada o espaço de estados, conseguindo assim uma boa solução em tempo real.

Este relatório explica algumas das importantes heurísticas que são úteis neste tipo de desafios, tanto como o estado-da-arte que menciona abordagens importantes neste tema. Este projeto tem como objetivo o desenvolvimento de uma abordagem para concurso de *International Timetabling Competition 2007* considerando os melhores concorrentes que participaram no concurso e abordagens mais recentes.

É dos objetivos do projeto criar uma abordagem que siga as regras do *International Timetabling Competition 2007* ao qual irá incidir na criação de horários de exames para a faculdade (Examination timetabling). Este projeto utiliza uma abordagem de heurísticas hibridas. Isto significa que utiliza múltiplas heurísticas para a obter a melhor solução possível. Utiliza uma variância de Graph Coloring para obter uma solução válida e meta-heurísticas chamadas Simulated Annealing e Hill Climbing para melhorar a solução o máximo possível.

Este projeto possui uma arquitetura com 6 camadas. Camada de dados, camada de acesso a dados, camada de negócio, camada de heurísticas, camada de ferramentas e camadas de apresentação. A primeira é responsável pelo armazenamento de dados, ao qual são armazenados em repositórios em memória volátil. A camada de acesso a dados disponibiliza os repositórios das entidades que fornece funções como adicionar, remover, alterar e obter para essas mesmas entidades. A camada de dados fornece funções de acesso aos repositórios, ao qual as funções são mais ricas do que as funções fornecidas pelos repositórios. Dentro do mesmo nível estão presentes a camada de heurísticas, que possui

todas as heurísticas, e a camada de ferramentas, que é utilizada pelas heurísticas e pela camada de apresentação. E por fim a camada de apresentação, que simplesmente serve como debug e para verificação de resultados de testes.

No final os resultados vão ser avaliados e comparados com os cinco melhores participantes do concurso e outras abordagens mais recentes.

Palavras Chave

Heurísticas; Meta-heurísticas; International Timetabling Competition 2007; Timetable; Horários; Horários de exames; Graph Coloring; Simulated Annealing;

Abstract

In the last few years the creation of timetables is being a well-studied subject. In many places, the creation of timetables is still manual, so it will normally result on creating a faulty timetable, unlike being created by a machine, which can produce better results.

It is not easy to create timetables, even for a machine. For example, scholar/university timetables need to follow certain type of constraints or rules for them to be considered valid. But since the solution space is so vast, it is impossible to create a brute force algorithm to get the best possible solution in acceptable time, considering the given rules/constraints. Hence the use of heuristics which navigate through the solution space in a guided way, obtaining then a good solution in acceptable time.

The main objective of this project is to create an approach that follows the *International Timetabling Competition 2007* rules, focusing on creating examination timetables. This project will use a hybrid approach. This means it will use an approach that includes multiple heuristics in order to find the best possible solution. This approach uses a variant of the Graph Coloring heuristic to find an initial valid solution, and a meta-heuristic called Simulated Annealing to improve that solution.

The final results were satisfactory, as in some instances we were able to obtain results that match the results of the five finalists from 2007 timetabling contest.

Keywords

Heuristics; Meta-heuristics; International Timetabling Competition 2007; Timetable; Examination Timetabling; Graph Coloring; Simulated Annealing;

Contents

List of Figures

List of Tables

List of Code Listings

1

Introduction

Many people believe that Artificial Intelligence (AI) was created to imitate human behavior and the way humans think and act. Even though people are not wrong, AI was also created to solve problems that humans are unable to solve, or to solve them in a shorter time window, with a better solution. For hard problems like timetabling, job shop, traffic routing, clustering, among others, humans may take days to find a solution, or may not find a solution that fits their needs. Optimization algorithms, that is, methods that seek to minimize or to maximize some criterion, may deliver a very good solution in minutes, hours or days, depending on how much time the human is willing to use in order to get a proper solution.

A concrete example of this type of problems is the creation of timetables. Timetables can be used for educational purposes, in sports scheduling, or in transportation timetabling, among other applications. The timetabling problem consists in scheduling a set of events (e.g., exams, people, trains) to a specified set of time slots, while respecting a predefined set of rules.

1.1 Educational Timetabling Problems

This class of timetabling problems involve the scheduling of classes, lectures or exams on a school or university in a predefined set of time slots while satisfying a set of rules or constraints. Examples of rules are: a student can't be present in two classes at the same time, a student can't have two exams on the same day or an exam must be scheduled before another.

Depending on the institution type and if we're scheduling classes/lectures or exams, the timetabling problem is divided into three main types:

- Examination timetabling – consists on scheduling university course exams, while avoiding the overlap of exams containing students from the same course and spreading the exams as much as possible in the timetable.
- Course timetabling – consists on scheduling lectures considering the multiple university courses, avoiding the overlap of lectures with common students.
- School timetabling – consists on scheduling all classes in a school, avoiding the need of students being present at multiple classes at the same time.

In this project, the main focus is the examination timetabling problem.

The type of rules/constraints to satisfy depend on the particular timetabling problem specifications. The constraints are generally divided into two constraint categories: hard and soft. Hard constraints are a set of rules which must be followed in order to get a *feasible* solution. On the other hand, soft constraints represent the views of the different interested players (e.g., institution, students, nurses, train operators) on the resulting timetable. The satisfaction of this type of constraints is not mandatory as is for the case of the hard constraints. In the timetabling problem, the goal is usually to optimize a function with a weighted combination of the different soft constraints, while satisfying the set of hard constraints.

1.2 Objectives

This project's main objective is the production of a prototype application which serves as an examination timetable generator tool. The problem at hand focus on the specifications introduced in the International Timetabling Competition 2007 (ITC 2007), *First track*, which includes 12 benchmark instances. In the ITC 2007 specification, the examination timetabling problem considers a set of periods, room assignment, and the existence of constraints analogous to the ones present in real instances.

The application's requirements are the following:

- Automated generation of examination timetables, considering the ITC 2007 specifications (*mandatory*).
- Validation (correction and quality) of a timetable provided by the user (*mandatory*).
- Graphical User Interface to allow the user to edit generated solutions and to optimize user's edited solutions (*optional*).

This project is divided into two main phases. The first phase consists on studying some techniques and solutions for this problem emphasizing meta-heuristics like: Genetic Algorithms (GA) [**?**], Simulated Annealing (SA) [**?**], Tabu Search (TS) [**?**], and some of its hybridizations. The second phase consists in the development of the selected algorithms and promising hybridizations, and to test them using the ITC 2007 data. A performance comparison between the proposed algorithms and the state-of-the-art algorithms will be made.

1.3 Planning

This section provides more details about the development of the two project phases. On the first phase the author studied the educational timetabling problem and in particular the examination timetabling problem and related literature. This work is documented in the progress report submitted in March, 2015. The second phase's main goal is to develop solutions for the ITC 2007 problem instance. The work developed in the second phase spanned from March to July 2015, and is documented in the present document.

One of the approaches to be developed will use a local search algorithm (e.g., SA) to improve the solution obtained using a Graph Coloring (GC) heuristic. In a subsequent approach, instead of using a single-solution based meta-heuristic, the author intends to use

a population-based meta-heuristic (e.g., GA) hybridized with a local search algorithm (e.g., SA), or a combination of other meta-heuristics. A performance comparison will be made in which the proposed solution methods are compared against the five ITC 2007 finalists and other state-of-the-art approaches.

As an optional project requirement, a GUI for editing generated solutions by the human planner will be developed.

The Gantt diagram on Figure 1.1 shows a detailed planning for the development of all the main topics of this project including both phases mentioned above. The colors presented on the diagram are green and blue, which designate the first and second phase, respectively.

1.4 Document Organization

The remainder of this report is organized as follows. Chapter 2, addresses the timetabling problem focusing on examination timetabling and existing approaches applied to the ITC 2007 benchmark data. This chapter includes a survey of the most important paradigms and algorithmic strategies to tackle the timetabling problem. Next, the methods of the five ITC 2007 finalists are summarized. The next chapters address the implementation aspects of the solution method. This includes a chapter that explains the organization of the project and its architecture, following by chapters that explain the heuristics and the Loader module, ending with the experimental results, conclusions, and future work.

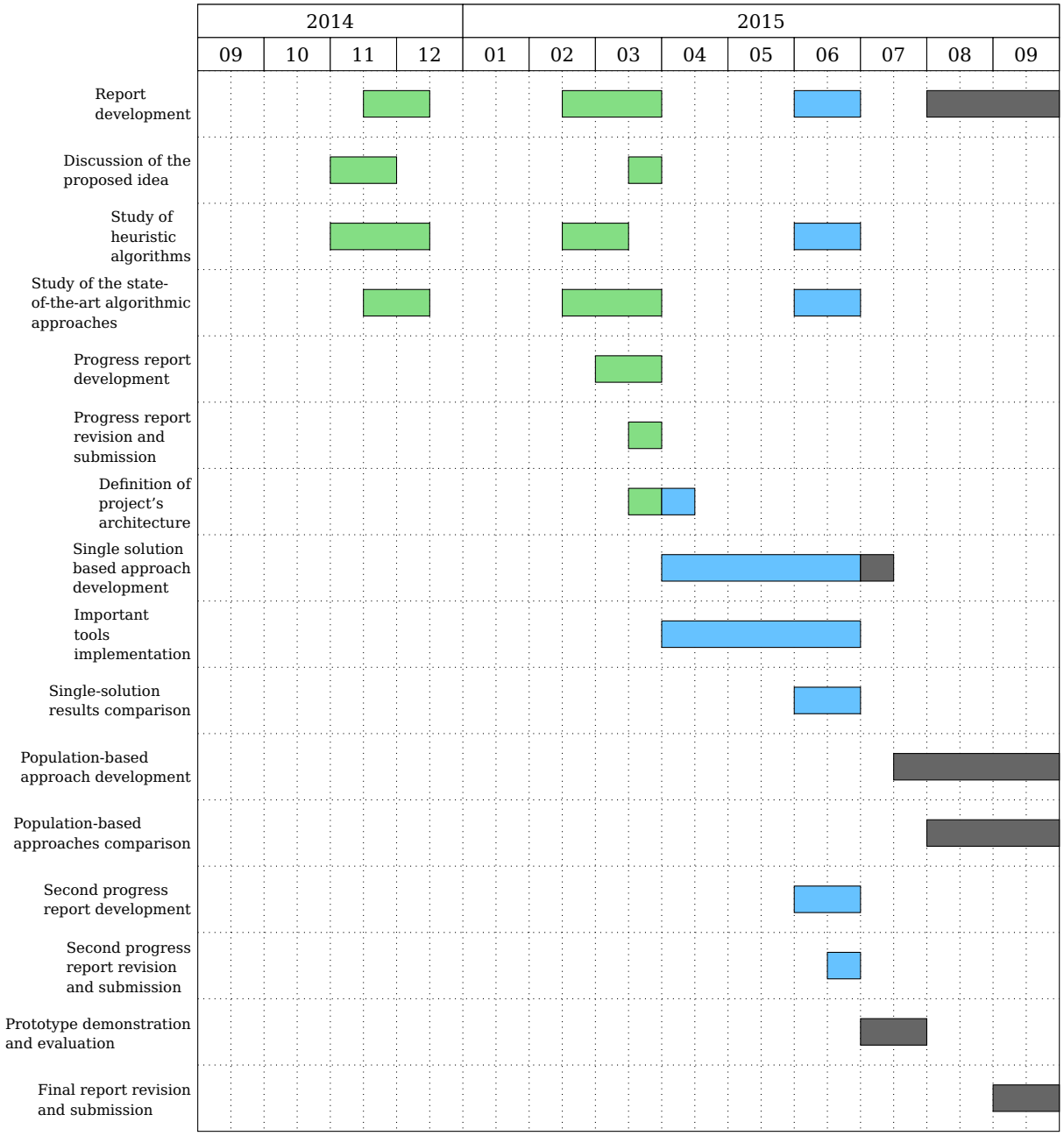


Figure 1.1: Gantt diagram of the project activities.

2

State-of-the-Art

In this chapter, we review the state-of-the-art of the problem at hand. We start by describing why timetabling is a rather complex problem, some possible approaches to solve it and some of the existing solutions, specifically for the ITC 2007 benchmarks.

2.1 Timetabling Problem

When solving timetabling problems, it is possible to generate one of multiple types of solutions which are: *feasible*, *non feasible*, *optimal* or *sub-optimal*. A feasible solution solves all the mandatory constraints, unlike non feasible solutions. An optimal solution is the best possible feasible solution given the problem constraints. A problem may have multiple optimal solutions. Lastly, sub-optimal solutions are feasible solutions with sub-optimal values.

Timetabling automation is a subject that has been a target of research for about 50 years. The timetabling problem may be formulated as a search or an optimization problem [**?**]. As a search problem, the goal consists on finding a feasible solution that satisfies all the hard constraints, while ignoring the soft constraints. By posing the timetabling problem as an optimization problem, one seeks to minimize the violations of soft constraints while satisfying the hard constraints. Typically, the optimization is done after the use of a search procedure to find an initial feasible solution.

The basic examination timetabling problem, where only the *clash* hard constraint is observed, reduces to the well-known graph coloring problem [**?**]. The clash hard constraint specifies that no conflicting exams should be scheduled at the same time slot. Deciding whether a solution exists in the graph coloring problem, is a NP-complete [**?**] problem [**?**]. Considering the graph coloring as an optimization problem, it is proven that the task of finding the optimal solution is also a NP-Hard [**?**] problem [**?**]. Graph Coloring problems are further explained in Section 2.2

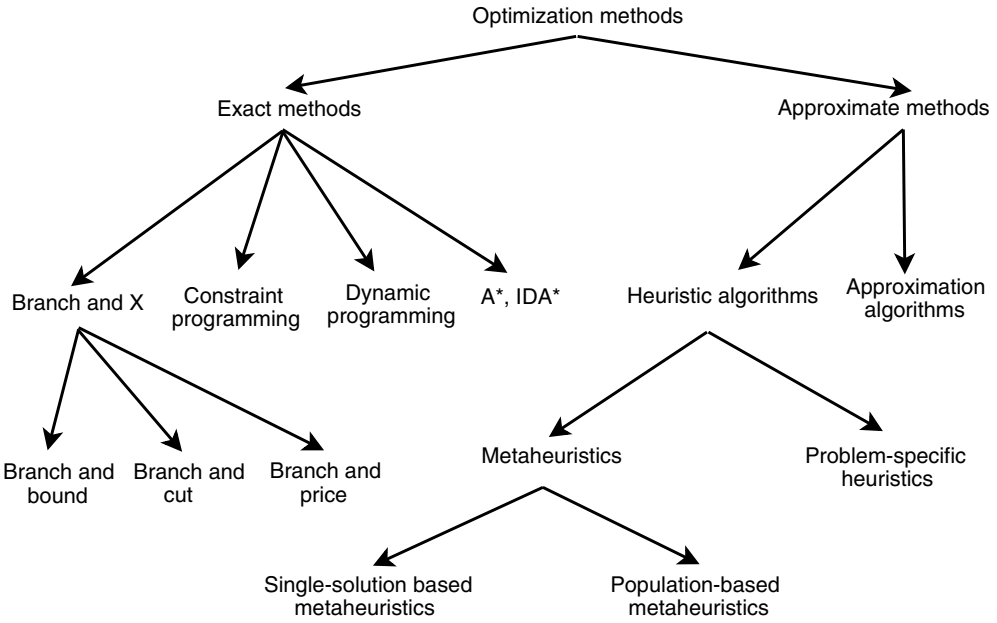


Figure 2.1: Optimization methods: taxonomy and organization (adapted from [**?**]).

2.2 Existing Approaches

Figure 2.1 depicts a taxonomy for the known optimization methods. These methods are divided into *Exact methods* and *Approximate methods*.

Timetabling solution approaches are usually divided into the following categories [**?**]: *exact algorithms* (Branch-and-Bound, Constraint Programming), *graph based sequential techniques*, *Single-solution based meta-heuristics* (Tabu Search, Simulated Annealing, Great Deluge), *population based algorithms* (Evolutionary Algorithms, Memetic algorithms, Ant Colony algorithms, Artificial immune algorithms), *Multi-criteria techniques*, *Hyper-heuristics*, and *Decomposition/clustering techniques*. Hybrid algorithms, which combine features of several algorithms, comprise the state-of-the-art. Due to its complexity, approaching the examination timetabling problem using exact method approaches, can only be done for small size instances. Real problem instances found in practice, are usually of large size, making the use of exact methods impracticable. Heuristic solution algorithms have been usually employed to solve this problem.

Real problem instances are usually solved by applying algorithms which use both *heuristics* and *meta-heuristics*. Heuristic algorithms are problem-dependent, meaning that these are adapted to a specific problem in which one can take advantage of its details. Heuristics are usually used to obtain a solution (feasible or not). For example, graph-coloring heuristics are used to obtain solutions for a given timetable problem instance. Usually only the hard constraints are considered in this phase. Meta-heuristics, on the other hand, are problem-independent, and are used to optimize any type problem. In these, one usually consider both

hard and soft requirements.

Most of the existing meta-heuristic algorithms belong to one of the following three categories: One-Stage algorithms, Two-Stage algorithms and algorithms that allow relaxations [**?**]. The One-Stage algorithm is used to get a solution, which the goal is to satisfy both hard and soft constraints at the same time. The Two-Stage algorithms are the most used types of approaches. This category is divided in two phases: the first phase consists in not considering the soft constraints and focusing on solving hard constraints to obtain a feasible solution; the second phase is an attempt to find the best solution, trying to solve the largest number of soft constraints as possible, given the solution of the first phase. Algorithms that allow relaxation can weaken some constraints in order to solve the *relaxed problem*, while considering the satisfaction of the original constraints that were weakened, on a later stage of the algorithm.

2.2.1 Exact methods

Approximation algorithms like heuristics and meta-heuristics proceed to enumerate partially the search space and, for that reason, they can't guarantee finding the optimal solution. Exact approaches perform an implicit enumeration of the search space and thus guarantee that the encountered solution is optimal. A negative aspect is the time taken to find the solution. If the decision problem is very difficult (e.g., NP-Complete), in practical scenarios, given the large size problem instances, it may not be possible to use this approach due to the prohibitive time.

Constraint-Programming Based Technique

The Constraint Programming Based Technique (CPBT) allows direct programming with constraints which gives ease and flexibility in solving problems like timetabling. Two important features of this technique are the use of backtracking and logical variables. Constraint programming is different from other types of programming, as in these types it is specified the steps that need to be executed, but in constraint programming only the properties (hard constraints) of the solution, or the properties that should not be in the solution, are specified [**?**].

Integer Programming

The Integer Programming (IP) is a mathematical programming technique in which the optimization problem to be solved must be formulated as an Integer Problem. If the objective function and the constraints must be linear, and all problem variables are integer valued, then the IP problem is termed Integer Linear Problem (ILP). In the presence of both integer and continuous variables, then the problem is called Mixed-Integer Linear Programming (MILP). Schaerf [**?**] surveys some approaches using the MILP technique to school, course, and examination timetabling.

2.2.2 Graph Coloring Based Techniques

As mentioned previously, timetabling problems can be reduced to a graph coloring problem. Exploiting the connection between these two problems, several authors used two-phase algorithms in which graph coloring heuristics are applied in the first phase, to obtain an initial feasible solution.

Graph Coloring Problem

The GC problem consists in assigning colors to an element type of a graph which must follow certain constraints. The simplest sub-type is the *vertex coloring*, which the main goal is to, given a number of vertices and edges, color the vertices so that no adjacent vertices have the same color. In this case, the goal is to find a solution with the lowest number of colors as possible.

The examination timetabling problem can be transformed into a graph coloring problem as follows. The exams corresponds to vertices and there exists an edge connecting each pair of conflicting exams (exams that have students in common). With this mapping only the clash hard constraint is take into consideration. Thus, soft constraints are ignored [**?**].

Given the mapping between the GC problem and the examination timetabling problem, GC heuristics like *Saturation Degree Ordering* are very commonly used to get the initial solutions. Others like *First Fit* and other *Degree Based Ordering* techniques (*Largest Degree Ordering*, *Incidence Degree Ordering*) are also heuristic techniques for coloring graphs [**?**].

2.2.3 Meta-heuristics

Meta-heuristics, as mentioned above, usually provide solutions for optimization problems. In timetabling problems, meta-heuristic algorithms are used to optimize the feasible solutions provided by heuristics, like the GC heuristics. Meta-heuristics are divided in two main subtypes, which are *Single-solution meta-heuristics* and *Population-based meta-heuristics* [**?**].

Single-solution meta-heuristics

Single-solution meta-heuristics main goal is to modify and to optimize one single solution, maintaining the search focused on local regions. This type of meta-heuristic is therefore exploitation oriented. Some examples of this type are *SA*, *Variable-Neighborhood Search*, *TS*, and *Guided Local Search* [**?**].

Population-based meta-heuristics

Population-based meta-heuristics main goal is to modify and to optimize multiple candidate solutions, maintaining the search focused in the whole space. This type of meta-heuristic is therefore exploration oriented. Some examples of this type are *Particle Swarm*, *Evolutionary Algorithms*, and *Genetic Algorithms* [**?**].

2.2.4 ITC2007 Examination timetabling problem: some approaches

In this section, the five ITC 2007 - Examination timetabling track - finalists approaches are described. This timetabling problem comprises 12 instances of different degree of complexity. Through the available website, competitors could submit their solutions for the given benchmark instances. The submitted solutions were evaluated as follows. First, it is checked if the solution is feasible and a so-called distance to the feasibility is computed. If it is feasible, the solution is further evaluated based on the fitness function, which measures the soft constraints total penalty. Then, competitors' solutions are ranked based on the distance to feasibility and solution's fitness value. The method achieving the lower distance to feasibility value is the winner. In the case of a tie, the competitor's solution with the lowest fitness value wins. A solution is considered feasible if the value of distance to feasibility is zero. The set of hard constraints is the following:

- no student must be elected to be present in more than one exam at the same time;
- the number of students in a class must not exceed the room's capacity;
- exam's length must not surpass the length of the assigned time slot;
- exams ordering hard constraints must be followed; e.g., $Exam_1$ must be scheduled after $Exam_2$;
- room assignments hard constraints must be followed; e.g., $Exam_1$ must be scheduled in $Room_1$.

It is also necessary to compute the fitness value of the solution which is calculated as an average sum of the soft constraints penalty. The soft constraints are listed below:

- two exams in a row – a student should not be assigned to be in two adjacent exams in the same day;
- two exams in a day – a student should not be assigned to be in two non adjacent exams in the same day;
- period spread – the number of times a student is assigned to be in two exams that are N time slots apart should be minimized;
- mixed durations – the number of exams with different durations that occur in the same room and period should be minimized;
- larger exams constraints - reduce the number of large exams that occur later in the timetable;
- room penalty – avoid assigning exams to rooms with penalty;
- period penalty – avoid assigning exams to periods with penalty.

To get a detailed explanation on how to compute the values of fitness and distance to feasibility based on the weight of each constraint, please check the ITC 2007 website [**?**].

We now review the ITC 2007's five winners approaches. The winners list of the ITC 2007 competition is as follows:

- 1st Place - Tomáš Müller
- 2nd Place - Christos Gogos
- 3rd Place - Mitsunori Atsuta, Koji Nonobe, and Toshihide Ibaraki
- 4th Place - Geoffrey De Smet
- 5th Place - Nelishia Pillay

We now briefly describe these approaches.

Tomáš Müller's approach [**?**] was actually used to solve all three problems established by the ITC 2007 competition. He was able to win two of them and to be finalist on the third. For solving the problems, he opted for an hybrid approach, organized in a two-phase algorithm. In the first phase, Tomáš used the Iterative Forward Search (IFS) algorithm [**?**] to obtain feasible solutions and Conflict-based Statistics [**?**] to prevent IFS from looping. The second phase consists in using multiple optimization algorithms. These algorithms are applied in this order: Hill Climbing (HC) [**?**], Great Deluge (GD) [**?**], and optionally SA [**?**].

Gogos was able to reach second place in the Examination Timetabling track. Gogos' approach [**?**], like Müller's, is a two-phase approach. The first phase starts the application of a pre-processing stage, in which the hidden dependencies between exams are discovered in order to speed up the optimization phase. After the pre-processing stage, a construction stage takes place, using a meta-heuristic called *Greedy Randomized Adaptive Search Procedure (GRASP)*. In the second phase, optimization methods are applied in this order: HC, SA, IP (the Branch and Bound procedure), finishing with the so-called Shaking Stage, which is only used on certain conditions. The Shaking Stage *shakes* the current solution creating an equally good solution, which is given to the SA. The objective of this stage to make SA restart with more promising solutions and generate better results.

Atsuta et al. ended up in third place on the Examination Timetabling track and won third and second places on the other tracks, with the same approach for all of them. Their approach [**?**] consists on applying a constraint satisfaction problem solver adopting an hybridization of TS and Iterated Local Search.

Geoffrey De Smet's approach [**?**] differs from all others because he decided not to use a known problem-specific heuristic to obtain a feasible solution, but instead used what is called the *Drool's rule engine*, named *drools-solver* [**?**]. The drools-solver is a combination of optimization heuristics and meta-heuristics with very efficient score calculation. A solution's score is the sum of the weight of the constraints being broken. After obtaining a feasible solution, Geoffrey opted to use a local search algorithm (TS) to improve the solutions obtained using the drools-solver.

Nelishia Pillay opted to use a two-phase algorithm variation, using a *Developmental Approach based on Cell Biology* [**?**], which goal consists in forming a well-developed organism by the process of creating a cell, proceeding with cell division, cell interaction, and cell migration. In this approach, each cell represents a time slot. The first phase represents the process of creating the first cell, cell division and cell interaction. The second phase represents the cell migration.

2.2.5 Other methods

Abdullah et al.'s 2009 approach [**?**] consists on using an hybridization of an electromagnetic-like mechanism and the GD algorithm. In this approach, the electromagnetism-like mechanism starts with a population of timetables randomly generated. Electromagnetic-like mechanism is a meta-heuristic algorithm using an *attraction-repulsion* mechanism [**?**] to move the

solutions the region of optimal solutions.

McCollum et al.'s 2009 two phased approach [**?**] use an adaptive ordering heuristic from [**?**], proceeding with an *extended version* of GD. As the author stated, this approach is robust and genetic considering the obtained results on the benchmark datasets from ITC 2007.

Alzaqebah et al.'s 2011 two phase approach [**?**] starts by using a graph coloring heuristic (largest degree ordering) to generate the initial solution and ends by utilizing the *Artificial Bee Colony* search algorithm to optimize the solution.

Turabieh and Abdullah's 2011 approach [**?**] utilizes a two phase algorithm. The first phase consists on constructing initial solutions by using an hybridization of graph coloring heuristics (least saturation degree, largest degree first and largest enrollment). The second phase utilizes an hybridization of electromagnetic-like mechanism and GD algorithm, just like in [**?**].

Turabieh and Abdullah proposed another approach in 2012 [**?**] that utilizes a Tabu-based memetic algorithm which consists on an hybridization of a genetic algorithm with a Tabu Search algorithm. The authors claim that this approach produces some of the best results, when tested on ITC 2007's datasets.

Demeester et al. in 2012 created an hyper-heuristic approach [**?**]. The heuristics utilized are 'improved or equal' (equivalent to hill climbing that accepts equally good solutions), SA, GD and an adapted version of the *late acceptance* strategy [**?**]. These heuristics are used on already-created initial solutions. Initial solutions are constructed using an algorithm which does not guarantee the feasibility of the solution.

McCollum et al.'s 2012 approach [**?**] introduce an IP formulation to the ITC 2007 instance, and also a solver using the CPLEX software.

Sabar et al.'s utilized a graphical coloring hyper-heuristic on its approach in 2012 [**?**]. This hyper-heuristic is composed of four hybridizations of these four methods: last degree, saturation degree, largest colored degree and largest enrollment. This approach seems to compete with the winners' approaches from ITC 2007, considering the benchmark results.

Sabar et al.'s 2012 approach [**?**] utilizes a two phase algorithm. It starts by using an hybridization of graph coloring heuristics to obtain feasible solutions and a variant of honey-bee algorithm for optimization. The hybridization is composed of least saturation degree, largest degree first, and largest enrollment first, applied in this order.

Abdullah and Alzaqebah opted to create an hybridization approach in 2013 [**?**], mixing the utilization of a modified bees algorithm with local search algorithms (i.e. SA and late acceptance HC).

Salwani Abdullah and Malek Alzaqebah in 2014 constructed an approach [**?**] that utilizes an hybridization of a modified artificial bee colony with local search algorithm (i.e. late acceptance HC).

Burke et al.'s 2014 approach [**?**] uses an hyper-heuristic with hybridization of low level heuristics (neighbor operations) to improve the solutions. The low level heuristics are *move exam*, *swap exam*, *kempe chain move* and *swap times lot*. After applying this hyper-heuristic with the hybridizations, the hybridization with the best results was tested with multiple exam ordering methods, applying another hyper-heuristic with hybridizations. The heuristics applied are *largest degree*, *largest weighted degree*, *saturation degree*, *largest penalty*, and *random ordering*.

Hmer and Mouhoub's approach [**?**] uses a multi-phase hybridization of meta-heuristics. Works like the two phase algorithm but includes a pre-processing phase before the construction phase. This pre-processing phase is divided in two phases: the propagation of ordering constraints and implicit constraints discovery. The construction phase utilizes a variant of TS. The optimization phase uses hybridization of HC, SA and an extended version of the GD algorithm.

Hamilton-Bryce et al. [**?**] in 2014 opted to use a non-stochastic method on their approach [**?**], when choosing examinations in the neighborhood searching process on the optimization phase. Instead, it uses a technique to make an intelligent selection of examinations using information gathered in the construction phase. This approach is divided into 3 phases. The first phase uses a *Squeaky Wheel* constructor which generates multiple initial timetables and a weighted list for each timetable. Only the best timetable and its weighted list is passed to the second phase. The second phase is the *Directed Selection Optimization* phase which uses the weighted list created in the construction phase to influence the selection of examinations for the neighbor search process. Only the best timetable is passed onto the next phase. The third phase is the *Highest Soft Constraint Optimization* phase, which is similar to the previous phase but a weighted list values are calculated, based on the solution's individual soft constraints penalty.

Rahman et al.'s approach [**?**] is a constructive one. This divides examinations in sets called *easy sets* and *hard sets*. Easy sets contain the examinations that are easy to schedule on a timetable and on the contrary, hard sets contain the ones that are hard to schedule and so are identified as the ones creating infeasibility. This allows to use the examinations present on the hard sets first on future construction attempts. There's also a sub-set within the easy set, called *Boundary Set* which helps on the examinations' ordering and shuffling. Initial examinations' ordering are accomplished by using graph coloring heuristics like largest degree and saturation degree heuristics.

Rahman et al.'s approach [**?**] utilizes adaptive linear combinations of graph coloring heuristics (largest degree and saturation degree) with an heuristic modifier. These adaptive linear combinations allows the attribution of difficulty scores to examinations depending on how hard their scheduling is. The ones with higher score, and so harder to schedule, are scheduled using two strategies: using single or multiple heuristics and with or without heuristic modifier. The authors conclude that multiple heuristics with heuristic modifier offers good quality solutions, and the presented adaptive linear combination is a highly effective method.

Table 2.1 is a timeline that represents the previous mentioned approaches chronologically ordered.

Table 2.1 Approaches timeline

2007	Atsuta et al. - Constraint satisfaction problem solver using an hybridization of TS and iterater local search.
	Smet - drool's solver with TS.
	Pillay - Two phase approach using Developmental Approach based on Cell Biology (creating the first cell, cell division, cell iteration and cell migrations).
2009	Müller - Two-phase approach with hybridization, which the first phase includes Iterative Forward Search (IFS) and Conflict-based Statistics, and the second phase is composed of HC, GD and SA.
	Abdullah et al. - Hybridization of electromagnetic-like mechanism and GD algorithm.
	McCollum et al. - Two phase approach, which first phase consists on using adaptive ordering heuristic, and the second phase utilizes an *extended version* of GD.
2011	Alzaqebah and Abdullah - Two phase approach, which the first phase uses the largest degree ordering, and the second phase utilizes an Artificial Bee Colony search algorithm.
	Turabeih and Abdullah - Two phase approach, which the first phase utilizes an hybridization of graph coloring heuristics, and the second phase uses an hybridization of electromagnetic-like mechanism and GD algorithm.
2012	Gogos - Considered a two-phase approach with a pre-processing stage for hidden dependencies. The first phase uses the *greedy randomized adaptive search procedure*, and the second phase is composed of HC, SA, IP with Branch and Bound, finishing with a shaking stage.
	Turabieh and Abdullah - Tabu-based memetic algorithm which is an hybridization of a genetic algorithm with TS.
	Demeester et al. - Hyper-heuristic approach of 'improved or equal', SA, GD and late acceptance strategy applied on already created solutions.
	McCollum et al. - Approach based on IP formulation.
	Sabar et al. - Graph coloring hyper-heuristic approach using last degree, saturation degree, largest colored degree and largest enrollment.
	Sabar et al. - Two phase approach, which the first phase is composed of an hybridization of graph coloring heuristics and the second phase uses an honey-bee algorithm.
2013	Abdullah and Alzaqebah - Hybridization approach with a modified bee algorithm and local search algorithms like SA and late acceptance HC.
2014	Abdullah and Alzaqebah - Hybridization approach with a modified artificial bee colony with local search algorithm like late acceptance HC.
	Burke et al. - Approach uses an hyper-heuristic with hybridization of low level heuristics (neighbor operations) like, thereafter uses an hyper-heuristic with hybridization of exam ordering methods.
	Hmer and Mouhoub - Multi-phase hybridization of meta-heuristics. A two phase approach with pre-processing phase. First phase uses a variant of TS, and the second phase utilzies an hybridization of HC, SA and an extended version of GD algorithm.
	Brice et al. - Approach with three phases. First phase uses a Squeaky Wheel constructor, second phase utilizes the weighted list created in the first phase for the neighbor search process, and the third phase uses a weighted list based on the solutions' soft constraints penalty.
	Rahman et al. - Constructive approach that divides examinations into easy and hard sets.
	Rahman et al. - Approach utilizes adaptive linear combinations of graph coloring heuristics, like largest degree and saturation degree, with heuristic modifier.

3

Architecture

In this chapter, a description of the architecture is given. The subsystems that compose the architecture are detailed. The proposed software architecture was designed taking into consideration aspects such as: code readability, extensibility, and efficiency.

3.1 System Architecture

The architecture of this project is divided in multiple layers. These are independent from one another and each of them has its unique features considering the objectives of this project. The layers presented in the project are named *Data Layer (DL)*, *Data Access Layer (DAL)*, *Business Layer (BL)*, *Heuristics Layer (HL)*, *Tools Layer (TL)*, and *Presentation Layer (PL)*. The assortment, dependencies and the main classes of each layer can be seen in Figure 3.1.

3.1.1 Data Layer

The DL stores all entities. The entities, which represent the different elements of a timetable, such as exam, room, or timeslot, are instantiated after reading an ITC 2007 benchmark file. Entities are maintained in memory and discarded after the program is finished.

3.1.2 Data Access Layer

The DAL allows access to the data stored in the DL. This layer provides repositories of each type of entity. The repository was implemented in a way that its signature is generic, and so can only be created with objects that implement the `IEntity` interface. This is mandatory because the generic repository's implementation uses the identification presented in `IEntity`.

The `Repository` class stores the entities in a list, with indexes corresponding to the entities identifiers. The `Repository` provides basic Create, Read, Update and Delete (CRUD) functions to access and edit the stored entities. The signature of the entities and all the specifications of the generic repository can be seen in Figure 3.2.

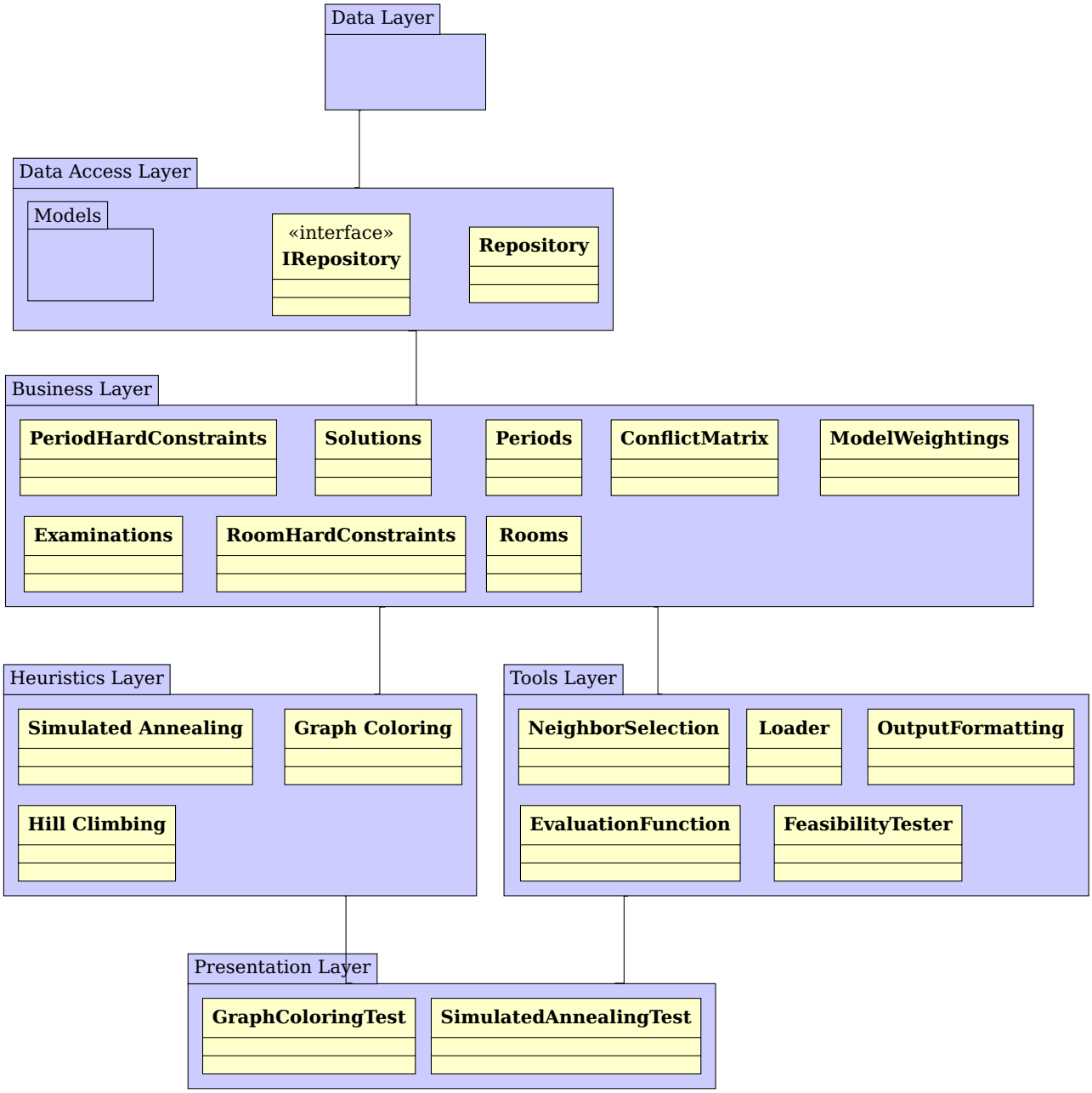


Figure 3.1: Overview of subsystems that compose the system architecture.

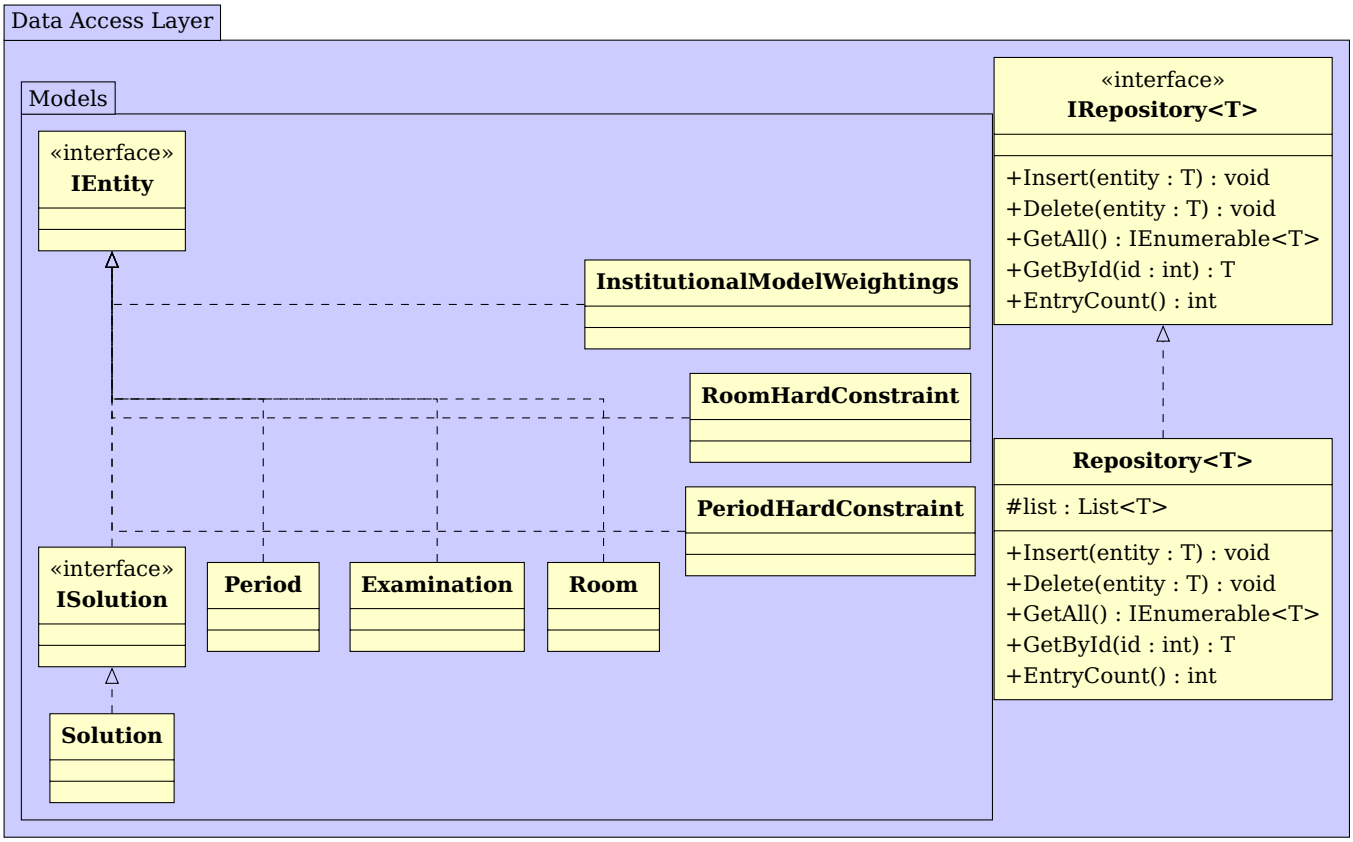


Figure 3.2: Overview of the DAL and the present entity types and repositories.

3.1.3 Business Layer

The BL provides access to the repositories explained above by, in each of the business classes, with CRUD functions or get/set functions, and specific functions that depend on the type of the repository. One example of these latter functions is the following. Considering the room hard constraints repository, one could invoke a method for obtaining all room hard constraints of a given type. This can be seen in Figure 3.3, which includes all the BL classes, methods and variables. The CRUD functions provided by some of the business classes use the CRUD functions from the Repository instance, which is presented on that same business class.

It's possible to store multiple instances of a certain type of entity, recurring to the BL classes, which provide `Repository` functions for that objective. If that's the case, a `Repository` instance of that type of entity is used. Thus, business classes that only store one instance, do not provide CRUD functions, just *set* and *get* functions. This makes sense, considering it only stores one instance of an entity, instead of multiple entity instances, not needing the use of a `Repository`. One example of these classes is the `ConflictMatrix`.

The `ConflictMatrix` class represents the *Conflict matrix*, of size equal to the number of

examinations. Each matrix element (i, j) contains the number of conflicts between examinations i and j. Even though it's not an entity that implements `IEntity`, it must be easily accessed in the lower layers. There's only one instance of this class because there's only one conflict matrix for each set. Each set must be loaded using the `Loader` if that set is to be tested.

All the business classes implement the *Singleton* pattern. This decision was made because it makes sense to keep only one repository of each entity since it must be populated using the Loader each time a set is tested. Another reason is to avoid passing the instances references of the business classes to all the heuristics and tools that use them, and so, the instances can easily be accessed statically.

3.1.4 Tools Layer

The TL contains all the tools used by the HL and by the lower layers, while using the BL to access the stored entities. These tools are named `EvaluationFunction`, `Loader`, `NeighborSelection`, `FeasibilityTester`, and `OutputFormatting`.

`EvaluationFunction` is a tool for solution validation, and computation of solution's fitness and distance to feasibility. A solution is only valid if the examinations are all scheduled, even if the solution is not feasible. The distance to feasibility determines the number of violated hard constraints and the fitness determines the score of the solution depending on the violated soft constraints and its penalty values. The distance to feasibility is used by the GC heuristic to guarantee that the end solution is feasible, while the fitness is used by the metaheuristics used, such as SA, to compare different solutions.

The `Loader` loads all the information presented in a benchmark file into the repositories. This tool is the first to be run, allowing the heuristics and other tools to use the entities through the repositories. More information about this tool is given in Section 4.1.

The `NeighborSelection` is a tool that provides functions that verify if a certain neighbor function can be applied in the current solution. If so, it returns a `Neighbor` object. A `Neighbor` object does not represent a neighbor solution, but the changes that need to be applied to the current solution if this neighbor is to be accepted. Details about are given in Section 5.3.

The `FeasibilityTester` is a tool that provides functions, which efficiently checks if a certain examination can be placed in a certain period or room. An exam could be moved by only changing the period, the room, or both. This tool is used by both the GC and the SA, even though it only works if the examination to check is not yet set in the provided solution.

The `OutputFormatting` tool is used to create the output file, given the final solution. This file obeys the output file rules of the ITC 2007's site [**?**], in order to be able to submit the solution [**?**]. Submitting the solution allows to check all violated hard constraints, soft constraints, distance to feasibility and fitness values on the site's page.

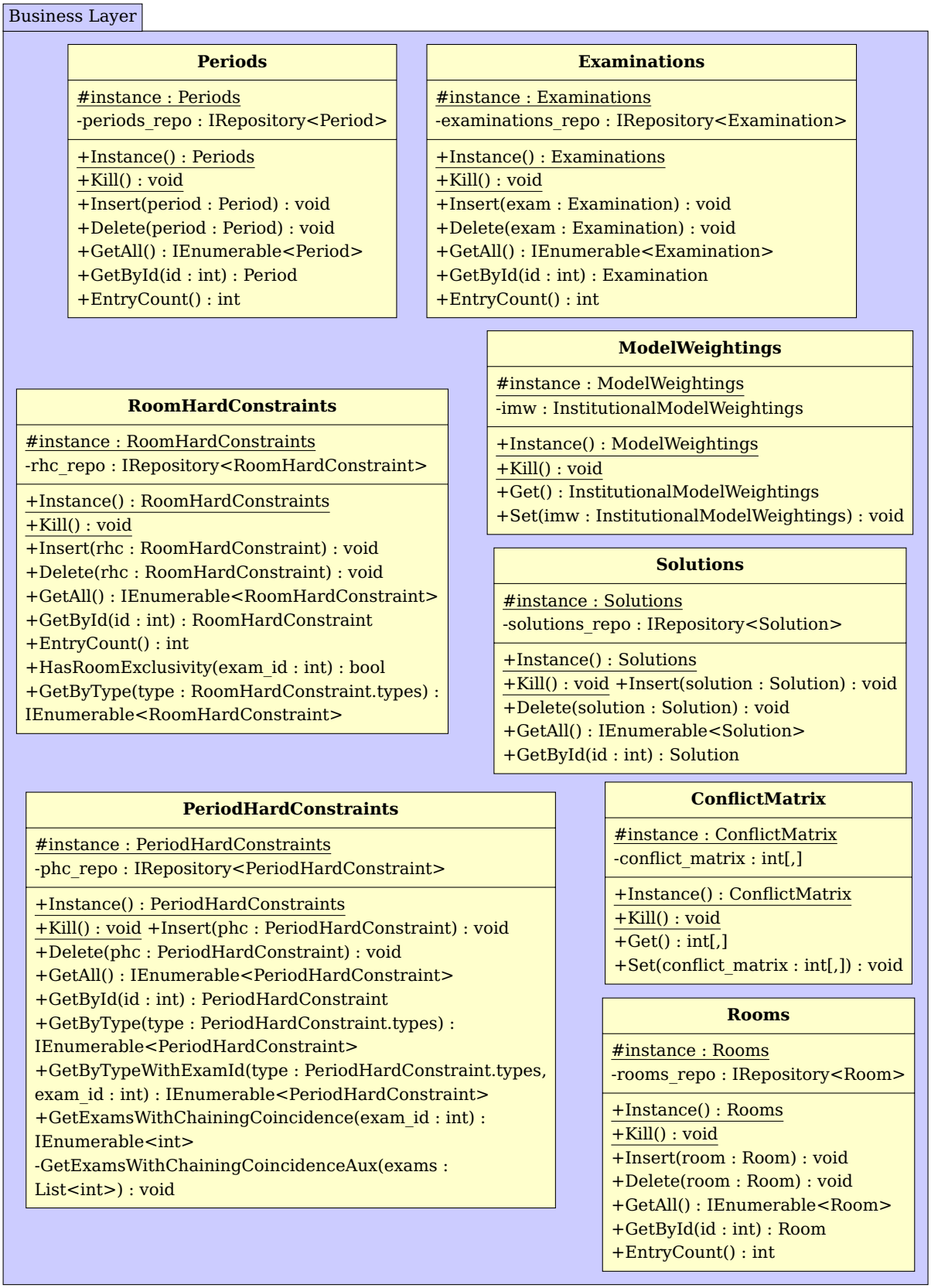


Figure 3.3: Overview of the BL and its main classes.

3.1.5 Heuristics Layer

The HL offers access to all the implemented heuristics. These are the GC, SA, and HC. All these heuristics are used to create the best timetable possible given a limited time. Heuristics like SA and HC make use of neighbor solutions, and so they utilize the `NeighborSelection` tool for this effect. They also use tools like `FeasibilityTester` and `EvaluationFunction` to help build the initial solution and check the fitness while improving the current solution, respectively.

Detailed explanation about these heuristics are given in Chapters 4 and 5.

3.1.6 Presentation Layer

The PL, in this phase, works mainly as a debugger to run the project functionalities and to check the final results. It's in this layer that all the tests are made, such as checking execution time and changing input parameters on both SA and HC, to check if better results can be achieved.

4

Loader and solution initialization

The Loader and the solution initializer (heuristic) are the first tools used in this project. The Loader and Graph Coloring heuristic (solution initializer) will only be executed once, so the major part of the execution time will be used by the meta-heuristic(s).

4.1 Loader Module

The Loader's job is to load all the information presented in the dataset files. Each set file includes information about examinations and the enrolled students, the periods, the rooms, and their penalties, as well as the period and room hard constraints, and the information about the soft constraints, named *Institutional Weightings*. The presence of period and room hard constraints are optional.

This tool not only loads all the data to its corresponding repositories, but also creates and populates the conflict matrix depending on the data obtained previously. The conflict matrix is a matrix that has the information about the conflicts of each pair of examinations.

4.1.1 Analysis of benchmark data

Figure 4.1 presents the specifications of the 12 datasets of the ITC 2007. The instances presented have different degrees of complexity, that is, ease of finding a feasible solution and number of feasible solutions. Using the GC heuristic developed (described later in Section 4.2), Instance 4 is the most complex one, as no feasible solution could be obtained. The high conflict matrix density, in addition to the fact there's only one room (with capacity 1200 seats), and the presence of 40 period hard constraints, help to explain the dataset complexity.

All the specifications and benchmark data from the 12 datasets of the ITC 2007 timetabling problem are shown in the Table 4.1.

4.1.2 Implementation

The development of the `ILoader` tool is divided into two main parts: the loading part, which loads the dataset file into the repositories using the business layer, and the creation and

Instance	# students	# exams	# rooms	conflict matrix density	# time slots
1	7891	607	7	0.05	54
2	12 743	870	49	0.01	40
3	16 439	934	48	0.03	36
4	5045	273	1	0.15	21
5	9253	1018	3	0.009	42
6	7909	242	8	0.06	16
7	14 676	1096	15	0.02	80
8	7718	598	8	0.05	80
9	655	169	3	0.08	25
10	1577	214	48	0.05	32
11	16 439	934	40	0.03	26
12	1653	78	50	0.18	12

Table 4.1: Specifications of the 12 datasets of the ITC 2007 examination timetabling problem.

population of the conflict matrix.

The loader was implemented using the `Loader` base class, from which the `LoaderTimetable` extends. The `Loader` class implements functions to make it easier to run through a file. These two classes are depicted in Figure 4.1

Unlike the `Loader`, `LoaderTimetable` depends on the structure of the dataset files. This class will use the Loader functions to go through a dataset file, and so, populate the repositories depending on the information read by the `Loader` class. The `LoaderTimetable` offers operations like `Load` and `Unload` to load all the information in a dataset file and to empty the repositories, respectively.

The implementation of the `LoaderTimetable` class is all about the `Load` method. This public method will be asking for new lines and reading the tokens out of it, using the `Loader` class. This procedure will take place as long as there are new lines to read. It's a pretty simple cycle that gets a new line and checks if, for example, the string "Exams" is contained on that line. If so, it runs `InitExaminations`, if not, checks if "Periods" is contained on that line, and so on, until it runs out of file. The pseudo code of this method can be seen on Algorithm 1.

The method `InitExaminations` reads each examination and enrolled students, and store them in a Hashmap, which stores the students as keys and the examinations which they attend as values. With this student-examinations organization, the `InitConflictMatrix` simply goes to all pairs of examinations for each student, and add a conflict in the matrix for those pair of examinations.

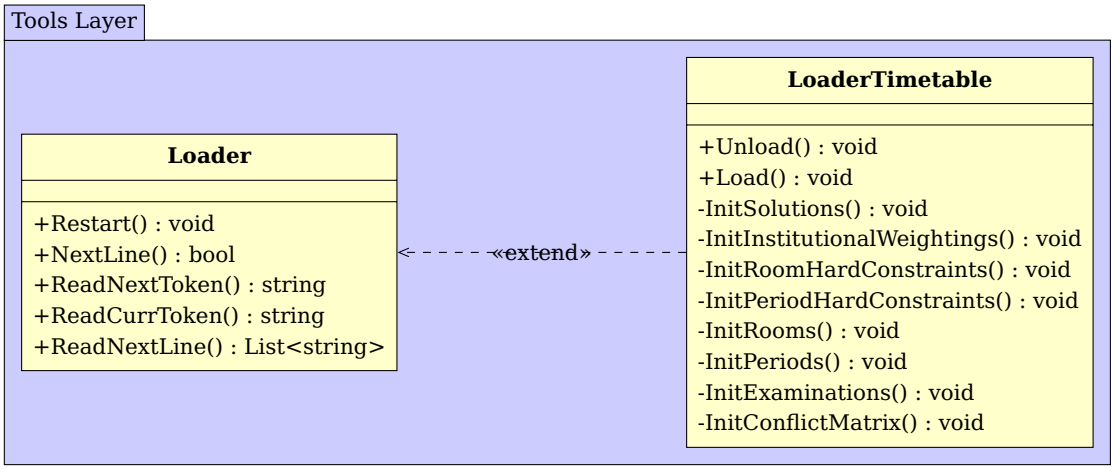


Figure 4.1: Specification of Loader and LoaderTimetable tools

4.2 Graph Coloring

Graph Coloring is the heuristic used to generate a feasible solution. This heuristic is ran right after the loader. The implementation of this heuristic was based on Müller's approach [**?**].

4.2.1 Implementation

The computation of the proposed heuristic is divided into four phases. In the first phase, it starts by editing the conflict matrix, in order to add the exclusion hard constraints to the conflict matrix. This process is possible because the exclusion hard constraint is also a clash between a pair of examinations. This makes the algorithm easier to implement later on, because checking the conflict matrix for a clash between a pair of examinations now works for

Algorithm 1 LoaderTimetabling's Load method.

Read new line
repeat
  Read next token $token$
  If $token == null$ Then $break$
  If $token$ Contains "$Exams$" Then $InitExaminations()$
  Else If $token$ Contains "$Periods$" **Then** $InitPeriods()$
  Else If $token$ Contains "$Rooms$" **Then** $InitRooms()$
  Else If $token$ Contains "$PeriodHardConstraints$" **Then** $InitPeriodHardConstraints()$
  Else If $token$ Contains "$RoomHardConstraints$" **Then** $InitRoomHardConstraints()$
  Else If $token$ Contains "$InstitutionalWeightings$" **Then** $InitInstitutionalWeightings()$
  Else If Cannot read new line **Then** $break$
until Always
$InitSolutions()$
$InitConflictMatrix()$

the student conflicts and exclusion.

The second phase simply erases all examination coincidence hard constraints' occurrences that have student conflicts. It is mentioned in the ITC 2007 site [**?**] that if two examinations have the examination coincidence hard constraint and yet 'clash' with each other due to student enrollment, this hard constraint is ignored.

The third phase populates and sort the assignment lists. The assignment lists are four lists that hold the unassigned examinations. These four lists contain:

- Unassigned examinations with "room exclusivity" hard constraint
- Unassigned examinations with "after" hard constraint
- Unassigned examinations with "examination coincidence" hard constraint
- All other unassigned examinations

The Largest Degree Ordering Graph Coloring heuristic is used on these four lists, and so, each list is sorted by number of students conflicts. The examination assignment is done taking the present list ordering. First all the examinations with room exclusivity are assigned, then all that have the after constraints, and finally all with examination coincidence.

The fourth phase is the examination assignment phase (the most important phase of this heuristic). It is based on Müller's approach [**?**]. It starts to assign the examinations with higher conflict, as mentioned above, using the four lists method. There are two types of assignment:

- Normal assignment – If it's possible to assign the chosen examination to a period and room, a normal assignment is processed. In this type of assignment, of all the possible periods to assign, one of them is chosen randomly. It should be noted that a possible period to assign means that the examination can be assigned to that period and at least in one room on that period. After choosing the period, the same will be done to the rooms, and so, a random room will be chosen from all possible assignable rooms for that examination and period. If the current examination has to be coincident to another, and so, set to the same period as the other, the rules explained will not occur. Instead, only that period will be considered and if the period is not feasible to the current examination, the normal assignment will not take place.

- Forcing assignment – Occurs if there are no possible periods to assign the chosen examination, because the normal assignment was not possible. A random period and room are selected and the examination will be forced to be assigned on those, unassigning all the examinations that conflict with this assignment. As the normal assignment, there are exceptions to this rule. If a coincident examination is already set, the examination to be set will be forced to be on the same period as the coincident examination, in a random room. Forcing an examination to a specific period because of a coincident examination sometimes caused infinite or very long loops in the dataset 6. Because of this, there's a chance of 25% that the previous rule does not occur, but instead, it unassigns all coincident examinations and try to assign the current examination to a random period instead.

The Graph Coloring heuristic implementation only realize assignments and unassignments of exams examinations and checks examination clashes when forcing an assignment. The feasibility checking done to periods and rooms is are made by the tool FeasibilityTester, as mentioned in Section 3.1.3. The GraphColoring and FeasibilityTester classes, with all the variables and methods, can be seen in Figure 4.2. The algorithm of the graph coloring heuristic, which was explained in this section can be seen in Algorithm 2.

Algorithm 2 Graph Coloring algorithm.

- Initial solution $solution$

1: Add exclusion to conflict matrix
2: Erase coincidence HC that contains conflict HC
3: Populate and sort assignment examination lists
4: **repeat**
5: Get the right list to use $list$
6: Remove last examination from $list$, $exam$
7: **If Not** NormalAssign($solution$, $exam$) **Then** ForceAssign($solution$, $exam$)
8: **until** No more examinations to assign
9: **Output:** $solution$

4.3 Solution Initialization Results

As mentioned previously, the goal of the initialization procedure is not to find the best solution possible (in terms of fitness), but the find of feasible solution. Some sets are simpler than others, always getting good and stable execution times. Others can be harder, getting worse execution timings and instability. An unstable set means the results vary too much, and so some tests show very good execution times and others not so much. The Graph Coloring heuristic results on the 12 sets can be seen in Table 4.2. These results were obtained by running the heuristic, 10 times for each set, and computing the average for both fitness and execution time fields.

The table 4.2 features many tests performed to this first phase. It features, as mentioned before, the average fitness of the solutions created for each dataset, and so the average execution time, its standard deviation, and the percentage of time used in the first and second phase of this project. The standard deviation was applied because of the instability on execution times of certain datasets when creating initial solutions, using the GC heuristic. By checking the standard deviation, the datasets 6, 11 and 12 are unstable. The datasets 11 and 12, even thought the average execution time was 3405 and 3690, the tested values varied from 864 to 7642 and 201 to 6452, respectively.

The allowed execution time is 221000 milliseconds for each test made to each dataset. This time was picked by the benchmark program provided by the ITC 2007 site [**?**] when executed on the machine where all testes were performed. In the results presented on the Table 4.2, we can conclude that a very short amount of time is used on this first phase,

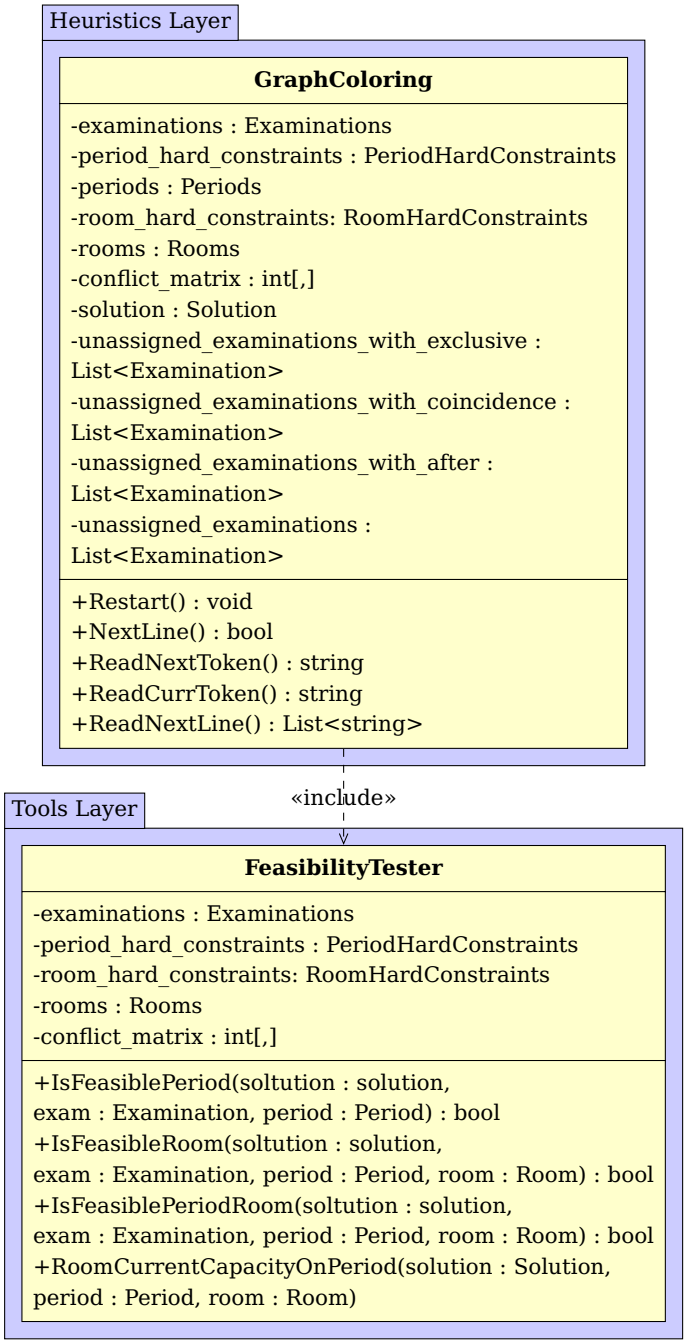


Figure 4.2: Graph Coloring and Feasibility Tester

	Fitness	Execution time (ms)	Standard Deviation σ (ms)	Time used in the 1_{st} phase (%)	Time used in the 2_{nd} phase (%)
SET 1	49 028	202	61	0.09	99.91
SET 2	103 907	250	2	0.11	99.89
SET 3	170 232	942	20	0.43	99.57
SET 4	–	–	–	–	–
SET 5	349 319	227	5	0.10	99.9
SET 6	60 857	297	192	0.13	99.87
SET 7	155 708	569	19	0.26	99.74
SET 8	397 868	243	8	0.11	99.89
SET 9	15 680	12	1	0.01	99.99
SET 10	121 164	110	6	0.05	99.95
SET 11	260 310	3405	2170	1.54	98.46
SET 12	11 887	3690	1829	1.67	98.33

Table 4.2: Some of the Graph Coloring's performance features.

compared to the one being used on the second phase.

As shown in table 4.2, the heuristic could not get a feasible solution for the set 4. This problem might be present because of the presence of an infinite cycle of normal and forcing assignments, resulting in assigning and unassigning the same examinations. Different approaches were tried in order to try obtaining results for set 4. These approaches include using only one unsorted list of unassigned examinations, using all four unsorted lists, and keeping the four lists sorted but changing the priority order of their usage. Oddly, using only one unsorted list led to the best results, sometimes only leaving 20 to 30 examinations to sign, while the default approach varied between 90 and 120. Unfortunately none of the approaches were good enough to generate a feasible solution.

One possible and probably good approach would be to order the lists by examination conflict. The difference between these conflict values and the ones presented in the conflict matrix, which is used in the default approach, is that the conflict matrix's values are the total student conflicts between one examination and all the others, while this new approach results in ordering the examination lists by the number of examinations each examination has conflicts with.

5

Proposed Approach: Local Search

The proposed solution consists about using a local search meta-heuristic(s) to improve the solution given by the GC heuristic. This approach uses SA, based on Müller's approach [**?**], followed by the use of HC. The use of HC is justified by the fact that SA does not guarantee a good control of the execution time, and so the parameters are given to make it run almost all the available time. The rest of the optimization is executed on HC, whose execution time is perfectly controllable.

5.1 Simulated Annealing

SA is a single-solution meta-heuristic (section 2.2.3). This meta-heuristic optimizes a solution by generating neighbor solutions which might be accepted given an acceptance criterion. A neighbor solution is obtained by applying a movement operator (also known as neighbor operator) to the current solution, creating a new solution which is a neighbor of the current solution. A neighbor operator, in this context, could be the movement of an examination to another time slot. Being a single-solution meta-heuristic, it only generates one neighbor at the time. The neighbor operators and acceptance criterion are the most important part of this algorithm. Little changes on one of these, may get the algorithm to behave in very different ways and end up with much different solutions.

The acceptance criterion will, considering the current solution and a neighbor solution, give the percentage of acceptance of the neighbor solution. Most of the approaches using this heuristic accept a new neighbor solution if this is *better* than the current solution. Otherwise, there's a chance that the neighbor solution is still accepted, depending on certain parameters. These parameters are the *Temperature* (normally given as maximum and minimum temperature) and the *Cooling Schedule*. By definition, the higher the temperature, the higher is the chance to accept a worse solution over the current solution. The cooling schedule, as the name suggests, is a function that lowers the temperature at a given rate. The SA algorithm finishes when the current temperature is lower or equal to the minimum temperature. The temperature should start high enough in order to be able to escape from local optima, by accepting worse solutions found during the trajectory.

Algorithm 3 Simulated Annealing method.

Input:

- s // Initial solution
- $TMax$ // Maximum temperature
- $TMin$ // Minimum temperature
- $loops$ // Number of loops per temperature

$T = Tmax$; // Starting temperature
$Ac = AcInit()$; // Acceptance criterion initializer
repeat
  repeat
    Generate a random neighbor s';
    $\delta E = f(s') - f(s)$;
    If $E \leq 0$ **Then** $s = s'$ // Accept the neighbor solution
    Else Accept s' with a probability computed using the Ac;
  until Number of iterations reach $loops$
  $T = g(T)$ // Temperature update
until $T < TMin$
Output: s // return the current (best) solution

5.1.1 Implementation

The SA was implemented in a way that it is independent from the type of the cooling schedule and neighbor generator. The SA base class is abstract and implements everything except for the neighbor generator, which is an abstract method that must be implemented in order to decide how the neighbor generator behaves. It also does not implement the evaluation function (the one that computes the fitness value of a solution or neighbor). The `SimulatedAnnealing` and `SimulatedAnnealingTimetable`'s methods and variables can be seen in Figure 5.1.

The `SimulatedAnnealing` abstract class has the methods `Exec`, `Exec2`, and `ExecLinearTimer`, which are all similar, but were created to test different approaches. All these methods share the same code, in exception to the cooling schedule (the way the temperature is updated) and acceptance criterion. The pseudo code of these can be seen in Algorithm 3.

The `ExecLinearTimer` has a linear cooling schedule, which is proportional to the running time, and uses the acceptance criterion:

$$P(\delta E, T) = e^{\frac{-\delta E}{T}}$$

T $\rightarrow$ Current temperature
δE $\rightarrow$ Fitness difference between the new neighbor and current solution

The `Exec` method shares the same acceptance criterion but uses a geometric cooling schedule:

$$T(i+1) = T(i).r$$

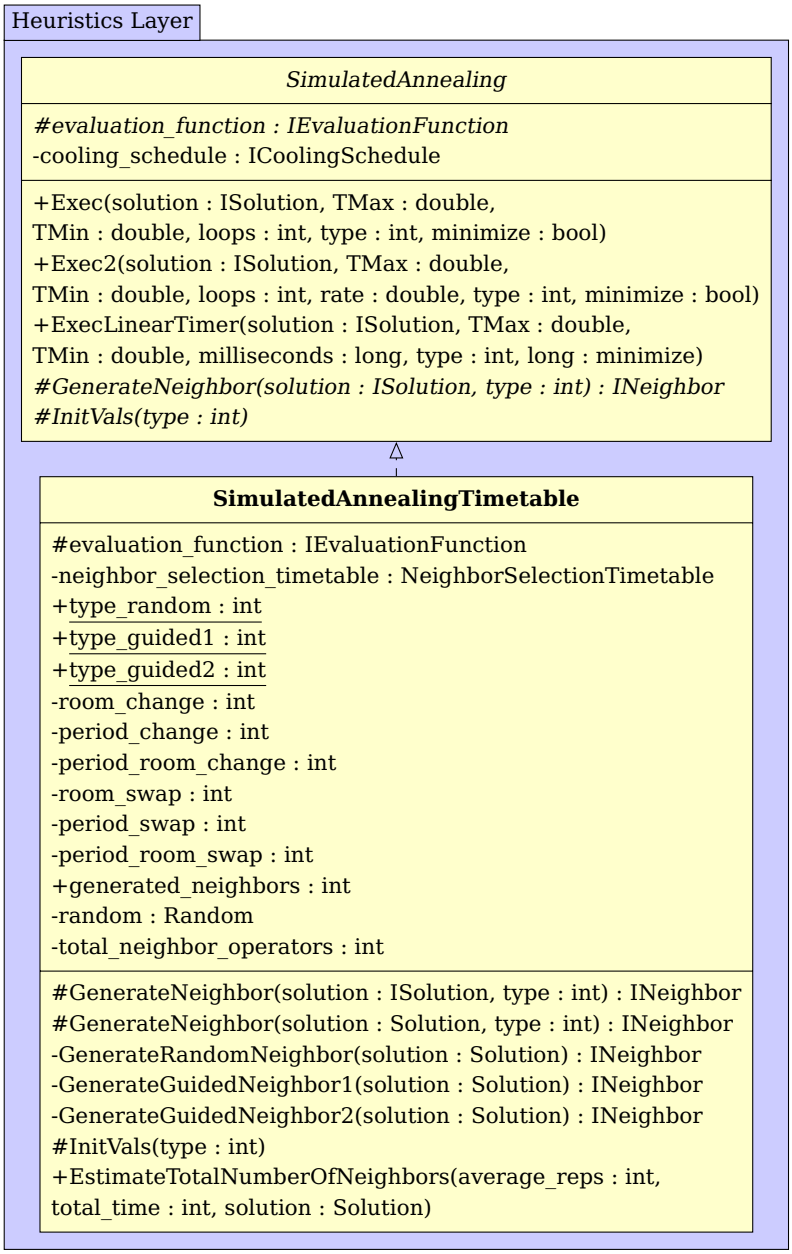


Figure 5.1: Simulated Annealing classes

r $\rightarrow$ Temperature decreasing rate (0 < r < 1).

The rate must belong in the interval]0,1[. In the geometric cooling schedule, the closer the rate is to unity, the longer the algorithm takes to finish and wider is the area of solutions to be analyzed in the solution space.

The `Exec2` method is the one used in this project. It uses an exponential (decreasing) cooling schedule [**?**]:

$$T = T_{max}e^{-R.t}$$

t $\rightarrow$ Current span, counter initiated at 0
T_{max} $\rightarrow$ Maximum/initial temperature
R $\rightarrow$ Decreasing rate.

This method also uses a different acceptance criterion:

$$P(\delta E, T, SF) = e^{\frac{-\delta E}{T \cdot f(s)}}$$

f(s) $\rightarrow$ Solution fitness

The behavior of this heuristic depends on the given parameters (maximum and minimum temperature, rate, number of loops per temperature, type of the cooling schedule), and the difficulty of the set is also important, considering the execution time limit. Knowing this, it's important to choose the parameters wisely to obtain the best possible results. But, each set has its own characteristics and using parameters for one set does not guarantee that the results will be equivalently good for the others. One example is finding the best parameters for the first set, and make it try run for about 200 milliseconds. This does not mean the others will run for about the same amount of time, degrading the effectiveness of this heuristic. Thus, a variable rate was implemented.

The variable rate was implemented to make this heuristic run closer to the given time limit. Considering it is not certain that the algorithm will run within the given 221000 milliseconds, as being a stochastic algorithm, a time limit was added to this meta-heuristic as well, ending this heuristic automatically if the time limit is reached. If this happens, it degrades the meta-heuristic's performance because it ends before it's suppose to. To avoid this, an offset was created. The offset is a percentage which is removed from a part of the simulation to, instead of pointing the heuristic to run for 221000 milliseconds, it points to 185640 milliseconds, to have a margin of safety. The offset used is 16%.

The algorithm starts by simulating the execution of this heuristic, by running all the neighbor operators *n* times and using the elapsed time and the given time limit, we estimate the number of neighbors that would be generated if this heuristic was to be run within the time limit. To calculate the said number of total neighbors, we use this math expression: $CompNeighbs = TotalTime/CompTime * AverageReps * TotalOperats$. After that, we compute the exact number of the neighbors ($TotalNeighbs$) that will be generated for the given parameters, using the default rate. This is achieved by simulating this heuristic using those parameters, cooling the current temperature until it reaches the minimum and return-

Algorithm 4 Rate computing.

Input:

- s // Solution
- $TMax$ // Maximum temperature
- $TMin$ // Minimum temperature
- $reps$ // Number of loops per temperature
- $exec\_time$ // Execution time limit

$sa = SAInit()$;
$n = 50$; // Number of times each operator runs
$est\_neighbors = sa.EstimateNumberNeighbors(n, exec\_time, s)$;
$rate = 1.50^{-04}$; // Initial default rate
$power = -4$;
$rate\_to\_sub = 10^{power}$; // Rate decrementing
$total\_neighbors = sa.GetNumberNeighbors(TMax, rate, reps, TMin)$;
repeat
  If $rate - rate\_to\_sub \leq 0$ **Then** $power = power - 1$; $rate\_to\_sub = 10^{power}$;
  $rate = rate - rate\_to\_sub$;
  $total\_neighbors = sa.GetNumberNeighbors(TMax, rate, reps, TMin)$;
until $total\_neighbors < est\_neighbors$
$rate = rate + rate\_to\_sub$; // To guarantee that total_neighbors < est_neighbors
Output: $rate$ // Return computed rate

ing the number supposed generated neighbors. If the $TotalNeighbs$ is way higher than the $CompNeighbs$, a lower rate will be used to make another simulation, until the $TotalNeighbs$ for the given rate reaches a value that is close to the $TotalNeighbs$. The pseudo code of this method can be seen in Algorithm 4.

Some testings were made in order to check this heuristic's behavior, using the following parameters: *TMax* = 0.1, *TMin* = $1e-06$, *loops* = 5, *exec_time* = 50000, and the computed_rate = 0.00016. As can be seen in Figure 5.2, it starts by accepting all worse and better neighbor solutions. In the end, the temperature is so low that it becomes harder to accept worse solutions, ending up acting similar to the HC procedure.

The tests performed on all the sets are shown and explained in Chapter 6.

5.2 Hill Climbing

HC is a meta-heuristic different to the SA family of meta-heuristics, in the sense that only accepts improving solutions. So, as long as it reaches a local optimum, it can't get out of that point because every neighbor solutions are worse. In this way, HC only has one parameter that is the number of iterations or time limit which controls the algorithms' execution time.

In the evaluation undertaken, the best results were obtained with the `Exec2` version of SA. SA was parametrized in order to finish execution within the specified time limit imposed by the ITC 2007 rules. HC is executed after SA until the time limit is reached.

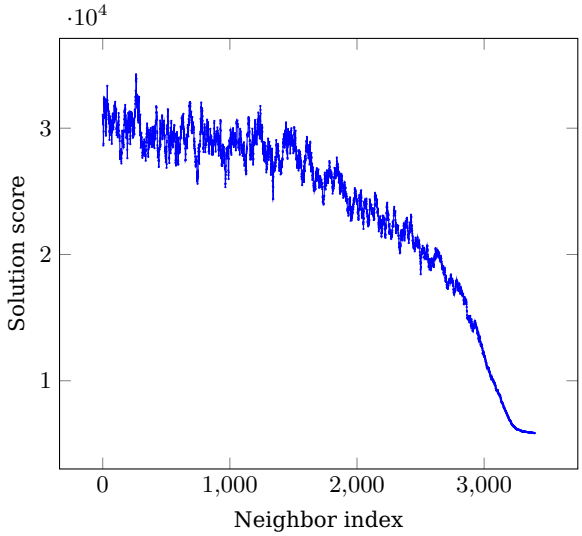


Figure 5.2: Simulated Annealing results: score value as a function of the temperature

5.2.1 Implementation

The implementation of this heuristic is very similar to the SA, also containing the classes `HillClimbing` and `HillClimbingTimetable`, which are simplified versions of the SA classes. The `HillClimbing` and `HillClimbingTimetable`'s methods and variables can be seen in Figure 5.3.

5.3 Neighborhood Operators

Neighborhood operators are operations applied to a solution, in order to create other valid solutions (neighbor solutions), but not necessarily feasible. In this context, the core of all operations are the relocation of the examinations.

The implementation of neighborhood selection went through three different approaches. Firstly, the random selection was implemented. This approach always chooses a random operator to generate a new neighbor. Thereafter two guided approaches were implemented. The first one raised the probability of selecting one operator if this one generated a better neighbor solution. The probability of that operator is reduced in an equal amount if the operator generated a worse solution. The other guided approach simply lowers the probability of an operator in case of success, and raises it in case of unsuccess.

The second guided approach presented worse results compared to the first one, as expected. Oddly, the random approach almost always showed better results compared to the first guided approach, even after suffering major changes in order to try to get it to generate

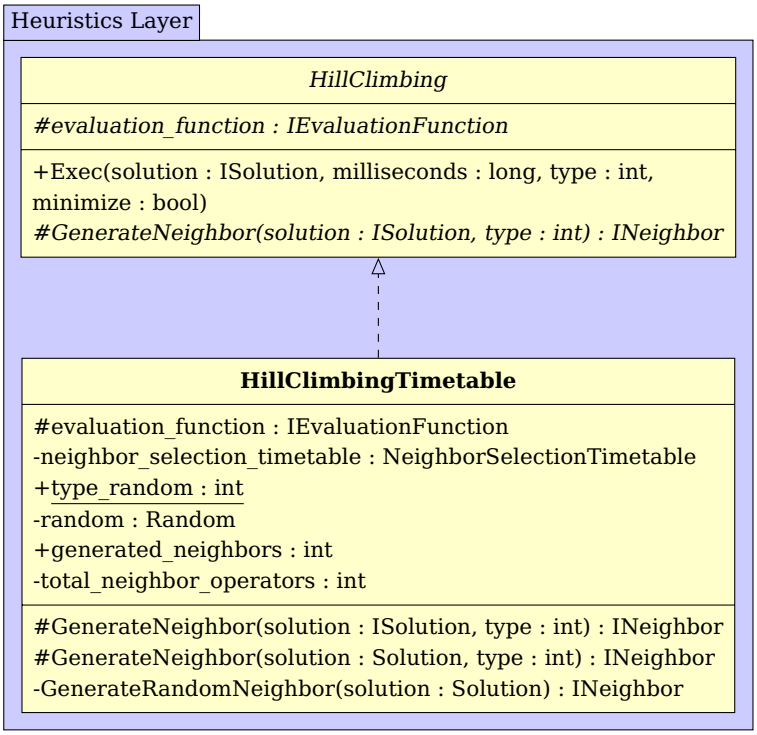


Figure 5.3: Hill Climbing classes

better results. These changes include raising the probabilities even more or less when successfully or unsuccessfully created a better solution, and instead of lowering the probability for an operator when created a worse solution, it is returned to its default value.

The neighborhood operators, in this context, are all based on moving examinations to another place (period or room). This implementation uses six different neighborhood operators:

- *Room Change* - A random examination is selected. After that, a random room is randomly selected. If the assignment of the random examination to the random room, while maintaining the period, does not violate any hard constraints, that neighbor is returned. If not, the adjacent rooms are tested until one of them creates a feasible solution. If it reaches the limit of rooms and no feasible solution is found, no neighbor is returned;

- *Period Change* - A random examination is selected. After that, a random period is randomly selected. If the assignment of the random examination to the random period, while maintaining the room, does not clash with any hard constraints, that neighbor is returned. If not, the adjacent periods are sequentially tested until one of them creates a feasible solution. If it reaches the limit of periods and no feasible solution was found, no neighbor is returned;

- *Period & Room Change* - A random examination is selected. After that, a random room and period are randomly selected. If the assignment of the random examination to the random room and period does not clash with any hard constraints, that neighbor is returned. If not, the next rooms are tested for each of the next periods, until one of them creates a feasible solution. If it reaches the limit of periods and rooms and no feasible solution was found, no neighbor is returned;

- *Room Swap* - A random examination is selected. After that, a random room is selected. If the selected examination can be placed in that room, while maintaining the period, then a *Room Change* neighbor is returned instead. If not, if the swapping of the random examination with any of the examinations presented in the random room, keeping the same period, does not clash with any hard constraints, that neighbor is returned. If not, the examinations presented in the next rooms are tested until a feasible solution is found (always testing first if a *Room Change* can be returned instead). If it reaches the limit of rooms and no feasible solution was found, no neighbor is returned;

- *Period Swap* - A random examination is selected. After that, a random period is selected. If the selected examination can be placed in that period, while maintaining the room, then a *Period Change* neighbor is returned instead. If not, if the swapping of the random examination with any of the examinations presented in the random period, keeping the same room, does not clash with any hard constraints, that neighbor is returned. If not, the examinations presented in the next periods are tested until a feasible solution is found (always testing first if a *Period Change* can be returned instead). If it reaches the limit of periods and no feasible solution was found, no neighbor is returned;

- *Period & Room Swap* - A random examination is selected. After that, a random period and room are selected. If the selected examination can be placed in that period and room, then a *Period Change* neighbor is returned instead. If not, if the swapping of the random examination with any of the examinations presented in the random period and room does not clash with any hard constraints, that neighbor is returned. If not, the examinations presented in the next periods and rooms are tested until a feasible solution is found (always testing first if a *Period & Room Change* can be returned instead). If it reaches the limit of periods and rooms and no feasible solution was found, no neighbor is returned;

5.3.1 Implementation

The original concept of neighbor solution is to have another solution apart from the current one, which is the result of applying the neighborhood operator to the current solution. In order to have an efficient implementation, the neighbor only keeps the changes introduced in the solution, and not the changed solution. With this design, there's no need to replicate the original solution and apply the neighborhood operator to it in order to obtain the neighbor solution. The process of replacing the original solution with the neighbor, consists in applying to the current solution the movement registered in the neighbor.

Every neighbor object must implement the interface `INeighbor`, which presents the methods `Accept`, `Reverse` and a real value that represents the fitness of the neighbor (the fitness

of the new solution if this neighbor is to be accepted). The `Accept` method moves the current solution to the neighbor solution. The `Reverse` method undoes the operation, getting then back the old solution. The different neighbors and their methods are illustrated in Figure 5.4.

5.4 Fitness Computation

The fitness computation is an important topic, when taking performance into consideration. As mentioned in the Subsection 3.1.4, this value is computed using the `EvaluationFunction` tool, which in a first approach, implied for generated neighbors, the recalculation of their fitness value. Tests were made to study this approach since the fitness results were not as good as expected. The tests showed that this approach was having poor performance since most of the time was used to compute the fitness for each new neighbor generated solution.

A new approach was implemented, which consists in computing the fitness incrementally. This means for each new generated neighbor, a new fitness value is computed based on the current solution's fitness. This approach takes advantage of the fact that the operations applied to the current solution are simple and so the neighbor solutions are, in most part, equal to the current solution. Thus, the fitness computation is performed considering only the small changes between the current solution and the new generated neighbor solution.

Tests were made to compare both approaches and, using the same parameters, for the first set it was possible to achieve equivalent results, nineteen times faster. This means that if both approaches would use the same parameters, but the new approach using a lower rate to match the execution time of both approaches, the new approach would have generated nineteen times more neighbors.

5.4.1 Implementation

To compute the fitness of the neighbor solutions incrementally, a fitness function must be implemented depending on the type of neighbor. Considering all neighbors have a reference to the solution they derive from, and the methods `Accept` and `Reject`, it's possible to access the current solution and the neighbor generated solution (Reminding that the `Accept` will change the current solution and so the reference presented in this neighbor, replacing with the neighbor solution).

The differences between the fitness values of the current solution and the new neighbor's depend on the type of the neighbor created. For example, if a `RoomSwapNeighbor` is created, the changes will occur in the mixed durations constraints value of the periods and rooms of the swapped examinations. It is necessary to compute the impact (fitness values) of these conflicts in the current solution and subtract its value to the current fitness, proceeding with computing the same impact but now for the generated neighbor and sum its value to the current fitness, thus obtaining the new neighbor's fitness value. The impact computing mentioned above is a simple rule that is must be followed by all the soft constraints when computing the new neighbor's fitness incrementally.

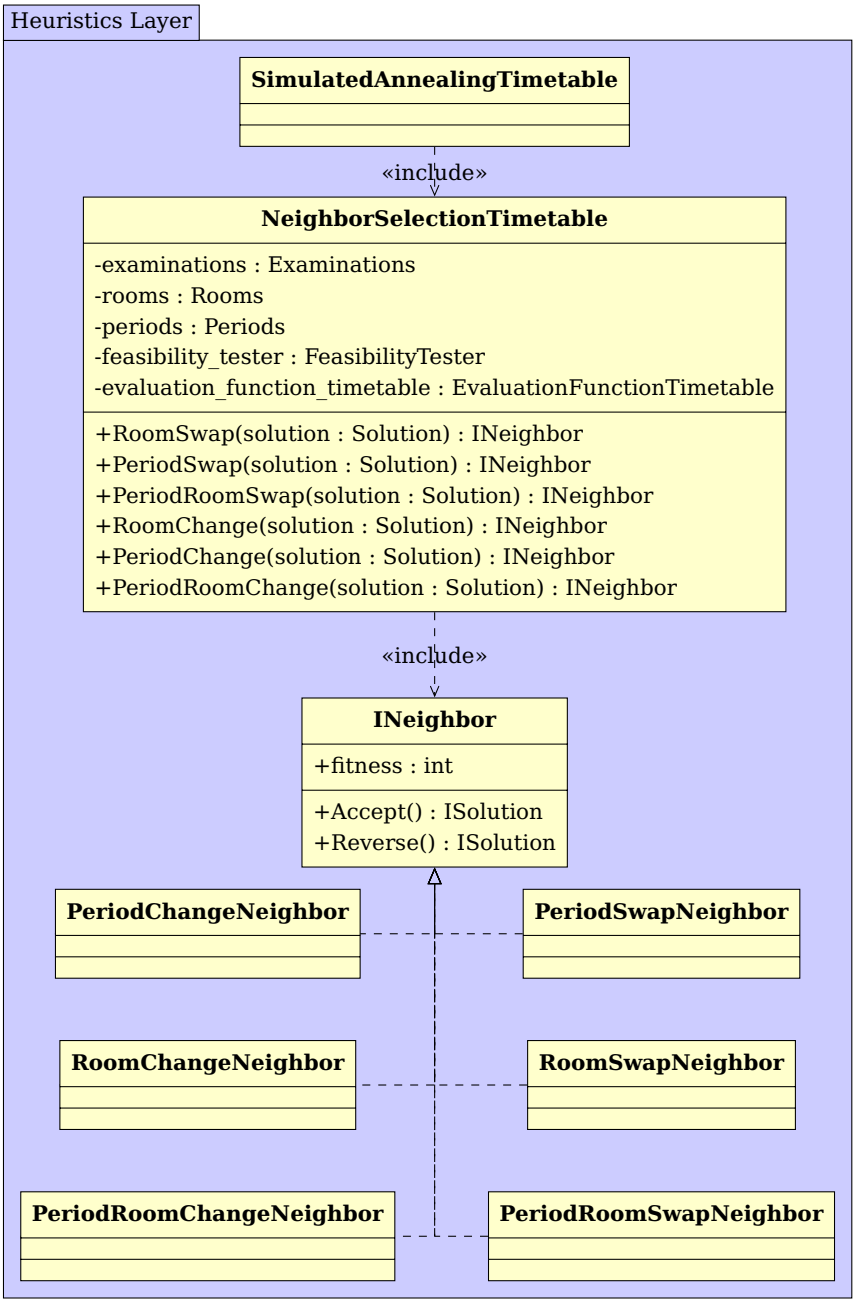


Figure 5.4: Neighborhood selection and operators

6

Experimental Results

In this chapter we will present the results obtained while running all the heuristics explained in the previous chapters. We also compare our results against the ones of the top 5 winners of the ITC 2007 contest and more up to date approaches.

The parameters used to run the SA were:

TMax = 0.1 → Maximum/initial temperature
TMin = 1e-06 → Minimum temperature
reps = 5 → Number of repetitions per temperature
rate = *real-time computed* → Temperature cooling rate

All the 12 sets were tested by running each set 20 times. In Table 6.1 we can see the results which are the values for average fitness, fitness' best and worst values, its standard deviation, and the average of feasible and unfeasible generated neighbors. Compared to the previous approaches, which excludes the use of incremental fitness computing and the real time computed rate, these results are noticeable better.

While studying the results, some of the were much worse compared to the other tests made to the same set. As can be seen in Table 6.1, the sets 2, 5, 6, 8, 10, and 12 have the worst fitness much more distant to the average fitness compared to the other sets. The fitness standard deviation itself, in these sets, is much smaller compared to the distance between the average fitness and the worst fitness of the 20 runs. On the 20 runs for these sets, only one or two had this kind of results. We believe this rarely happens because of the problem specified in Chapter X, the fact that examinations with coincidence hard constraints cannot be moved, it limits the algorithm performance to get better results.

In Table 6.2 we compare the results obtained in this project's approach versus the five winners of the ITC 2007. Not all of the sets were able to be right behind Müller [**?**], unfortunately. Being this approach was based on Müller's [**?**], some results were not as good as his, and this might be because of the use of the GD heuristic in his approach, together with the use of SA. Fortunately in some sets, this developed approach was able to reach and beat most of the contestants. However, the sets with highest scores, and so represent the ones with worst results, are the ones that have more coincident examinations hard constraints.

We believe that solving this approach limitation mentioned above, would make it to the third place, at least, on all the sets.

In table 6.3 this project's results are compared to more up to date approaches. As can be seen, Rahman et al. [**?**], Bryce et al. [**?**], and Mouhoub et al. [**?**] stole almost all the best results. Some of Rahman's [**?**] and Bryce's results surpass Müller's [**?**] results. None of the sets' score of this approach was able to beat all the other approaches shown on the table.

Table 6.1: All the project's results by running 20 times each set. The fitness and the generated neighbors represent the average for those 20 runs. "–" indicates that a feasible solution could not be obtained.

Instance	Fitness	Best Fitness	Worst Fitness	Fitness Standard Deviation	# Feasible Generated Neighbors	# Unfeasible Generated Neighbors
1	5055	4857	5307	123	1 803 391	13 314 066
2	523	451	921	102	2 226 202	5 181 268
3	15 228	13 375	17 755	1121	450 514	4 443 983
4	–	–	–	–	–	–
5	4819	3965	7737	1003	2 093 197	7 795 497
6	27 528	26 665	30 145	828	1 380 462	12 160 378
7	4912	4576	5448	282	1 051 390	4 724 867
8	8741	8238	11 670	687	1 248 848	6 139 766
9	1150	1033	1300	70	4 050 744	21 298 017
10	25 586	19 858	38 698	4778	445 664	10 929 700
11	45 630	39 150	53 611	4113	444 747	5 663 990
12	7679	6109	12 033	1684	1 825 580	34 767 637

Table 6.2: ITC 2007 results comparison to this project's approach. The best solutions are indicated in bold. "–" indicates that a feasible solution could not be obtained.

Instance	Müller 2009 [?]	Gogos et al. 2012 [?]	Atsuta et al. 2007 [?]	De Smet 2008 [?]	Pillay 2008 [?]	Proposed Approach 2015
1	**4370**	5905	8006	6670	12 035	5055
2	**400**	1008	3470	623	3074	523
3	**10 049**	13 862	18 622	–	15 917	15 228
4	**18 141**	18 674	22 559	–	23 582	–
5	**2988**	4139	4714	3847	6860	4819
6	**26 950**	27 640	29 155	27 815	32 250	27 528
7	**4213**	6683	10 473	5420	17 666	4912
8	**7861**	10 521	14 317	–	16 184	8741
9	**1047**	1159	1737	1288	2055	1150
10	16 682	–	15 085	**14 778**	17 724	25 586
11	**34 129**	43 888	–	–	40 535	45 630
12	5535	–	**5264**	–	6310	7679

Table 6.3: Up to date results comparison to this project's approach. The best solutions are indicated in bold. "–" indicates that a feasible solution could not be obtained, or the following sets were not tested.

Instance	Rahman et al. 2014 [?]	Bryce et al. 2014 [?]	Mouhoub al. 2014 [?]	De Smet 2014 [?]	Abdullah et al. 2014 [?]	Proposed Approach 2015
1	5231	5302	**4395**	6235	5517	5055
2	**433**	418	**433**	2974	537	523
3	**9265**	10 036	10 118	15 832	10 324	15 228
4	17 787	20 531	21 772	35 106	**16 589**	–
5	3083	3236	**2836**	4873	3631	4819
6	**26 060**	26 253	27 166	31 756	26 275	27 528
7	10 712	**4115**	4294	11 562	4592	4912
8	12 713	**7555**	7632	20 994	8328	8741
9	1111	**1089**	1109	–	–	1150
10	**14 825**	15 167	17 022	–	–	25 586
11	**28 891**	31 415	33 608	–	–	45 630
12	6181	**5464**	6364	–	–	7679

7

Conclusions and Future Work

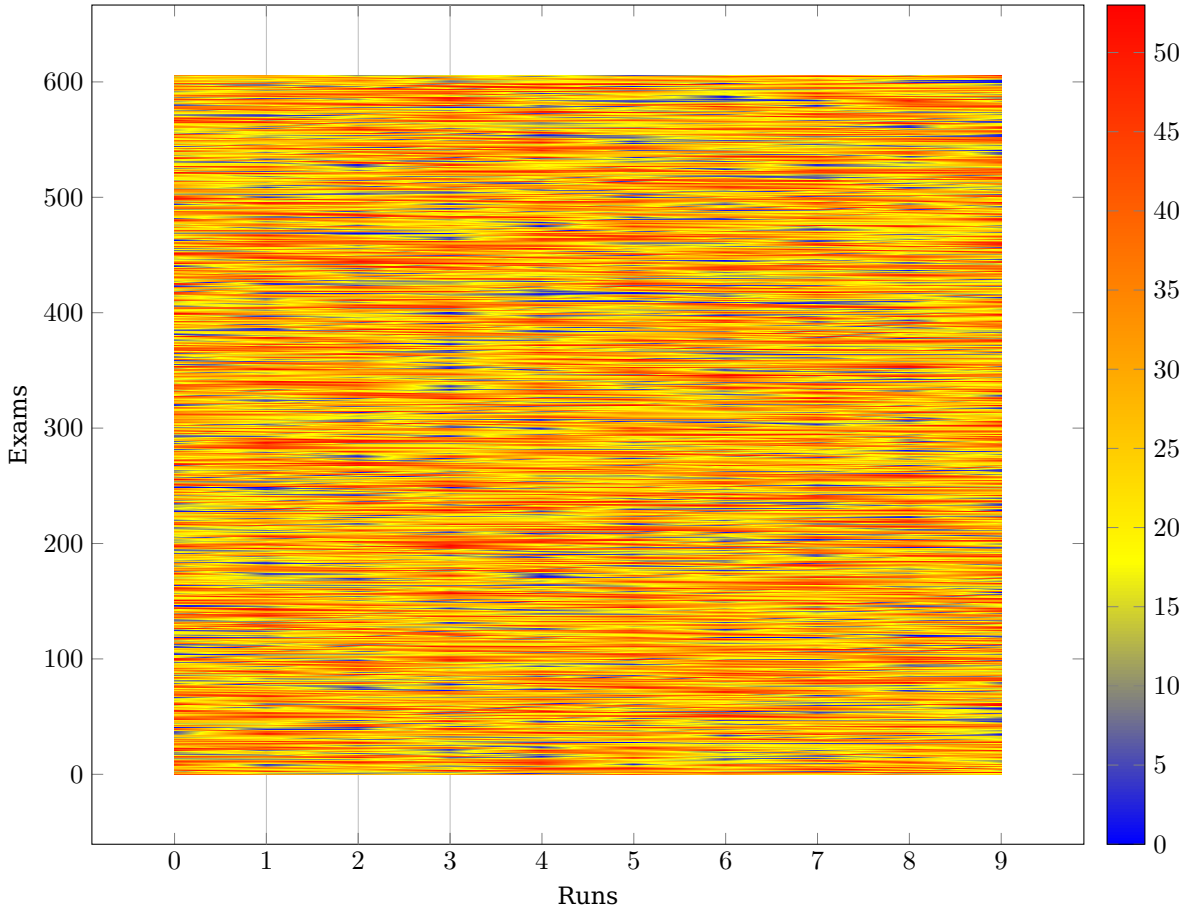
We were able to conclude that with the use of this hybrid approach of GC, SA, and HC we matched the results of the five winners of the ITC 2007 on some of the instances. It should be possible to be able to get better results if more tests were to be performed on the parameters of the SA meta-heuristic and edit some of the most used methods, to upgrade the performance of the heuristic and get better results.

In the future work, we plan on getting better results on all the sets by improving some features in the implemented code. This includes changing the input parameters for each set to obtain the best performance in order to deliver the best results on each one of them.

One of the main features that needs to be upgraded is the performance of the `FeasibilityTester` tool and the SA, because this heuristic for each new generated neighbor, computes a new fitness value. As some tests were made, we concluded that most of the time spent on this heuristic is used by the computation of the fitness value for each neighbor. We should get better results if the fitness value was computed based on the change that was made on the new neighbor (incremental evaluation of the neighbour solution), instead of computing it again. First we need to study if this feature is possible to implement. If it is, the performance boost should be very noticeable.

The graph coloring heuristic will probably be edited in order to try and get a feasible solution on all the sets, since the 4th set ends up in an infinite loop, and so it is unable to create a feasible solution.

Apart from the changes on the existing code, if there's time to implement new heuristics to test and compare to the top 5 winners, we plan on implementing a population-based algorithm like a Genetic Algorithm to be used as optimization method after the use of the already implemented GC.


Exams
600
500
400
300
200
100
0
0
1
2
3
4
5
6
7
8
9
Runs
50
45
40
35
30
25
20
15
10
5
0

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