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Applying optimization models in the scheduling of medical exams

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Abstract

The management of waiting lists in hospitals is a topic with relevance given its direct implication in the quality of healthcare services provided to the patients in the good management of human, material and financial resources. Ministry of Health in Portugal stipulates a guaranteed maximum response time for the execution of Complementary Means of Diagnosis and Therapeutics (CMDT), surgeries and outpatient appointments. This paper addresses an investigation conducted at the Centro Hospitalar e Universitário do Porto (CHUP) with the goal of optimizing decisions in the management of waiting lists for CMDT. This objective will be achieved through the development of hill climbing and simulated annealing models. With this study, it was possible to optimize the way these exams can be scheduled, reducing waiting lists, associated costs and waste, improving the quality of service provided to patients.

Keywords: Optimization; Hill Cimbing; Simmulated Annealing;

1. Introduction

By the Portuguese Ministry of Health, a maximum guaranteed response time (MGRT) is established for Complementary Means of Diagnosis and Therapeutics (CMDT), surgeries and outpatient appointments. This MGRT (30 days) is repeatedly exceeded, which often implies that health institutions are penalized for not complying with the MGRT and implies extra costs to recover the lists. Although it is impossible to have an empty waiting list, they can be reduced to their minimum values. Therefore, new ways to minimize the time of users spend on waiting lists are being considered, through optimization of the scheduling process. Thus, this paper presents the implementation

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of Hill Climbing (HC) and Simulated Annealing (SA) techniques to optimization the process of CMDT related to Computerized Axial Tomography (CAT).

2. Background

2.1. Waiting Lists in Healthcare

One of the best known approaches in the area of waiting list management is Queue Theory. This theory is part of a branch of operations research and mathematically addresses the phenomenon of queue formation, as well as its characteristics. The application of Queue Theory does not result in a solution, but rather a way to analyze the performance of queues and can help in decision making regarding the flow of systems [7]. Healthcare waiting lists are a very complex issue given the large number of different factors that can impact them. The late or no-show of both a patient or a doctor implies major disruptions in the existing schedule. Also, the possibility of emergencies implies acting differently than previously planned [3]. Over the years, several approaches have been presented that attempt to solve this type of problem. These approaches differ in the factors they take into consideration, as well as in the type of technique or method implemented. Regarding the analysis methods commonly used in appointment scheduling, three main types are pointed out: analytical, simulation-based and case study-based studies [3].

2.2. Related Works

Several studies were identified in this area. Pulido Martínez et al. (2014) [10] aimed to find the best sequence of surgeries capable of minimizing the costs inherent to the non-use of operating rooms, staff overtime and the inactivity of surgeons. To do so, they presented optimization methods through stochastic programming and the decomposition approach. Another study proposed the use of a hybrid approach of metaheuristic optimization harmonic search with HC to solve a problem that contained many constraints and involved assigning a set of shifts to a set of nurses [1]. Kapamara & Petrovic (2009) [6] addresses the steepest HC method in solving a scheduling problem on radiotherapy patients in a cancer treatment centre. Another work applied a genetic algorithm that compares the current optimal locations with future ones, and the number of ambulances to optimize the location of ambulance stations to reduce the average response time [11]. Braga, J. (2021) [2] presents the techniques of HC, SA and genetic algorithms in order to optimize the scheduling of surgeries in hospitals.

Finally, the study conducted by Sauré & Putinmann (2014) [12], which consists in the development of a game related to appointment scheduling should be highlighted. This game is presented as a learning tool in the management of appointment scheduling, also promoting an introduction to topics such as simulation and decision analysis.

3. Background

3.1. Design Science Research (DSR) and Cross-Industry Standard Process for Data Mining (CRISP-DM)

Design Science Research (DSR) methodology aims to encourage Information Systems (IS) professionals to try to solve real problems with applicable solutions, making IS research more applicable and accessible [9]. It is divided into six phases: Problem identification and motivation, Definition of solution objectives, Design and development, Demonstration, Evaluation and Communication, sequentially.

Created in 1996, the Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology is still considered a very relevant methodology today. This methodology focuses on describing approaches used in knowledge discovery projects and is independent of both industry sector and technology used [14]. It includes six steps: Business Understanding, Data Understanding, Data Preparation, Modelling, Evaluation, and Implementation and all of them were followed in the development of this project.

These methodologies eventually intersect, with business understanding crossing over with DSR phases 1 and 2, data understanding with phases 2 and 3, data preparation and modelling with phase 3, and finally both evaluation and implementation with phases 4 and 5 of DSR [5].

3.2. Tools and Algorithms

Prescriptive analytics, also known as Optimization, is a newer and up-and-coming area. Compared to descriptive and predictive analytics, it is still less mature and aims to suggest the best decision options to take advantage of predicting the future using large amounts of data. To achieve this goal, different techniques and tools are used, such as business rules, algorithms, machine learning, and computational modelling procedures. The effectiveness of the suggestions depends on how well these models incorporate a combination of structured and unstructured data, representing the domain under study and the impact of the decisions under analysis [13]. Prescriptive analysis focuses on solving optimization problems that typically involve three components [4]: solution representation, constraints, and evaluation function.

The optimization algorithms addressed in this study are HC and SA. HC is a modern local search-based optimization technique that works iteratively, searching for new solutions in the neighbourhood of the current solution. The goal of the change function is to produce a slightly different solution by performing a full search in the entire neighbourhood or by applying a small random change to the values of the current solution [4]. The SA algorithm is based on a temperature variable that used to calculate the probability of accepting inferior solutions, avoiding local optimums [8].

4. Case Study

4.1. Data Understanding

Data understanding involves collecting and analysing existing data sets to improve understanding and identify possible quality issues that may exist in them. The data used were provided by the CHUP and are divided into three data sets. The first contains information about the shifts practiced in the CHUP during 2020. The second concerns the performance of CMDT, their requesters and the conditions, involving factors such as clinical status, level of urgency and time constraints. It also contains the characterization of the CMDT and information on its execution, such as request date, scheduling date, and execution date. The last one contains the average CMDT execution time.

4.2. Data Preparation

The data preparation stage involves the activities associated with the construction of the final data sets, which will later be used to feed the optimization models. In this stage the data considered relevant were selected, cleaned and formatted, and new data necessary for the development of the project were built and integrated. These new data were related to the available and occupied time in each shift, the indication of whether the CMDT was already scheduled, the deadline for the execution of CMDT, considering the MGRT, and the penalty inherent to exceeding the deadline.

4.3. Modeling

The main objective of this research is the minimization of the CMDT penalty inherent to the exceeding of the scheduling deadline. The initial solution considers a set of constraints associated to the context of CMDT scheduling and agreed upon with the CHUP administration. It was also established that appointments would only be made after all requests were received. In this initial solution the CMDT were inserted into the scheduling list based on three factors:

- Urgency: CMDT with higher urgency values take priority over CDMT with lower urgency values;
- Longevity: CMDT ordered earlier have priority over those ordered later;
- CMDT duration and shift duration: The time required to perform the CMDT needs to be less than or equal to the time available on the shift.

The shifts have four slots and attributes related to CMDT execution. Slots were created so that it was possible to insert more than one CMDT in each shift and their number was defined by dividing the average value of each shift duration by the average value of the CMDT execution time duration. The evaluation function is responsible for summing the penalties resulting from CMDT scheduling and is obtained by considering the urgency of the CMDT. This evaluation function was used to obtain the total value of the penalty in the CMDT scheduling of the initial solution and the value relative to the total scheduling performed by the solution. Consequently, it was possible to compare the results obtained with the scheduling performed by the CHUP.

4.4. Evaluation

The total penalty values obtained for the different number of iterations when applying HC and SA are shown in Table 1.

Table 1 – Optimization results with HC and SA

Number of iterations	Optimal total penalty value	
	HC	SA
0	24462,5	24462,5
100	24462,5	24462,5
500	24462,5	24462,5
1000	24375	24337,5
5000	24337,5	24137,5
10000	-	23150
15000	-	21412,5

Using the initial solution in HC, is obtained a penalty of 24462.5. Subsequently, the application of the optimization algorithms results in a decrease of the penalty value whenever the number of interactions increases. In the HC algorithm it was possible to verify that the penalty value decreases only after 500 iterations and reaches the optimal penalty value of 24337.5 when 5000 iterations are performed.

The SA results show that the initial solution has a penalty value of 24462,5. This value decreases from the moment when SA technique is applied with 1000 iterations and reaches the optimal penalty value of 21412,5 with 15000 iterations. In SA, since it has a shorter execution time than HC, is possible to perform a greater number of iterations under the defined execution time limit (2 minutes).

Aiming to understand the variation in outcomes when using different sets of CMDT, five different scenarios were developed. For each scenario, a set of 2000 CMDT were randomly selected for scheduling. Table 2 presents the results obtained for each of these scenarios with execution time.

Table 2 – Optimization results in each scenario

	Optimal total penalty value					Runtime
Scenario	1	2	3	4	5	-
CHUP	303500	293425	312050	299975	309300	-
Initial solution	24462,5	31087,5	26387,5	20737,5	24887,5	01:37:00
HC 100i	24462,5	31087,5	26387,5	20737,5	24887,5	+00:01:50
HC 500i	24462,5	31087,5	26387,5	20737,5	24887,5	+00:03:35
HC 1000i	24375	31087,5	26387,5	20737,5	24887,5	+00:06:04
HC 5000i	24337,5	30625	26350	20612,5	24887,5	+00:23:00

SA 100i	24462,5	31087,5	26387,5	20737,5	24887,5	+00:01:12
SA 500i	24462,5	31087,5	26387,5	20737,5	24887,5	+00:01:58
SA 1000i	24337,5	30800	26387,5	20612,5	24837,5	+00:02:21
SA 5000i	24137,5	29637,5	25800	20262,5	24512,5	+00:09:01
SA 10000i	23150	29100	25087,5	19975	23162,5	+00.16:10
SA 15000i	21412,5	27050	23475	19237,5	22562,5	+00:23:55

Considering the results presented, it was possible to verify that the initial solution developed is responsible for minimizing the penalty in CMDT scheduling. This solution is quite advantageous since it gives priority to the most urgent CMDT, and those whose execution request was made earlier, indicating that these may lead to a higher penalty if not scheduled on time. In addition, the optimization techniques are also able to show a significant reduction in the penalty as the number of iterations increases. This reduction is most clear by applying the SA technique, which shows better results than the HC technique.

5. Results and Discussion

After analyzing the results, it is concluded that both techniques present very advantageous minimizations compared to the results from the current scheduling process of CHUP. It was possible to verify that the SA algorithm presents better results, managing to minimize on average 92% of the penalty adjacent to the CMDT scheduling. Additionally, it is understood that the percentage of minimization in each scenario does not present significant variations, so we can expect very profitable penalty values regardless of the set of CMDT to be scheduled.

In the type of techniques used, this research focused only on local search methods. The fact that new solutions are generated from a previous solution makes it possible to find an initial solution adjusted to the context of the problem, justifying the values presented in Table 2. Given the greater variability of results in population-based search algorithms, it is concluded not to explore these models, since the initial solution would not be able to answer the constraints imposed by the CHUP. The level of randomness of these models makes it difficult to improve results given the large number of scheduling possibilities that exist.

Finally, the computational effort of these solutions was also evaluated, a criterion with great implications in a hospital context. Both models present good solutions within the given execution time.

6. Conclusions

The developed research was able to prove the possibility to improve the whole process of scheduling CMDT, according to the criteria previously established by the CHUP. Considering the available resources and scheduling rules, it was possible to decrease the scheduling penalty compared to the CHUP method. The complexity evidenced by the scheduling process in a healthcare organization justifies highlighting that, although the results were satisfactory, further exploration of this theme is needed. The analysis of more algorithms together with the codification of other factors inherent to the scheduling process makes further work in this area possible. Additionally, we have projected a system capable of integrating the results developed, with new functionalities, to enable the extension of this solution to other clinical areas.

With this work, we pointed out that the integration of optimization techniques in the scheduling process can become very advantageous compared to a manual type of scheduling that does not consider factors such as urgency, longevity and CMDT duration. We emphasize that these are the factors that most impact the number of penalties inherent to exceeding the scheduling deadline by the CHUP and consequently deserve an additional concern by the entire administrative team.

Finally, the use of local search methods also presents themselves as good solutions, considering the context of the problem.

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