Optimization of Surgery Scheduling Problems Based on Prescriptive Analytics

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Abstract: Surgery scheduling plays a crucial role in modern healthcare systems, ensuring efficient use of resources, minimising patient waiting times and improving organisations' operational performance. Additionally, healthcare faces enormous challenges, with a general modernisation of all clinical and administrative processes expected, requiring organisations to keep up with the latest advances in Information Technology. The scheduling of surgeries is a crucial sector for the good functioning of hospitals, and the management of waiting lists is directly related to this process, which has seen the COVID-19 pandemic cause a significant increase in waiting times in some specialities. Surgery scheduling is considered a highly complex problem, influenced by numerous factors such as resource availability, operating shifts, patient priorities and scheduling restrictions, putting significant challenges to healthcare providers. In this research, in collaboration with one of the leading hospitals in Portugal, the Centro Hospitalar Universitário de Santo António (CHUdSA), we propose an approach based on Prescriptive Analytics, using optimisation algorithms to evaluate their performance in the management of the operating room. The results allow identifying the feasibility of this approach, taking into account the number of surgeries to be scheduled and surgical spaces in a time perspective, prevailing the priority of each surgery in the waiting list.

1 INTRODUCTION

Over the last few years, we have witnessed a growing concern for the quality of Healthcare provided to citizens. Organisations are increasingly seeking more efficiency, with stronger investments in Artificial Intelligence (van Hartskamp et al., 2019), seeking to assist health professionals in making increasingly complex and demanding decisions (Görgülü and Pickl, 2013). A system capable of improving, assessing and preventing future scenarios becomes a focal topic in hospital development due to organisational objectives that each entity needs to meet and the increasingly precise treatment that must be provided to patients (Briganti and Le Moine, 2020). Alongside this, there is a belief that the immense volume of data in a Hospital should be better utilised. The existence of organisational and clinical data allocated in Hospital Databases makes Healthcare an area with enormous potential for the application of Intelligent Systems, capable of improving the clinical follow-up provided to patients and managing the different organisational processes inherent to any clinical speciality (Jayaratne et al., 2019).

The Surgical Scheduling Problem (SSP) is one of the most debated issues in hospital management. The COVID-19 pandemic aggravated this process, as many specialities interrupted their normal functioning to respond more efficiently to other critical patients, increasing the number of patients waiting for a vacancy to perform the surgeries they need. This needs to be rethought, as the old scheduling processes have already resulted in long waiting lists, making it crucial to develop strategies that can mitigate waiting times and financial losses for these organisations.

In cooperation with the Centro Hospitalar Universitário de Santo António (CHUdSA), a study was carried out to understand the feasibility of a more autonomous solution, according to the intervention of each hospital manager. The aim is to codify the existing restrictions in this process and implement opti-

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misation algorithms that solve the increase in waiting lists and associated costs. This study covers the entire research process, from identifying and codifying constraints to selecting and developing optimisation algorithms, allowing a general understanding of the viability of this approach.

2 PROBLEM DEFINITION

2.1 Surgical Scheduling Problem

Room planning is a task that needs to be addressed in many fields. A notable field in healthcare is planning operation rooms for surgeries. Cost containment and reduction have become one of the primary goals in healthcare management, with hospital managers and professionals trying to understand each factor that includes the total cost of providing better services. Operating Rooms (OR) are one of the areas that have been gathering considerable attention since it is the most critical cost centre and consumes a large proportion of the Hospital's total expenses. As a result, they offer the potential for significant cost-saving, and the Surgery Scheduling Problem (SSP) has been studied over the years and generated a variety of approaches and heuristics (Visintin et al., 2017).

Based on these concepts, the SSP consists of assigning operations to a time interval so that surgery is only scheduled once, at a given time, and never overlaps with another (Agnetis et al., 2014). Despite the different development approaches, with very diverse implementations in the type of algorithms, there are different perspectives obtained from the time scale and the surrounding constraints, evidencing the inexistence of standard approaches to the problem of SSP that effectively prove its effectiveness compared to hospital management carried out nowadays. As a reflection, this problem still presents a scarcity of accurate proposals that may allow the establishment of standard rules and guidelines to manage this hospital process. In order to define the bases for the development of a decision support system, a research was designed to prove the effectiveness of different optimization algorithms in the conception of an approach with common restrictions to different specialties, aiming at a more global solution to the different health organizations.

2.2 Optimization Algorithms

Currently, there is a growing trend in the adoption of computational tools based on optimization methods. According to Cortez (Cortez, 2014), optimization methods are divided into three main categories: Blind Search (BS), Local Search (LS) and Population-Based Search (PBS). BS assumes the exhaustion of all alternatives, ensuring that all solutions are tested. It has an easy implementation, but its feasibility differs significantly if the search space is continuous or too large (Luke, 2012). LS is the most modern category of optimization and is based on new solutions that are generated from existing solutions. Several methods focus on a local neighbourhood through a given initial solution and use previous searches to guide the next one. PBS presents a new approach to optimization algorithms, using a set of candidate solutions instead of a single (Delen, 2019).

3 RESEARCH METHODOLOGY

Two methodologies were followed: Design Science Research (DSR) as a research methodology, providing the necessary guidelines, and Cross-Industry Standard Process for Data Mining (CRISP-DM). DSR consists of 6 phases: 1. Identifying the problem and motivation; 2. Defining objectives of the solution; 3. Design and development; 4. Demonstration; 5. Evaluation; 6. Communication (Peffers et al., 2007). For Data Mining (DM) projects was chosen CRISP-DM, providing a global perspective on the life cycle of a data mining project. Includes 6 phases: 1. Business Understanding; 2. Data Understanding; 3. Data Preparation; 4. Modelling; 5. Evaluation; 6. Deployment (Azevedo and Santos, 2009). Figure 1 represents the crossover between these two methodologies.

4 DATA UNDERSTANDING

For the development of this study, surgeries scheduled in a time interval were considered, as well as the existing shifts. Two new attributes were developed directly related to shifts: the total time associated to an operating room and an occupation time with the related time history as a control parameter. Only the medical speciality Obesity was considered. Each surgery involves the execution of all necessary procedures. Additionally, an estimated time is used, associated to each type of surgery, using the interquartile mean, obtained through the history of the times related to the performance of that surgery by ICD10 code in the last three years. The period under consideration is based on the non-consideration of atypical restrictions, such as the period between 2020 and 2021, associated to the COVID-19 pandemic. The CHUdSA provided all data.

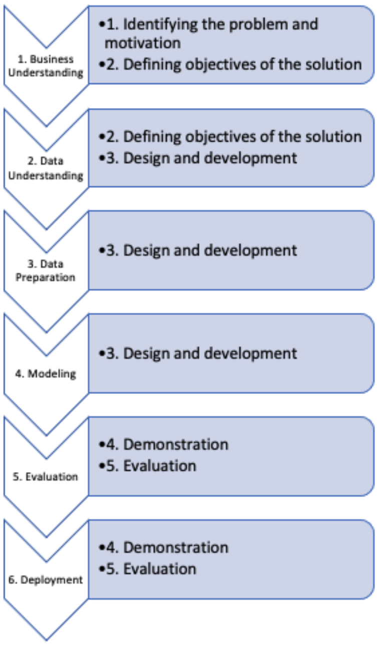

Figure 1: Crossover of Methodologies.

5 MODELING

The approach developed by the team takes into account the operational needs of CHUdSA, seeking to strike a balance between patient typology and priority with providing the best patient care. In this sense, hospital administrators must consider several factors when performing surgical planning, such as the shifts available to allocate a patient, the number of shifts and professionals available, and the ability to perform new admissions, always seeking to reduce the waiting list for surgery. Based on a set of basic rules used in any speciality and to model a solution for the PSS, we consider, for this study, a surgical area of a hospital, composed of S operating rooms, a finite horizon of periods H, in days, and a set N of selected patients waiting to have their surgeries scheduled. Each patient in {1, ..., N} has a type of surgery per ICD10 code and thus has an estimated time associated with that surgery. This time includes the duration of the surgery and an additional time for cleaning and pre-surgical preparation. Regarding operating rooms, each one specifies the day and the operating room. Additionally, it was considered that all surgeons could be assigned to surgery. Thus, minimizing the number of surgeries exceeding the Guaranteed Maximum Response Time (GMRT) is the primary goal of the optimization. This definition translates into wanting to obtain a solution capable of providing surgeries in a shorter timeframe to patients while reducing the monetary costs to the hospital inherent to paying significant fines for performing surgeries after the deadline.

The design considerations for this approach are:

1. There is a prioritized patient list for surgeries. Patient priority is defined based on medical and waiting time factors.
2. The hospital contains a specific set of ORs. Each one is unique and specially adapted for certain types of interventions.
3. A surgery that is programmed after its deadline earns a penalty depending on your priority.
4. After a scheduling proposal performed by the algorithms has been defined, the surgeries not scheduled remain on the waiting list for the next scheduling. The increase in waiting days for surgery makes these surgeries seen as priorities to be planned in future proposals;
5. Each surgery also has information regarding the time required to perform necessary procedures, such as cleaning room and preparing it.

The typical structure of these solutions is based on three main code sectors: Initial Solution (IS), Evaluation Function (EF) and Objective Function (OF), in this order.

1. IS is a first representation of the problem in a coding process. Ensures an initial guess, often called a "starting point" for the algorithm (Gandomi et al., 2013);
2. The definition of EF translates to evaluating a possible solution in the context of the problem to be maximised or minimised. The function allows different solutions to be compared, providing a ranking or a quality measure score (Michalewicz et al., 2006);
3. The OF is composed by the optimisation algorithms. The implementation depends on the type of algorithms to be deployed (blind search, local search, population-based search, multi-objective search) (Cortez, 2014).

The Initial Solution (IS) was obtained in random or sequential slots through the list of specialised surgeries by assigning one slot to each input surgery. It is implemented by the first fit method (Brent, 1989) and obtained by assigning surgeries in available slots, respecting the time constraints associated with each surgery and the existing turnovers with the addition of multiple surgeries to a given slot.

The performance is evaluated by a function developed for this purpose. Each solution considers the assigned surgeries by specifying a penalty (p) obtained in a surgery (represented mathematically as follows):

$$pt = \sum_{i=1}^{\mathrm{i}} p_i \quad (1)$$

The OF was developed considering two local optimisation algorithms:

1. Hill Climbing (HC) is a local optimization method that climbs a hill until a local optimum is found, adopting consecutive searches for new solutions within the neighbourhood of the current solution, adopting a new solution if it is better than the previous one (Balan, 2022). Hill Climbing (HC) implementation was retrieved and adapted from (Cortez, 2014) and can be perceived by the following function:

   $$hclimbing(par, fn, change, control, type) \quad (2)$$

   The input variables are presented as follows:

   - The initial solution (par);
   - The evaluation function (fn) that evaluates the total penalty of the allocated surgeries;
   - A change function (change), responsible for generating the next candidate, creating minor disturbances in the initial solution by swapping surgeries between different slots, and evaluating if this was profitable;
   - The variable control is a list that indicates the number of interactions to execute and the information to collect throughout the solution;
   - A last variable (type) indicates the main goal: minimisation.

2. Simulated Annealing (SA) implementation was also adapted from (Cortez, 2014). In contrast to HC, which adopts a fixed value for this control parameter, SA uses a variable temperature during the search. The method starts with a high temperature, gradually decreasing the control parameter until it reaches the minimum value or until the set number of iterations is reached. The following function represents the SA implementation:

   $$simulated\_annealing(func, s0, niter, step) \quad (3)$$

   The input variables are presented as:

   - The evaluation function (func) that evaluates the total penalty, similar to HC;
   - The initial solution (s0), also similar to HC;
   - Maximum number of iterations (niter);
   - Parameter to control the cooling speed of the model (step).

6 EVALUATION AND DEPLOYMENT

OR management by the CHUdSA can be classified by the number of surgeries performed in each speciality and the number of surgeries performed after the deadline. Such variables determine the total penalisation of the hospital, translating into costs that it will have to assume. Based on this, Table 1 represents a general analysis of the existing data considering the speciality chosen (Obesity) for this study to understand the relationship between the number of surgeries to be allocated and the number of available vacancies. The choice of this speciality takes into account the most frequent scenario in which the number of surgeries to be allocated is greater than the number of existing shifts. In this scenario, the optimisation of the ORs must be extremely efficient to achieve the greatest number of surgeries with the existing resources.

Table 1: Analysis between number of surgeries and available ORs in Obesity.

Number of surgeries	Number of Time Slots
198	122

The implementation of HC and SA algorithms leads to a set of results presented in Tables 2 and 3.

Table 2: Final Results of Hill Climbing Algorithm.

Hill Climbing Algorithm	Results
Penalty	0
Surgeries without Penalty	190
Surgeries with Penalty	0
Unscheduled surgeries	8

Table 3: Final Results of SA Algorithm.

SA Algorithm	Results
Penalty	0
Surgeries without Penalty	164
Surgeries with Penalty	1
Unscheduled surgeries	33

It was also possible to understand the impact of the algorithms on the scheduling of each surgery: the HC schedules 98% of surgeries for a more recent date, compared to the scheduling date performed by CHUdSA. In SA, it was possible to obtain a more recent date in 85% of surgeries.

To perform the deployment of this solution, an application was developed, which allows testing the different algorithms according to a set of variables that interfere directly with the type of scheduling proposals generated. In it, all the necessary information is available for a professional to validate the scheduling proposals and confirm a possible appointment. Figure 2 present the constitution of the final prototype.

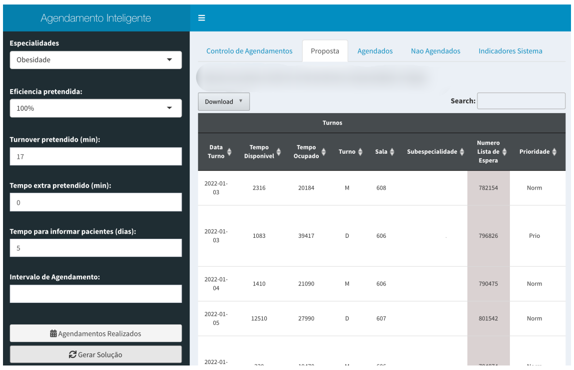

Figure 2: Prototype for visualisation of a scheduling proposal.

The main objective of this prototype is to integrate the ability to generate possible scheduling solutions for the physicians responsible for performing this process in each speciality. These should be able to test potential alternatives, edit the final solution, and change the variables that directly influence the ability to generate solutions (execution times, scheduling intervals and desired efficiency), having them the final responsibility of submitting the final proposal. Once a solution is approved, data is sent to the clinical system, as well as to the Database of the CHUdSA Business Intelligence system (AIDA-BI), allowing hospital professionals to consult the information at any time, such as responsible physicians, schedules, procedures, users and operating rooms.

7 DISCUSSION

Through the implementation of these algorithms, a set of results can be proven:

1. The penalty of automatic scheduling, according to the described optimisation algorithms, proves the feasibility of this approach as a response to the SSP.
2. All implemented algorithms can offer improvements in ORs management and organisation. Still, HC is the algorithm that achieves better scheduling capability;
3. The SA algorithm presents a higher than expected number of unscheduled surgeries. This can be justified by the fact that SA does not include as a determining factor the heuristic ability to establish new solutions from the defined number of iterations but through a probabilistic value (temperature) determining the ability to find new solutions. Common to both algorithms is that certain surgeries have a minimum execution time greater than the maximum time of an existing shift and, therefore, would never be scheduled in this optimisation process. By recommendation of CHUdSA professionals, these surgeries are always treated as exceptional cases and should be managed according to specific internal procedures;
4. Modeling the first solution with a surgery allocation algorithm, taking into account the priority and longevity of a surgery on a waiting list, represents an important improvement in the scheduling process. The total penalty proves the possibility of improving the management of surgeries in the possible time-space;
5. Additionally, this implementation focused on AI-based heuristics translates into a substantial improvement in the number of surgeries that are allocated after the surgical limit. Thus, we can notice a great capacity for improvement of OR management with a solution capable of optimising the scheduling process in this speciality.

8 CONCLUSION AND FUTURE WORK

The study of allocation and scheduling problems is always considered to be of great complexity. Taking this reality to healthcare, the responsibility to create an effective solution is even more significant since the priority must always be the care provided to patients, trying to pay attention to the existing resources and the practices of good organisational management increasingly important in the hospital context.

The developed approach offers a first sketch of what can be contemplated in an intelligent system to support all the decisions made in SSP. Considering a general constraints model for any hospital, implementing optimization algorithms, and considering the same constraints for generating the initial solution, it was possible to prove the ability to find better solutions for surgical scheduling. The HC and SA algorithms demonstrate the capacity to have a better occupation of the available ORs, with clear highlights to HC, which allocates a significant percentage of surgeries (96%), always trying to considering as main reference the scheduling limit without accumulating penalties. The use of many iterations in the implemented algorithms means a high computational load and a waiting time for solutions, which is still important in order to make it possible to find the best alternatives within each scheduling scenario.

Taking into account all the limitations found in scheduling problems and the high level of organisational complexity that a hospital currently has, we consider this approach a possible solution to SSP problems, of which the organisation of surgeries on time and the necessary cost control, crucial to optimise all management processes, always prevail. SA presents extremely satisfactory results, nullifying the number of surgeries with a penalty, i.e., surgeries with a scheduled date higher than the deadline. Furthermore, this algorithm provides a nearly optimal solution, reaching a stabilisation point after 100 iterations, something that does not happen in the HC and that may justify the fact that it does not allocate a greater number of surgeries.

In the first phase of this research, new perspectives were obtained on how an approach based on AI heuristics can translate into a solution capable of automating and improving this process. However, some scenarios could be further explored as future work:

1. Testing this study in other healthcare specialities will be the first step to understanding if the success of implementing this logic is well achieved in different environments.
2. A deeper study on the nullification of the scheduling penalty may be equated. While the hospital would like to pay the least amount of costs related to surgeries scheduled after the deadline, it may be pertinent to identify whether a proposal with a higher penalty will better serve the hospital's scheduling interests.
3. A new constraint can be added, always considering that there are urgent cases to be executed. Despite in this study only surgeries from the waiting list were considered, it is possible to complement the scheduling constraints with an additional rule, always leaving space in an OR for urgent cases;
4. Improving the efficiency of the optimization method by exploring new models and their configurations (only local search algorithms were addressed, but there is some scope for development for population-based, blind search or even multi-objective search algorithms).

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