Enhancing Surgery Scheduling with Artificial Intelligence: A Study on Metaheuristic Optimisation Models in Healthcare Settings

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Abstract

Background: Healthcare is facing enormous challenges. The most recent pandemic has caused a global reflection on how clinical and organisational processes should be organised, optimising decision-making by managers and healthcare professionals to provide increasingly patient-oriented healthcare. One of the most debated topics is efficiency in surgical scheduling, a crucial sector for the good functioning of hospitals, related to the management of waiting lists, and highly vulnerable to bad decisions due to the high number of variables and restrictions involved.

Objective: In this research, in collaboration with one of the leading hospitals in Portugal, Centro Hospitalar e Universitário de Santo António (CHUdSA), we propose a study on heuristic approaches to optimise the management of the surgical centre and reduce inherent costs.

Methods: A study was carried out into the scheduling process for a given period conducted by CHUdSA. Using heuristic approaches, optimization algorithms were implemented to determine the possible scheduling dates for a waiting list, with the aim of minimizing the scheduling penalty. The penalty represents the monetary cost that the hospital must bear for surgeries that are not scheduled by the deadline.

Results: The results obtained allow us to conclude that the implementation of these algorithms in a real context could represent a substantial advance in the scheduling process. This advance is evident in the ability of artificial intelligence algorithms not only to optimise the efficiency of the process, but also to make it possible to schedule surgeries for significantly earlier dates compared to the manual method used by hospital professionals.

Conclusions: This implementation clearly shows the benefit of using this proposal to increase the efficiency of this process and minimise the overall costs, highlighting the remarkable ability of algorithms to respond promptly and accurately to each context

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Original Paper

Enhancing Surgery Scheduling with Artificial Intelligence: A Study on Metaheuristic Optimisation Models in Healthcare Settings

Abstract

Background: Healthcare is facing enormous challenges. The recent pandemic has caused a global reflection on how clinical and organisational processes should be organised, optimising decision-making among managers and Healthcare professionals to deliver increasingly patient-centric care. Efficiency in surgical scheduling is particularly critical, affecting waiting list management and being susceptible to suboptimal decisions due to its complexity and constraints.
Objective: In this research, in collaboration with one of the leading hospitals in Portugal, Centro Hospitalar e Universitário de Santo António (CHUdSA), we propose a study on heuristic approaches to optimise the management of the surgical centre.
Methods: CHUdSA's surgical scheduling process was analysed over a specific period. By testing an optimisation approach, the research team was able to prove the potential of AI-based heuristic models in minimising scheduling penalties, representing the financial costs incurred by procedures not scheduled on time.
Results: The application of these approach demonstrated potential for significant improvements in scheduling efficacy, with 99% of surgeries being scheduled. Notably, the implementation of Hill Climbing (HC) and Simulated Annealing (SA) stand out in this implementation, significantly minimising the scheduling penalty (HC with *pt*=0 in Urology, Obesity and Paediatric Plastic Surgery; SA with *pt*=5100 in Urology, *pt*=1240 in Obesity and *pt*=30 in Paediatric Plastic Surgery), and highlighting the ability of AI-heuristics not only to optimise the efficiency of this process, but also to make it possible to schedule surgeries for significantly closer dates compared to the manual method used by hospital professionals.
Conclusions: Integrating these algorithmic solutions into the surgical scheduling process increases efficiency and significantly reduces costs. The practical implications are significant: hospitals can minimise patient wait times, maximise resource utilisation, and enhance surgical outcomes through improved planning by implementing these AI-driven strategies. This development highlights how AI algorithms can effectively adapt to changing Healthcare environments, having a transformative impact.

Keywords: Healthcare; Optimisation; Surgery Scheduling Problems.

Introduction

The effective delivery of hospital services depends on the efficient execution of several processes, increasingly reliant on computer resources capable of responding to specific situations [20]. A system capable of improving, evaluating, and preventing future scenarios becomes crucial to Healthcare organisations, given the objectives each entity must meet and the requisite patient care [3, 35].

Simultaneously, the volume of patient-centred data in healthcare is burgeoning. An example of this is illustrated by Jayaratne et al. [17], which highlights the data-rich environment of the Intensive Care Unit, where extensive data streams continuously emanate from patient monitoring and observation. These data encompass various facets such as laboratory results, medical prescriptions, therapeutic decisions, clinical observations by healthcare providers, among others. The richness of these systems depends on the available data, and the Healthcare system has a great scope at this level. In 2018, Feldman et al. showcased the great diversity of these systems, categorising them into groups based on the data's nature and associating them with relevant areas of interest. This wide range, which includes clinical and organisational data, makes it an area with a lot of potential [13]. Business Intelligence systems are crucial for these entities, which require tools capable of organising this data in a more perceptible way [29]. The rise of Artificial Intelligence (AI) has led to profound reflection on these systems, allowing them to be transformed to integrate future data and provide advice on optimal decision-making that affects organisational management [18, 35]. Improving the decision-making process is based on combining data storage with analytical tools, applications, and methodologies, and attempts to incorporate and find relationships between existing data, providing real-time access and offering proper analysis of historical and current data, obtaining insights that were not possible before [16, 27].

For a long time, one of the most discussed topics in hospital organisations has been the Surgical Scheduling Problem (SSP). This process became even worse by the COVID-19 pandemic, as numerous specialties had to halt their treatments in order to prioritise handling other patients. There have been clear repercussions from this management, including an increase in the number of patients on waiting lists and a need for managers to find clinically and organizationally effective approaches to reduce them. A study was carried out in collaboration with the Centro Hospitalar e Universitário de Santo António (CHUdSA) to determine whether a metaheuristic approach could be used as one of the strategies to be implemented in a hospital organisation.

Related Work

Room planning is a task that needs to be addressed in many fields particularly within healthcare, such as in planning operating rooms for surgeries. Cost containment and reduction have emerged as primary objectives in healthcare management, with hospital managers and professionals trying to understand each factor contributing to the total cost of delivering better services. Operating Rooms (OR) are one of the areas that have been gathering considerable attention since its the most critical cost centre and consumes a large proportion of the hospital's total expenses. Consequently, they offer substantial potential for cost savings, with SSP having been studied over the years and generated a variety of approaches and heuristics [14]. Currently, there is a growing trend in adopting computational tools based on optimization methods. As outlined by Cortez [12], 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, guaranteeing that all solutions are tested. It is only admissible for discrete search spaces and is easy to implement. The major disadvantage of this technique is its feasibility when the search space is continuous or too large. It tends to require more computational effort since the search is performed through a set of candidate solutions rather than a single solution. LS is the most modern optimization technique and is based on new solutions that are generated from existing ones. Several methods focus on a local neighbourhood through a given initial solution and use previous searches to guide the next. PBS present a new approach to Optimization algorithms, using a set of candidate solutions instead of one [19].

Studies conducted by the scientific community suggest that this area holds promise as a potential solution to the problem at hand, although they diverge on the primary factors directly impacting the performance of a surgical schedule. Some studies adopt a more specific approach, such as the one developed by Fügener et al. [14], which introduces a variable called planned capacity slack for OR days with the application of the Simulated Annealing (SA) algorithm to minimise planned slack and maximise OR utilisation. The planned slack aimed to minimise overtime by absorbing the variability of surgery duration. Min and Yuehwern designed a surgical calendar for surgery patients with uncertain surgical operations, including uncertainty in the period of surgery and the availability of resources such as the surgical intensive care unit, employing a stochastic approach to minimise the sum of costs directly related to patients and expected costs associated to overtime [23]. Visintin et al. [32] propose that creating an effective surgical scheduling system requires grouping patients into homogeneous surgical groups, developing an approach solely focused on this constraint, and scheduling surgical groups rather than actual patients. Most authors state that the performance of an OR depends mainly on how surgical activities are scheduled. This perspective is reflected in the study conducted by Su et al. [30], which based on this fact, proposes a SOMO-based approach to solve the surgical scheduling problem. Banditori et al. [6] also introduced a mixed integer programming model assuming that a hospital's waiting list cases can be categorised into homogeneous surgical groups based on the resources they are anticipated to necessitate. Agnetis et al. [2] adopted a weekly basis for surgical scheduling, allocating various specialties to available sessions and considering only patients immediately eligible for surgery, selected from a waiting list based on parameters such as surgery duration and waiting time. More recently, a similar approach, with Brit et al. [10] considering multiple stakeholders (including surgeons, equipment, operating rooms, and recovery ward beds) in their optimisation strategy to meet waiting time objectives by maximizing OR utilisation. Tyagi et al. [36] explore various models and techniques used for scheduling, emphasizing the importance of strategic (long-term), tactical (medium-term), and operational (short-term) scheduling levels, demonstrating that daily planning and scheduling using detailed procedural times and sophisticated algorithms substantially enhance OR utilization. Wang et al. [37] propose a fuzzy model to manage these uncertainties, integrated with a hybrid Genetic Algorithm (GA-P) for optimization. The model effectively balances the costs and benefits associated with using an overflow strategy, where patients are assigned to undesignated departments to manage capacity utilization better.

Despite the varied development approaches and implementations of algorithms, different perspectives emerge regarding the time scale and surrounding constraints, highlighting the absence of standard approaches to the SSP problem that conclusively prove effectiveness compared to current hospital management practices. 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 without affecting the organizational policies of the different specialities. Considering this, the research question is associated with a study aimed at demonstrating the effectiveness of a selected set of optimisation algorithms, customised to time/resource allocation problems, in designing an approach addressing common constraints across various specialties. The primary goal is to provide a more comprehensive solution applicable to different healthcare organisations.

Methods

An optimisation model-based approach was developed to demonstrate the application of heuristic algorithms. Our analysis focuses on optimising the temporal allocation of surgeries, depending on the date placed on the waiting list and its priority.

Study design

Two methodologies were followed: Design Science Research (DSR) as a research methodology and Cross-Industry Standard Process for Data Mining (CRISP-DM). DSR consists of 6 phases: Identifying the problem and motivation, Defining objectives of the solution, Design and development, Demonstration, Evaluation and Communication. These phases provide guidelines for a research project [25]. To put DSR in action, it was necessary to use a practical methodology for Data

Mining (DM) projects. The CRISP-DM method provides a global perspective on the life cycle of a DM project. Comprises the following six stages: Business Understanding, Data Understanding, Data Preparation, Modelling, Evaluation and Deployment [4]. There are dependencies between them and does not have a rigid structure [28]. Since both methodologies are used concurrently, the relationship between them throughout the project phases is described. These are presented in Figure 1.

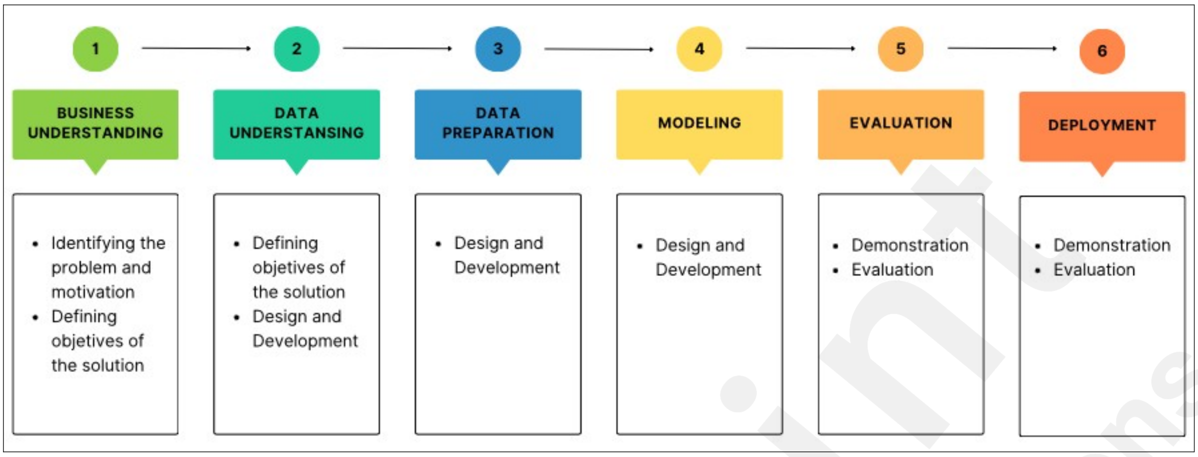

Figure 1: Crossover of Methodologies. DSR and CRISP-DM.

Problem Statement

Hospital administrators attempt to reduce costs while providing the best care possible for their patients. To achieve this aim, they take into account a number of factors that directly affect the quality of the scheduling that needs to be done. These factors include the number of professionals available for each day, the specialty related to each type of diagnosis performed, the availability of slots, and the ability to perform new admissions with an aim of continuously reducing waiting time. Under this perspective, the Surgical Area of a Hospital (SAH) is the main optimisation target for the development of a metaheuristic method. Each SAH is made up of S operating rooms, a finite H number of days, and a group of N patients who are waiting for a surgical appointment. Thus, the problem consists in allocating patients to available operating rooms and determining the sequence of surgeries to be performed. A surgery time ST is assigned to each patient in $\{1, \ldots N\}$. This time includes the period of a procedure as well as extra time for pre-operative cleaning and preparation. Depending on the type of study, an organization can always establish different restrictions that directly influence how the algorithm generates solutions, referred to as hard (primary objectives) and soft (secondary objectives) constraints.

Finally, the goal is to define a global optimisation strategy for more than one specialty. Hard constraints involve the inclusion of a maximum limit for the number of candidates assigned to a vacancy, room capacity constraints, and time constraints, so that the algorithms always consider shifts that are available in certain time blocks. Simultaneously, this includes reducing the number of patients whose surgeries exceed the time limit of the Guaranteed Maximum Response Time (GMRT). Additionally, it is possible that not all operating rooms are open every day, with some only open during specific times. As a result, each one indicates the day and the operating room in consideration. The design factors for this approach include:

1. Each speciality is assigned one, more than one or no OR. These assignments are decided in the stage before the block schedule;
2. Patient priority is defined based on medical and waiting time factors, considering always a prioritised patient list for surgeries;
3. Each surgical speciality manages its patients independently;

4. The hospital contains a specific set of ORs, which each one is unique and adapted for certain types of interventions;
5. A surgery that is programmed after its deadline earns a penalty depending on your priority;
6. Each surgery has information regarding the time required to clean the room and prepare it for next surgery;
7. A patient cannot be operated on more than once in the same scheduling period.

For this problem, was considered that all surgeons are able to be assigned to surgery. Daily availability plans of CHUdSA are also considered so that a specific surgery allocation respects the existing resources for each day, namely the number of ORs and available medical doctors. The following chapters explain the heuristic approaches.

Data Understanding and Preparation

The surgery data analysed is considered event-based. Each surgery undergone by a patient represents an event associated with a medical specialty at a specific time, comprising the execution of all requisite procedures. Additionally, data containing information related to the time blocks available in each speciality are used. The data were derived from medical specialities previously selected by CHUdSA interlocutors, including a scheduling process carried out in 2019. This time frame was chosen due to hospital administration did not take pandemic constraints into consideration, making it possible to examine a scheduling procedure under standard circumstances without any unusual restrictions.

Proposed Metaheuristic Algorithms

Metaheuristic algorithms is a search procedure designed to find better solutions to an optimization problem that is considered complex to solve [1]. They are categorised according to how they operate in the search space and how new solutions will be discovered [12] such as "nature-inspired vs non-nature-inspired, population-based vs local search, dynamic vs static objective functions, one vs multiple neighbourhood structures” [8]. The typical structure of these solutions is based on three main code sectors: Initial Solution (IS), representing the first structure of the problem, ensuring an initial guess, often called a "starting point" for the algorithm. Evaluation Function (EF) that analyse a possible solution in the context of the problem, comparing different solutions and providing a ranking or a quality measure score. Objective Function (OF), composed by the implementation of different optimisation algorithms [15].

Hill Climbing

Hill Climbing (HC) is a local optimization algorithm that climbs a hill until a local optimum with the goal of maximizing. The method iteratively searches for new solutions inside the existing solution's neighbourhood, adopting a new solution if it is better than the previous one [5]. The purpose is to discover an improvement by running an extensive search within the defined neighbourhood borders and the ability of the algorithm to produce successful results is determined entirely by the initial solution [12, 19]. Figure 2 represents the logic associated to HC algorithm.

Inputs: S, f, C ▷ S is the initial solution, f is the evaluation function, C includes control parameters
$i \leftarrow 0$ ▷ i is the number of iterations of the method
while not $termination\_criteria(S, f, C, i)$ **do**
  $S' \leftarrow change(S, C)$ ▷ new solution
  $B \leftarrow best(S, S', f)$ ▷ best solution for next iteration
  $S \leftarrow B$ ▷ deterministic select function
  $i \leftarrow i + 1$
end while
Output: B ▷ the best solution

Figure 2: Hill Climbing Algorithm [12].

Simulated Annealing

Metropolis et al. [21] designed simulated annealing (SA), which is primarily inspired on a cooling operation in heating-based metallurgy. SA begins with a randomly generated initial solution and a high-temperature *T*. During the cooling phase, the algorithm will converge to an estimate solution, moving away from the local optimum to locate the near-optimal solution, and the method will grow more accurate with each iteration to obtain a better solution [12]. Another solution will be randomly created near the initial solution and the difference in function values is calculated as:

$$\Delta = f(xn) - f(xc)$$

If Δ is smaller, the new solution automatically becomes the current solution from which the search will continue [1]. Figure 3 represents the logic associated with SA algorithm.

Inputs: S, f, C ▷ S is the initial solution, f is the evaluation function, C contains control parameters ($maxit$, T and $tmax$)
$maxit \leftarrow get\_maxit(C)$ ▷ maximum number of iterations
$T \leftarrow get\_temperature(C)$ ▷ temperature, should be a high number
$tmax \leftarrow get\_tmax(C)$ ▷ number of evaluations at each temperature
$fs \leftarrow f(S)$ ▷ evaluation of S
$B \leftarrow S$ ▷ best solution
$i \leftarrow 0$ ▷ i is the number of iterations of the method
while $i < maxit$ **do** ▷ $maxit$ is the termination criterion
  for $j = 1 \rightarrow tmax$ **do** ▷ cycle j from 1 to $tmax$
    $S' \leftarrow change(S, C)$ ▷ new solution (might depend on T)
    $fs' \leftarrow f(S')$ ▷ evaluation of S'
    $r \leftarrow \mathcal{U}(0, 1)$ ▷ random number, uniform within [0, 1]
    $p \leftarrow \exp\left(\frac{fs' - fs}{T}\right)$ ▷ probability $P(S, S', T)$ (Metropolis function)
    if $fs' < fs \vee r < p$ **then** $S \leftarrow S'$ ▷ accept best solution or worst if $r < p$
    end if
    if $fs' < fs$ **then** $B \leftarrow S'$
    end if
    $i \leftarrow i + 1$
  end for
  $T \leftarrow \frac{T}{\log(i/tmax) \times tmax + \exp(1)}$ ▷ cooling step (decrease temperature)
end while
Output: B ▷ the best solution

Figure 3: Simulated Annealing Algorithm [12].

Particle Swarm

Kennedy and Eberhart, in 1995, conducted a study on the social behaviour of a group of animals and concluded that being in a group increases one's chances of surviving. This is corroborated by the fact that species share information, which increases the probability of finding the optimal hunting location. The Particle Swarm (PS) algorithm operates on this conceptual foundation, attempting to identify the best solution in a high-dimensional solution space. It is all about either maximizing profits or limiting losses. There can be multiple local maximum and minimum in a function, but only one global maximum and/or minimum. In summary, PS is a population-based algorithm and can be defined by the direct and indirect interactions between distinct sets of information to affect the results obtained, consequently preserving an organized pattern among the data set [12]. Figure 4 represents the logic associated with PS algorithm.

```
Inputs: f, C                          ▷ f is the fitness function, C includes control parameters
P ← initialization(C)                 ▷ set initial swarm (topology, random position and velocity,
previous best and previous best position found in the neighborhood)
B ← best(P, f)                                                              ▷ best particle
i ← 0                                               ▷ i is the number of iterations of the method
while not termination_criteria(P, f, C, i) do
    for each particle x = (s, v, p, l) ∈ P do                               ▷ cycle all particles
        v ← velocity(s, v, p, l)                                  ▷ compute new velocity for x
        s ← s + v                               ▷ move the particle to new position s (mutation)
        s ← confinement(s, C)                          ▷ adjust position s if it is outside bounds
        if f(s) < f(p) then p ← s                                     ▷ update previous best
        end if
        x ← (s, v, p, l)                                                   ▷ update particle
        if f(s) < f(B) then B ← s                                        ▷ update best value
        end if
    end for
    i ← i + 1
end while
Output: B                                                                   ▷ best solution
```

Figure 4: Particle Swarm Algorithm [12].

Modelling the Initial Solution

By assigning one slot to each input operation, the Initial Solution (IS) was obtained in random or sequential slots using the list of specialist surgeries. Depending on the number of slots and surgeries, the bottom and upper parameters are defined as the highest and lowest values for each dimension. It is obtained by assigning surgeries in available slots for a specific speciality and is implemented by the first fit approach [9]. The challenge with this initial method is respecting the time limits connected with each surgery as well as the current turnovers with the addition of surgeries to a particular slot. It was also decided that the production of the first solution should include all potential constraints. The graphical representation of how the first solution is generated is included in Multimedia Appendix 1.

The performance is evaluated using a function designed for this purpose. Each solution considers the assigned surgeries by specifying a total solution penalty (*pt*), calculated using the sum of each penalty *p* earned in a surgery, as shown mathematically below.

$$pt=\sum_{i=1}^{i} pi$$

Each penalty is calculated by multiplying the number of days that the surgery is overdue by each deadline (*ds*) and the priority associated with that same surgery (*pr*), presented in the following equation:

$$p=f(ds)-f(pr)$$

Modelling the Objective Solution

For this purpose, an objective function was used based on the implementation of different algorithms, which through several iterations, will search for a better solution than the existing one. For each iteration, a total penalty is given to the surgeries, making comparisons with other solutions. The iterations end at the defined limit, returning the best solution.

Hill Climbing Implementation

Hill Climbing (HC) implementation was retrieved and adapted from Cortez [12] and can be perceived by the following function:

$$hclimbing(par, fn, change, control, type)$$

The input variables are presented as follows:

1. The initial solution (*par*), obtained by allocating the surgeries to available slots and already explained in the previous chapter;
2. The evaluation function (*fn*) evaluates the total penalty of the allocated surgeries;
3. 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;
4. The variable *control* is a list that indicates the number of interactions to execute and the information to collect throughout the solution;
5. A last variable (*type*) indicates the main goal: minimisation.

Simulated Annealing Implementation

Simulated Annealing (SA) implementation was also adapted from Cortez [12]. It employs a variable temperature as opposed to HC, which chooses a fixed value for this control parameter. Starting at a high temperature, the method gradually lowers the control parameter until it reaches the desired minimum value or a predetermined number of iterations. The following function represents the SA implementation:

$$simulated_{annealing}(, par, niter, step)$$

The input variables are presented as:

1. The evaluation function (*func*) that computes the total penalty, similar to HC;
2. The initial solution (*par*), also similar to HC;
3. Maximum number of iterations (*niter*);
4. Parameter to control the cooling speed of the model (*step*).

Particle Swarm Implementation

The implementation of Particle Swarm (PS) follows a different perspective from that presented in the other two models. It's an algorithm that seeks to efficiently search within a specified boundary, using the iterations between particles to find the best solution possible [12]. The implementation of this method was obtained by the *psoptim* method from the *pso* package [26]. The function described has six input parameters:

psoptim¿

These are represented sequentially by:

1. Vector containing the initial list of surgeries to schedule;
2. Penalty minimisation function;
3. Lower bounds on the variables, belonging to the minimum scheduling shift;
4. Upper bounds on the variables belonging to the maximum scheduling shift;
5. List of control variables, belonging to the best solution found, number of interactions, swarm size and continuous trace of solutions found.
6. Evaluation function to compute the total penalty, like the other methods.

Results

The number of surgeries performed by each specialty and the number of surgeries performed after the deadline can be used by the CHUdSA to categorise its OR management. Such variables determine the total penalty of the hospital, translating into costs that it will have to assume. Table 1 represents a general analysis of the existing data considering the specialties chosen for this study to understand the relationship between the number of surgeries to be allocated and the number of existing slots for each specialty under study. The choice of specialties considers the most frequent scenario, in which the number of surgeries to be allocated is higher than the number of existing slots. In this case, the greatest number of surgeries using the available resources requires the ORs to be optimised with maximum effectiveness.

Table 1. General analysis between number of surgeries in each specialty with available ORs.

Medical Specialities	**Number of Surgeries**	**Number of Time Slots**
Obesity	198	122
Urology	133	89
Paediatric Plastic Surgery	98	45

The first approach was carried out to understand which algorithms obtained the best performance, considering the optimisation objective: minimisation of the penalty, meaning maximisation of the number of surgeries scheduled within deadline. Table 2 summarises the values obtained in implementing the algorithms described above.

Table 2. General analysis of optimization algorithms performance.

Algorithms	**Penalty Obesity**	**Penalty Urology**	**Penalty Paediatric Plastic Surgery**

Hill Climbing	0	0	0
Simulated Annealing	5100	1240	30
Particle Swarm	42702	30000	53108

Since this initial approach considers a first custom solution with the defined scheduling rules, it is realised that the local search algorithms obtain better scheduling performances. Consequently, a deeper examination of the HC and SA algorithms was done. The implementation of these algorithms leads to a set of results presented in Tables 3 e 4. These values follow the goal of comparing the management performed by the algorithms as a response to the SSP.

Table 3. Measure the impact of Hill Climbing Algorithm.

Metrics	**Penalty**	**Surgeries without penalty**	**Surgeries with penalty**	**Unscheduled Surgeries**
CHUdSA management Obesity	643550	4	194	0
HC Optimisation Obesity	0	190	0	8
CHUdSA management Urology	37030	91	42	0
HC Optimisation Urology	0	132	0	6
CHUdSA management Paediatric Plastic Surgery	14760	81	17	0
HC Optimisation Paediatric Plastic Surgery	0	98	0	0

Table 4. Measure the impact of Simulated Annealing Algorithm.

Metrics	**Penalty**	**Surgeries without penalty**	**Surgeries with penalty**	**Unscheduled Surgeries**
CHUdSA management Obesity	643550	4	194	0
SA Optimisation Obesity	5100	164	1	33
CHUdSA management Urology	37030	91	42	0
SA Optimisation Urology	1240	128	4	1
CHUdSA management Paediatric Plastic Surgery	14760	81	17	0
SA Optimisation Paediatric Plastic Surgery	30	34	1	33

Discussion

Through the implementation of these algorithms, compared to CHUdSA's manual scheduling process, several results can be proven:

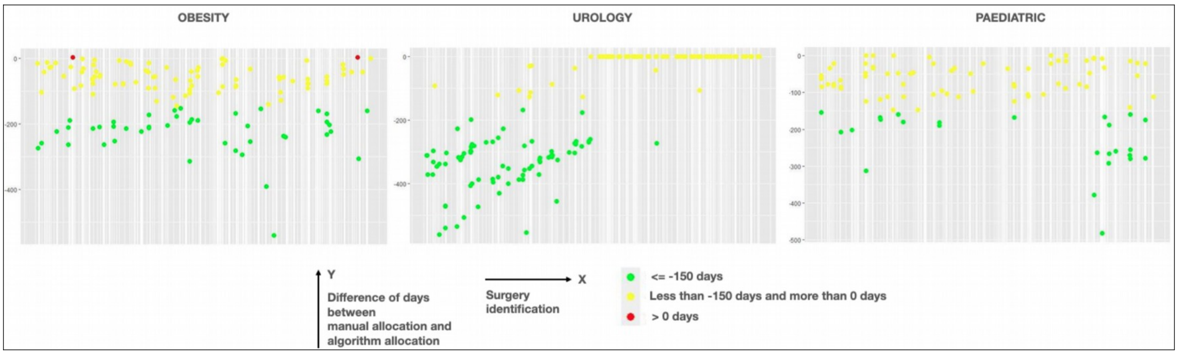

Figure 5: Hill Climbing Evaluation. Overall Performance by surgeries.

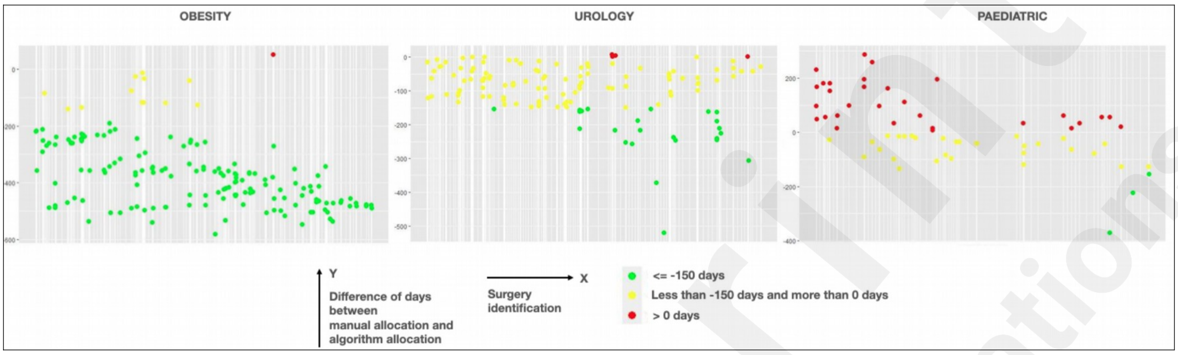

Figure 6: Simulated Annealing Evaluation. Overall Performance by surgeries.

1. Based on the optimisation algorithms developed, the penalty is significantly lower than the penalty of scheduling done by CHUdSA professionals, and in certain situations, it can even be cancelled. Therefore, it can be said that any of the local optimisation algorithms that have been put into practice can provide improvements to the administration and organisation of ORs;
2. The PS algorithm proved unable to be a possible answer to this problem since its ability to minimise the scheduling penalty is much lower than HC and SA. It is evident that local search algorithms produce better answers, on all existing criteria, compared to population-based search algorithms;
3. Figures 5 and 6 represent the evaluation of the scheduling over time for each surgery, allowing an understanding of whether the respective algorithm schedules it before or after the day it was performed in CHUdSA. The majority of surgeries could have been scheduled and carried out days earlier in any of the local optimisation algorithms, HC and SA;
4. The number of surgeries that remain to be scheduled occasionally exceeds the number that the CHUdSA' professionals had anticipated. This is logical given that the heuristic has shown there is never any overlap in surgery. Furthermore, some surgeries cannot be scheduled in this optimisation process because their minimum execution time exceeds the maximum duration of an existing shift. These surgeries are always handled as exceptional cases at the recommendation of CHUdSA professionals. Therefore, from a management perspective, the professionals personally should schedule the surgeries in accordance with particular internal protocols.

Key Findings

This implementation highlights exactly what Figures 5 and 6 prove: it is possible to more effectively allocate surgeries within the same time frame despite using the same resources. Leveraging the specification of a set of global variables for enhancing the scheduling process, four significant conclusions can be drawn:

1. Scheduling is greatly improved when the first solution is modelled using a surgery allocation algorithm that takes waiting list longevity and priority into account. The final penalty is significantly lowered, demonstrating the potential to enhance surgical management within the constraints of time and space;
2. Analysing the algorithms, HC shows the best result, with SA producing very similar results. However, PSO was not only not able to significantly improve surgery allocation, but it also occasionally managed to arrange surgeries worse in time-space when the number of iterations in HC and SA was kept equal. For these reasons, PSO was discarded;
3. HC and SA are particularly noteworthy since they arrive at the ideal number of iterations after 100 iterations. Thus, these algorithms can yield significantly better planning than manual hospital allocation in a runtime of about 30 seconds. These results also support the exclusion of PSO for future implementations, as it is more computationally demanding model;
4. In conclusion, the application of AI-based heuristics results in a notable enhancement in the quantity of surgeries allocated. Therefore, there is an immense potential to improve OR management with a system capable of maximise the scheduling procedure for each specialty. It also demonstrates how the scheduling solutions assigned by the HC and the SA differ significantly in terms of space and time. In the perspective of a decision support system, it may be best to offer the user a variety of scheduling solutions as possible, based on the implemented optimisation models, even though it is not necessary to determine which is the best or worst solution. As a result, the user can select the planning that best fits the group of surgeries that require to be scheduled.

Comparison with Prior Work

Based on the development and use of optimisation algorithms, the proposed research presents an innovative approach for scheduling surgeries from waiting lists. It is crucial to emphasise the primary objective of reducing costs, considering a variety of factors involving different medical specialisations.

In contrast to prior studies, the research by Fügener et al. [14] focuses on the integration of HC and SA to optimise the utilisation of ORs. Min and Yuehwern's study [23] concentrate on a stochastic surgical calendar tailored for patients with uncertain surgical needs. Similarly, Banditori et al. [6] categorise waiting list cases into homogeneous groups, offering a more adaptable solution for diverse medical specialties. However, because the criteria used to make decisions vary amongst medical specialisations, research so far have never produced conclusive sufficient proof to support their widespread use in a Healthcare organisation. This work stood out from other studies since it employs global and specific variables that are readily applied to any medical specialty without compromising the quality of surgical scheduling, a key factor in reducing operating costs in hospitals.

By overcoming the limitations of previous models, diverging from them in the strategy implemented, a more precise and effective solution is provided, aimed at maximising the performance of ORs, benefiting both the patients and the healthcare professionals involved in the surgical process.

Conclusions

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. The approach developed not only provides a solution to this problem in all its dimensions but also conceives a generic adoption for any Healthcare organisation and in a

considerable number of medical specialities.
Considering a general constraints model for any Healthcare organisation, implementing an automatic allocation algorithm, and considering the same constraints for the generation of the initial solution, prove the ability to find better solutions for surgery scheduling. The HC and SA algorithms demonstrate the capacity to have a better occupation of ORs, always considering as reference the scheduling limit without accumulating penalties. PS proved to be an algorithm that needs a greater computational effort. The fact that it does not use an initial solution, according to previously defined programming rules, justifies its unclear results.
Taking into consideration all the limitations found in scheduling problems and the high level of organisational complexity, this approach can be considered as a possible solution for SSP, prevailing the organisation of surgeries on time and the necessary cost control, crucial to optimise operating costs. HC and SA show extremely satisfactory results, decreasing the number of surgeries with penalty, i.e surgeries with a scheduled date higher than the deadline date. Additionally, this approach provides a near optimal solution, reaching a stabilization point after 100 iterations, since the initial solution had already produced very satisfactory results. 99% of the surgeries were assigned, and only 1% were not assigned. The majority of these surgeries are special cases where their duration exceeds the maximum time available each day. In some cases, the number of surgeries not scheduled by the algorithms is higher than the scheduling performed by the hospital, although it is not considered a negative point of this solution. Our application has addressed multiple challenges, offering a scalable solution across diverse organisational frameworks. However, to deepen the utility and precision of our approach, several topics about limitations and future work have been identified:

1. Testing this study in other Healthcare organisations will be a crucial step to understand if this logic is well achieved in different contexts. In addition, it is necessary to prove the estimated times of each surgery to increase the reliability of the schedule as a solution. In this study, an interquartile mean was used to associate each type of surgery through time history, but a more accurate method is needed to translate an optimal accuracy. Machine Learning models could be used to predict the times of each surgery for greater reliability, which is a crucial factor in the allocation of surgeries;
2. It is also possible to consider more constraints, including subspecialties in this mapping. This is considered a significant step since the division of ORs includes an allocation to each subspecialty. This requires a complete mapping between specialities and the International Classification of Diseases 10th Revision (ICD10) codes;
3. Additionally, a deeper study on the nullification of the scheduling penalty may be equated. While a 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 scheduling interests;
4. Another even more complex hypothesis is to condition the surgical mapping by considering the human resources available for each period. Not being possible in the current context, considering the available data, an annual organisation of medical professionals (surgeons, nurses, anaesthesiologists) in real-time is necessary;
5. Improving the efficiency of the optimization method by exploring more models and their configurations is another direction to consider in future research.

The results of this study are summarised below, highlighting the key messages and learnings that underline the transformative potential of this approach in Healthcare scheduling:

1. The integration of AI-based heuristic algorithms significantly improves the efficiency of surgical scheduling, leading to a reduction in patient waiting times;
2. The algorithms developed have demonstrated higher performance in the penalties obtained

with the scheduling performed by CHUdSA. Any model developed makes it possible to reduce costs in the scheduling process by reducing the penalties associated with surgeries scheduled beyond the deadline.
3. The models developed do not compromise scalability and adaptability, as they can be adapted to various contexts and medical specialities, and generalised implementation is possible by adding or removing restrictions;
4. The potential that a system capable of integrating these models will have in any organisation is proven, optimising the inherent management processes and consequently the healthcare provided to patients.

Adopting this approach, following these research directions, promises to further refine our method, seeking more optimised and agile Healthcare systems that are patient-centred and cost-effective.

Conflicts of Interest

None declared.

Abbreviations

CHUdSA: Centro Hospitalar e Universitário de Santo António
AI: Artificial Intelligence
SSP: Surgery Scheduling Problems
OR: Operating Room
BS: Blind Search
LS: Local Search
PBS: Population-Based Search
SA: Simulated Annealing
HC: Hill Climbing
DSR: Design Science Research
CRISP-DM: Cross Industry Standard Process for Data Mining
DM: Data Mining
SAH: Surgical Area of a Hospital
GMRT: Guarantee Maximum Response Time
IS: Initial Solution
EF: Evaluation Function
OF: Objective Function

Multimedia Appendix 1

Graphical description of how the first solution is generated, considering the process of optimising a surgical planning.

References

1. Ge Abdel-Basset, M., Abdel-Fatah, L., & Sangaiah, A. K. (2018). Meta- heuristic Algorithms: A Comprehensive Review. Computational Intelligence for Multimedia Big Data on the Cloud with Engineering Applications (pp. 185–231). Elsevier. https://doi.org/10.1016/B978-0- 12-813314-9.00010-4.
2. Agnetis, Alessandro, Alberto Coppi, Matteo Corsini, Gabriella Dellino, Carlo Meloni, e Marco Pranzo. «A Decomposition Approach for the Combined Master Surgical Schedule and Surgical Case Assignment Problems». Health Care Management Science 17, n. 1 (2014): 49–59. https://doi.org/10.1007/s10729-013-9244-0.

3. Cutillo, C.M., Sharma, K.R., Foschini, L. et al. Machine intelligence in healthcare—perspectives on trustworthiness, explainability, usability, and transparency. npj Digit. Med. 3, 47 (2020). https://doi.org/10.1038/s41746-020-0254-2.
4. Schröer, C., Kruse, F., & Gómez, J. M. (2021). A Systematic Literature Review on Applying CRISP-DM Process Model. Procedia Computer Science, 181(1), 526–534.
5. Balan, S., Metaheuristics in Optimization: Algorithmic Perspective. https://www.informs.org/Publications/OR-MS- Tomorrow/Metaheuristics-in-Optimization-Algorithmic-Perspective.
6. Banditori, C., P. Cappanera, e F. Visintin. «A Combined Optimization- Simulation Approach to the Master Surgical Scheduling Problem». IMA Journal of Management Mathematics 24, n. 2 (2013): 155–87. https://doi.org/10.1093/imaman/dps033.
7. Batini, Carlo, Cinzia Cappiello, Chiara Francalanci, Andrea Maurino. «Methodologies for Data Quality Assessment and Improvement». ACM Computing Surveys 41, n. 3 (2009): 1–52. https://doi.org/10.1145/1541880.1541883.
8. Blum, C., & Roli, A. (2003). Metaheuristics in combinatorial optimization: Overview and conceptual comparison. ACM Computing Surveys, 35(3), 268–308. https://doi.org/10.1145/937503.937505.
9. Brent, R. P. (1989). Efficient implementation of the first fit strategy for dynamic storage allocation. ACM Transactions on Programming Languages and Systems, 11(3), 388–403. https://doi.org/10.1145/65979.65981.
10. Britt, Justin, M. Fazle Baki, Ahmed Azab, Abderrahmane Chaouch, e Xiangyong Li. «A Stochastic Hierarchical Approach for the Master Surgical Scheduling Problem». Computers & Industrial Engineering 158 (2021): 107385. https://doi.org/10.1016/j.cie.2021.107385.
11. Xin, J., & He. (2014). Business Intelligence and Big Data Analytics: An Overview. Communications of the IIMA, 14. https://scholarworks.lib.csusb.edu/cgi/viewcontent.cgi?article=1358&context=ciima.
12. Cortez, P. (2014). Modern optimization with R. Springer.
13. Feldman, K., Johnson, R. A., & Chawla, N. V. (2018). The State of Data in Healthcare: Path Towards Standardization. Journal of Healthcare In- formatics Research, 2(3), 248–271. https://doi.org/10.1007/s41666-018- 0019-8.
14. Fügener, Andreas, Erwin W. Hans, Rainer Kolisch, Nikky Kortbeek, e Peter T. Vanberkel. «Master Surgery Scheduling with Consideration of Multiple Downstream Units». European Journal of Operational Research 239, n. 1 (2014): 227–36. https://doi.org/10.1016/j.ejor.2014.05.009.
15. Gandomi, A. H., Yang, X.-S., Talatahari, S., & Alavi, A. H. (2013). Metaheuristic Algorithms in Modeling and Optimization. Em Meta- heuristic Applications in Structures and Infrastructures (pp. 1–24). El- sevier. https://doi.org/10.1016/B978-0-12-398364-0.00001-2.
16. Görgülü, Z.-K., & Pickl, S. (2013). Adaptive Business Intelligence: The Integration of Data Mining and Systems Engineering into an Advanced Decision Support as an Integral Part of the Business Strategy. P. Rausch, A. F. Sheta, & A. Ayesh (Eds.), Business Intelligence and Performance Management (pp. 43–58). Springer London. https://doi.org/10.1007/978-1-4471-4866-1_4.
17. Jayaratne, M., Nallaperuma, D., De Silva, D., Alahakoon, D., Devitt, B., Webster, K. E., & Chilamkurti, N. (2019). A data integration platform for patient-centered e-healthcare and clinical decision support. Future Generation Computer Systems, 92, 996–1008. https://doi.org/10.1016/j.future.2018.07.061.
18. Lopes, J., Guimarães, T., & Santos, M. F. (2020). Predictive and Prescriptive Analytics in Healthcare: A Survey. Procedia Computer Science, 170, 1029–1034. https://doi.org/10.1016/j.procs.2020.03.078.
19. Luke, S. (2013). Essentials of metaheuristics (2. Ed). Lulu.

20. Sun, T. Q., & Medaglia, R. (2019). Mapping the challenges of Artificial Intelligence in the public sector: Evidence from public healthcare. Government Information Quarterly, 36(2), 368–383. https://doi.org/10.1016/j.giq.2018.09.008.
21. Metropolis, N., Rosenbluth, A. W., Rosenbluth, M. N., Teller, A. H., & Teller, E. (1953). Equation of State Calculations by Fast Computing Machines. The Journal of Chemical Physics, 21(6), 1087–1092. https://doi.org/10.1063/1.1699114.
22. Michalewicz, Z., Chiriac, C., Michalewicz, M., & Schmidt, M. (2010). Adaptive business intelligence. Springer.
23. Min, Daiki, e Yuehwern Yih. «uling Elective Surgery under Uncertainty and Downstream Capacity Constraints». European Journal of Operational Research 206, n. 3 (2010): 642–52. https://doi.org/10.1016/j.ejor.2010.03.014.
24. Moon, J. D., & Galea, M. P. (Eds.). (2016). Improving Health Management through Clinical Decision Support Systems: IGI Global. https://doi.org/10.4018/978-1-4666-9432-3.
25. Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2007). A Design Science Research Methodology for Information Systems Re- search. Journal of Management Information Systems, 24(3), 45–77. https://doi.org/10.2753/MIS0742-1222240302.
26. Bendtsen, C.. (2022). Package ‘pso’. https://cran.r- project.org/web/packages/pso/pso.pdf.
27. Santos, M. F., & Azevedo, C. S. (2005). Data mining: Descoberta de conhecimento em bases de dados. FCA – Editora de Informática, Lda. http://hdl.handle.net/1822/19136.
28. Schröer, C., Kruse, F., & Gómez, J. M. (2021). A Systematic Literature Review on Applying CRISP-DM Process Model. Procedia Computer Science, 181, 526–534. https://doi.org/10.1016/j.procs.2021.01.199.
29. Sharda, R., Delen, D., & Turban, E. (2013). Business Intelligence and Analytics: Systems for Decision Support (10th edition). Pearson.
30. Su, Mu-Chun, Shih-Chang Lai, Pa-Chun Wang, Yi-Zeng Hsieh, e Shih-Chieh Lin. «A SOMO-Based Approach to the Operating Room Scheduling Problem». Expert Systems with Applications 38, n. 12 (2011): 15447–54. https://doi.org/10.1016/j.eswa.2011.06.016.
31. Turban, E. (2015). Business intelligence and analytics: Systems for decision support (Tenth edition). Pearson.
32. Visintin, Filippo, Paola Cappanera, Carlo Banditori, e Pamela Danese. «Development and Implementation of an Operating Room Scheduling Tool: An Action Research Study». Production Planning & Control 28, n. 9 (2017): 758–75. https://doi.org/10.1080/09537287.2017.1310328.
33. Dai H-P, Chen D-D, Zheng Z-S. Effects of Random Values for Particle Swarm Optimization Algorithm. Algorithms. 2018; 11(2):23. https://doi.org/10.3390/a11020023.
34. Zhang, B, P Murali, M M Dessouky, e D Belson. «A Mixed Integer Pro- gramming Approach for Allocating Operating Room Capacity». Journal of the Operational Research Society 60, n. 5 (2009): 663–73. https://doi.org/10.1057/palgrave.jors.2602596.
35. Sharma M, Savage C, Nair M, Larsson I, Svedberg P, Nygren J Artificial Intelligence Applications in Health Care Practice: Scoping Review J Med Internet Res 2022;24(10): e40238 URL: https://www.jmir.org/2022/10/e40238 DOI: 10.2196/40238.
36. Tyagi M, Tyagi PK, Singh S, Satpathy S, Kant S, Gupta SK, Singh R. Allocation scheduling leads to optimum utilization of operation theater time. Med J Armed Forces India. 2022 Sep;78(Suppl 1):S163-S171. doi: 10.1016/j.mjafi.2020.09.005. Epub 2021 Feb 20. PMID: 36147384; PMCID: PMC9485751.
37. Wang JJ, Dai Z, Chang AC, Shi JJ. Surgical scheduling by Fuzzy model considering inpatient beds shortage under uncertain surgery durations. Ann Oper Res. 2022;315(1):463-505. doi: 10.1007/s10479-022-04645-z. Epub 2022 Mar 22. PMID: 35340826; PMCID: PMC8939402.

Supplementary Files

Untitled.
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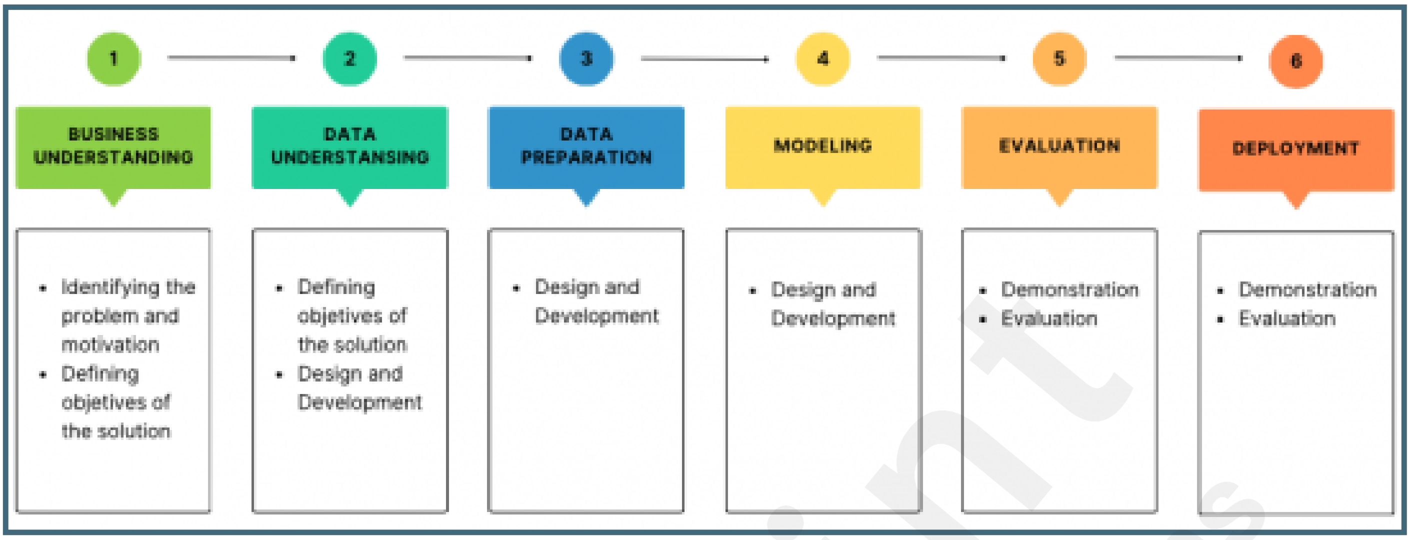
Figures

Crossover of Methodologies. DSR and CRISP-DM.



Hill Climbing Algorithm.

```
Inputs: S, f, C        ▷ S is the initial solution, f is the evaluation function, C includes control parameters
i ← 0                  ▷ i is the number of iterations of the method
while not termination_criteria(S, f, C, i) do
    S′ ← change(S, C)                    ▷ new solution
    B ← best(S, S′, f)                   ▷ best solution for next iteration
    S ← B                                ▷ deterministic select function
    i ← i + 1
end while
Output: B                                ▷ the best solution
```

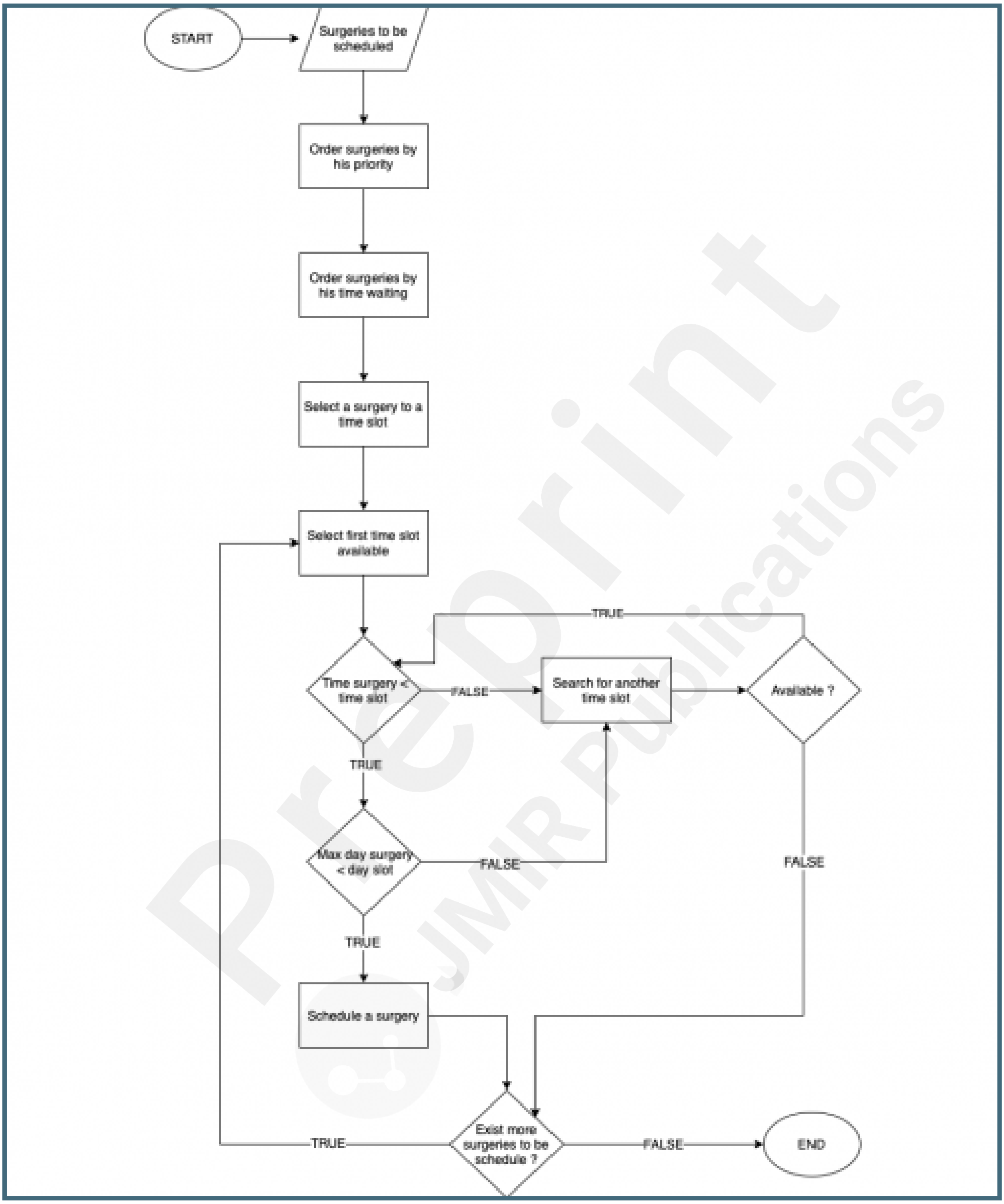
Simulated Annealing Algorithm.

Inputs: S, f, C ▷ S is the initial solution, f is the evaluation function, C contains control parameters ($maxit$, T and $tmax$)
$maxit \leftarrow get\_maxit(C)$ ▷ maximum number of iterations
$T \leftarrow get\_temperature(C)$ ▷ temperature, should be a high number
$tmax \leftarrow get\_tmax(C)$ ▷ number of evaluations at each temperature
$fs \leftarrow f(S)$ ▷ evaluation of S
$B \leftarrow S$ ▷ best solution
$i \leftarrow 0$ ▷ i is the number of iterations of the method
while $i < maxit$ **do** ▷ $maxit$ is the termination criterion
    for $j = 1 \rightarrow tmax$ **do** ▷ cycle j from 1 to $tmax$
        $S' \leftarrow change(S, C)$ ▷ new solution (might depend on T)
        $fs' \leftarrow f(S')$ ▷ evaluation of S'
        $r \leftarrow \mathcal{U}(0, 1)$ ▷ random number, uniform within [0, 1]
        $p \leftarrow \exp\left(\frac{fs' - fs}{T}\right)$ ▷ probability $P(S, S', T)$ (Metropolis function)
        if $fs' < fs \lor r < p$ **then** $S \leftarrow S'$ ▷ accept best solution or worst if $r < p$
        end if
        if $fs' < fs$ **then** $B \leftarrow S'$
        end if
        $i \leftarrow i + 1$
    end for
    $T \leftarrow \frac{T}{\log(i/tmax) \times tmax + \exp(1)}$ ▷ cooling step (decrease temperature)
end while
Output: B ▷ the best solution

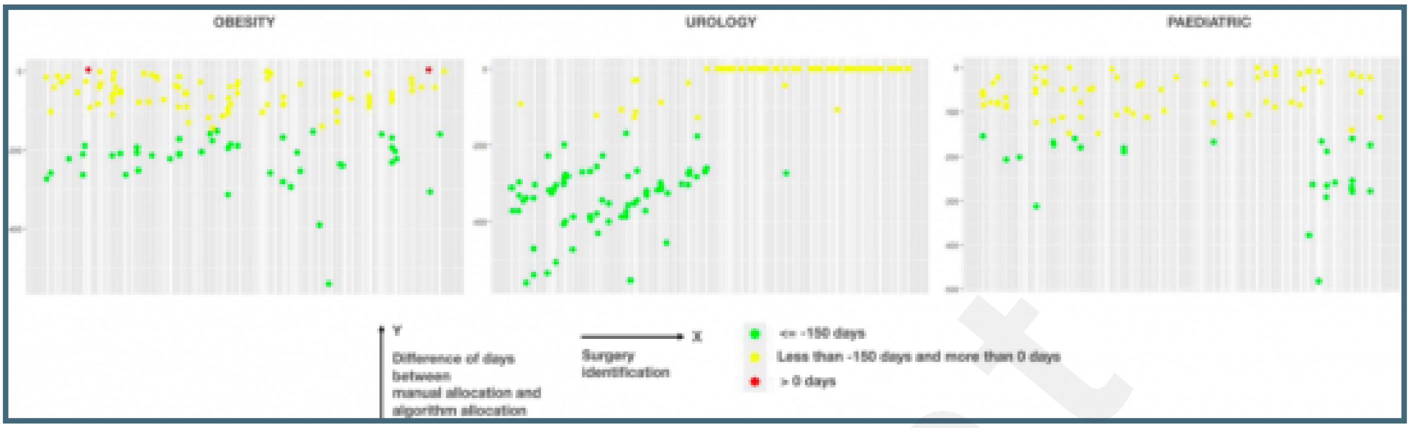
Particle Swarm Algorithm.

```
Inputs: f, C                                  ▷ f is the fitness function, C includes control parameters
P ← initialization(C)                         ▷ set initial swarm (topology, random position and velocity,
previous best and previous best position found in the neighborhood)
B ← best(P, f)                                ▷ best particle
i ← 0                                         ▷ i is the number of iterations of the method
while not termination_criteria(P, f, C, i) do
    for each particle x = (s, v, p, l) ∈ P do                ▷ cycle all particles
        v ← velocity(s, v, p, l)                             ▷ compute new velocity for x
        s ← s + v                                            ▷ move the particle to new position s (mutation)
        s ← confinement(s, C)                                ▷ adjust position s if it is outside bounds
        if f(s) < f(p) then p ← s                            ▷ update previous best
        end if
        x ← (s, v, p, l)                                     ▷ update particle
        if f(s) < f(B) then B ← s                            ▷ update best value
        end if
    end for
    i ← i + 1
end while
Output: B                                     ▷ best solution
```

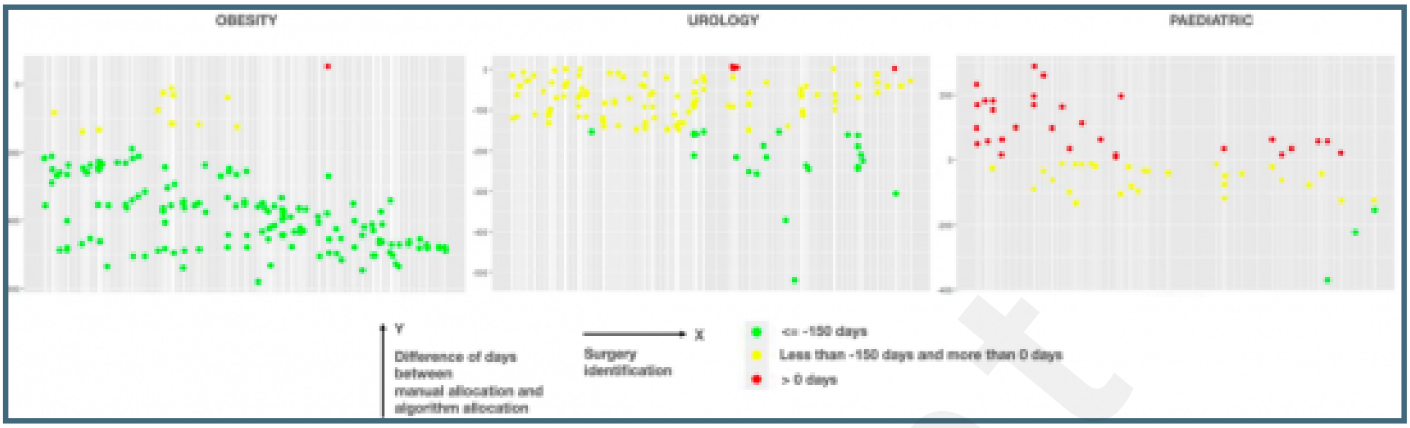
Structure for Initial Solution, according to first fit method.



Hill Climbing Evaluation. Overall Performance by surgeries.



Simulated Annealing Evaluation. Overall Performance by surgeries.



Multimedia Appendixes

Structure for Initial Solution, according to first fit method.
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