# Improvement of performance indicators in hospitals: an innovative approach through computational optimization

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**Abstract**
This work focus on the development of a computational algorithm optimization to solve the sequencing problem of cardiac elective surgeries. The objective was to reduce the waiting time for surgeries, as well as maximize the use of hospital resources, i.e., more patients without the need for investment in overtime payments.

**Keywords:** Sequencing Elective Surgeries, Optimization Computational Method, Heuristic Methods

## INTRODUCTION

The problem regarding to the performance indicators in hospitals has been extensively studied in the literature because of their social appeal and its practical importance in healthcare. According to Andrade (2012), hospitals want to reduce costs and improve their financial assets and administrative, on the other hand, considering the nature of service want to raise the level of patient satisfaction. Taking into account that the operating room is the most expensive sector of a health facility and, according to Macario et al. (1995) is the main hospital revenue generator, improve hospital indicators implies in both contributions: one corporate and another academic.

According to Smith et al. (2008), the performance measurement gives to the decision makers of the hospital administration an important opportunity to ensure improvements in the health and accountability systems. Its role is to improve the quality of decisions taken by all stakeholders in the health system, including patients, professionals, managers, and governments at all levels, insurers and other payers, politicians and citizens as financial supporters. Health systems, however, are still in relatively early stages of performance measurement and major improvements are needed in data collection, analytical methodologies, and the development and implementation of innovative methods to improve the quality of care.

According to Li et al. (2015), the most critical hospital performance indicator, related to the elective surgery scheduling, is the patient waiting time. The scheduling surgeries, considering that resources are limited, such as surgical team, nurses, anesthetist, medical equipment and recovery beds, is a complex process. A well-designed surgeries program should concern about the welfare of the whole system, allocating the available resources in an efficient and effective manner. For this reason, the approach of using computational resource optimization has been heavily used in solving complex problems like this.

Due to the great significance of elective surgery in hospital performance indicators and also based on the work of Bülbül (2011), we intend to use the computer heuristic method called Iterated Local Search (ILS), combined with two local search methods Variable Neighborhood Descent (VND) and Tabu Search (BT), to solve the problem of elective surgeries programming. The objective is to reduce the waiting time for surgeries and maximize the use of hospital resources, i.e., attend more patients without the need for investment in overtime payments. This motivation came from the fact of Bülbül (2011) had applied such methods to the job-shop scheduling problem and having achieved good results. Since the elective surgeries programming problem can be represented as a job-shop scheduling, it is believed that this approach will be able to produce good results as Bülbül (2011).

Therefore, that is the question: is this methodology capable of finding good solutions for the elective surgeries scheduling?

## LITERATURE REVIEW

The elective surgery-sequencing problem is widely studied; it has great importance in the field of Operational Research and belongs to the class of NP-hard combinatorial problem, according to Carter and Tovey (1992). Moreover, it is a daily problem in the hospitals and with a great impact on the performance indicators of these organizations (Nowik et al., 2015). The operating room, the main feature of the problem, is responsible for two thirds of the financial income of the hospital, according to Macario et al. (1995).

For Smith et al. (2008), the health system performance has a number of aspects, including population health, health outcomes compared to treatment, clinical quality and appropriateness of care and the ability to response and productivity. The first requirement of any performance measurement system is to formulate a solid conceptual framework within which performance measures can be developed. Performance indicators of the settings must then meet a number of criteria such as the validity of the sampling, reproducibility, acceptability, feasibility, reliability, sensitivity and predictive validity. In addition to technical considerations, decision makers should pay attention to the political and organizational context within which performance data should be collected and disseminated.

In the view of Riet and Demeulemeester (2014), the planning of operating rooms is a difficult process due to the different stakeholders. The true complexity, however, relates to the sources of variability. This variability cannot be ignored, because it influences the trade-offs between hospital costs and waiting times for patients. As a result, the need to orientate the manager according to the policies in dealing with trade-offs arises. Therefore, researchers investigated different possibilities to incorporate non-elective patients on schedule in order to maximize the number of surgeries performed. The results show an efficient model, since it was possible to increase by 15% the number of patients considering no investments in infrastructure or hiring medical staff.

There are several studies that use computational methods to solve the elective surgery-sequencing problem, particularly in European hospitals. This approach is because the significant improvement of hospital indicators, such as reduction the waiting time for surgeries in hospitals, besides the implementation of management and automation systems are very useful to the hospital management (Gartner and Kolisch, 2014). Continuous processes improvement, the use of computerized systems for the hospital operations management and the concerning of improving the hospitals performance indicators has encouraged the academic sphere searching, increasingly, methods to solve healthcare problems (Castro and Marques, 2015).

The paper of Zhang et al. (2012) uses computer simulation to solve the problem of Shanghai Hospital surgeries sequencing. As in other works, the surgeries are considered as tasks to be performed and hospital resources (surgeons, nurses, equipment) as the machines. As you can see, the surgeries sequencing is totally related to the job-shop scheduling. The computerized system developed allocates longer surgery in the begin of process and shorter surgery at the end, contributing to the planning, because they can manipulate the simple and short tasks in the end of the journey. The degree of each resource is used as a significant factor of the objective function, i.e., more expensive resources must be minimized its use and the number of operations performed maximized. The results showed very large gains, since it increased the number of surgeries to 10.33% and decreased the waiting time by 46%.

Chaabane et al. (2008) propose to compare two heuristic approaches (with different restrictions, but the same goal) methods based on the Open Scheduling and Block Scheduling. Linear programming methods, along with cost constraints associated with hospital resources are used to support the objective function of the problem. Actual data of a Belgian hospital called Tivoli are used to feed the two proposed algorithms. The goal is to perform the programming operations to obtain an effective surgical schedule, improving the coordination of services provided by the hospital, as well as the waiting time for patients. Both were able to produce good results.

The proposed of Fei et al. (2009) aims to maximize the use of operating rooms, minimizing the cost of overtime and idle time of physical resources (equipment, surgical unit). The authors divide the problem into two phases, one responsible for defining the operations scheduling and the other for defining the sequence of operations on each day, taking into account the availability of recovery beds. For the first phase, the authors propose an integer-programming model solved by a heuristic procedure based on column generation. As for the second stage is proposed a hybrid genetic algorithm based on the flow-shop machine scheduling problem.

According to Kim and Horowitz (2002), the operations sequencing problem may also be addressed by computer simulation. The authors propose the use of an anticipated schedule for elective surgeries exploring the use of a system with daily scheduling. The goal is to improve the performance of an intensive care unit (ICU) that serves patients from different departments in the hospital. A computer simulation proposal makes a research analyzing the scheduling possibilities of surgeries according to demand. Beneficial effects are observed for all test problems available in the literature.

According to Mancilla and Storer (2001), the approach regarding to the surgeries programming is performed in a different way compared to other studies in the literature. The authors allocate the same side in two parallel surgical operating rooms, as well as the problem of parallel sequencing machines. While performing the operation in one of them, the cleaning team performs the preparation of the other. The goal is to reduce the surgical team waiting time, as well as the cost of overtime and the idle time. To solve this optimization problem was proposed an integer stochastic algorithm, which uses the average sample approximation technique to perform the logical sequencing of operations. Calculation tests based on real data showed that the proposed methods were effective.

The large number of works that use heuristic methods to solve the surgery-sequencing problem is due to its complexity, this approach yields better results than the exact mathematical methods, since it does not solve a problem like this in polynomial time. According to Mine (2009), heuristic methods are local search procedures to resolve, approximately, an optimization problem, with the ability to escape the traps of great places, still far from the global optimum. They can be local or population search. At first, the exploration of solutions space is done through movements, which are applied to each step of the current solution, creating another promising solution in their neighborhood. In the second, it works with a range of solutions, recombining them in order to improve them. These methods are capable of producing high-quality solutions, even if not guaranteed arrival at the global optimum.

## METHODOLOGY

The sequencing problem of elective surgeries is based on the programming problem in identical parallel machines, where the main objective is to minimize the sum of the processing times. According to Pinedo (2008), the programming problem in identical parallel machines is represented by a set of $n$ tasks, where $N = \{1, ..., n\}$, to be processed by a set of $m$ identical machines $M_1, ..., M_m$, structured under the following restrictions:

1. each task should be processed only once and for only one machine;
2. each task $i$ has a $p_i$ processing time;
3. there is one machine preparation time called $t_i$, where each execution of a task $i$ the machine in question must be prepared to receive the next task $i+1$;
4. the process is continuous, with no interruption during the execution of any job.

The Figure 1 shows an example for programming tasks in parallel identical machines. It is possible to observe all the tasks $T(n)$ sequenced in each of the two machines available ($M_1$ and $M_2$) as well as the time of preparation represented in green. The time scale is represented on the X-axis.

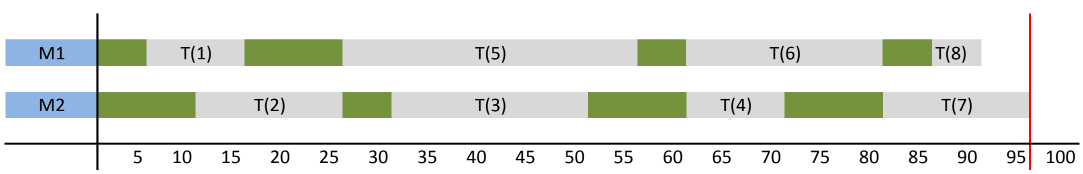


*Figure 1 - Sample task scheduling on two machines*

The authors Pham and Klinkert (2008) propose using the Mixed Integer Programming techniques to solve the scheduling problem called Multi-Mode Blocking Job-Shop. Relating the work of these authors with the problem of parallel machines, set up for the current proposal, there are an equivalence between machine and operating room, as well as task and surgery. The example shown in Figure 2 is capable of synthesizing the representation of surgeries sequencing problem, as all the variables involved in the scenario.

Figure 2 shows a complete example of the planning surgeries, as well as all the necessary resources involved. Note, therefore, that the first surgery is performed in the surgical block 2 by surgeon 1, and is initiated by the nurse 1 and completed by the nurse 2. This was used anesthetist 1 and equipment 2. The surgery 2 was held in the surgical block 1 by the surgeon 3. The intensive care unit was used in the process for some specific reason. Nurses 1 and 3 were involved in this second surgery, beyond the anesthetist 2 and equipment 1. Importantly commutative use of nurses and the surgical preparation time immediately after each surgery to ensure proper receipt of upcoming surgeries.

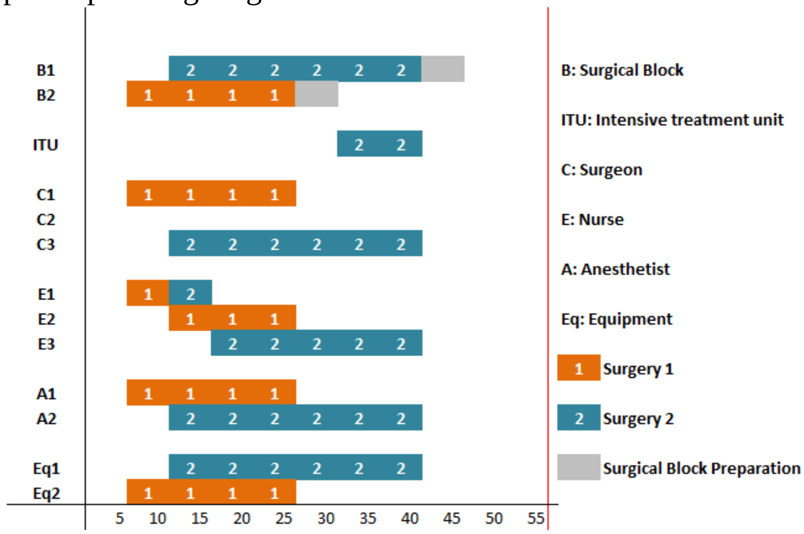


*Figure 2 - Sample sequencing of surgeries with all the resources involved*

The proposed algorithm, referred to as SC-ILS (Sequencing surgery via Itereted local search) using GRASP method (Greedy randomized adaptive search procedures) proposed by Feo and Resende (1995), is for generating an initial solution. This initial solution is the starting point for the solution of the problem, i.e., it is from there that the program will start refining method for the search for even better solutions. Therefore, any surgeries demand for a given hospital is used to supply the program. The GRASP method uses these input data to generate an initial solution and then this is refined by heuristics.

According to Feo and Resende (1995), the construction phase consists of the following steps. Initially, the surgeries are ordered decreasingly according to the processing time and resources required for its implementation. Let is $g(t)$ the processing time of the surgery $t$ and let is LC the list of non-allocated surgeries. Be still, $g_{min}$ the lowest processing time and $g_{max}$ the longest processing time of surgeries. Is also $\gamma \in \{0.0; 0.1; .. ; 0.7\}$ where $\gamma = 0.0$ is generating purely deterministic solutions, while $\gamma = 0.7$ produces solutions with 70% randomness. After that, is formed a candidate list called LRC that satisfy the following condition: LRC = $\{t \in \text{LC}: g(t) \geq g_{min} + \gamma\ (g_{max} - g_{min})\}$. A surgery $t \in$ LRC is then chosen at random, by updating the LC. This procedure is terminated when all tasks are properly allocated, that is, when LC = Ø. The pseudo-code presented by Figure 3 illustrates the generation of the initial solution based on the GRASP method.

The GRASP method, therefore, consists to generate random real number between 0.0 and 0.7 to determine the randomness index of the initial solution. Another parameter used in this method is the stopping criterion: Run-time (time_execution parameter) .The random choice of technique is to elect surgery randomly, to verify that the necessary resources for their implementation and finally allocate it in the processing schedule. A deterministic rule is based on allocating the surgeries according to the shorter processing times that they have, i.e., order them in the processing schedule in ascending order of execution.

```
GRASP - Initial Solution
f* ← +∞
While (time < time_execution) do
        s0 ← Build_Solution ( g(.), γ);
        s ← VND (s0);
        If ( f(s) < f*) then
                s* ← s;
                f* ← f(s);
        End If
End While
s ← s*;
Return s;
```

*Figure 3 - GRASP Algorithm*

Based on the work of Bülbül (2011), which uses the ILS method to solve the job-shop scheduling problem, it is proposed the computing method called SC-ILS (Figure 4) to solve the surgery scheduling problem combining heuristics Iterated Local Search (Lourenço et al. 2003) with the local search methods Variable Neighborhood Descent (Hansen and Mladenovic, 2001) and Tabu Search (Hansen, 1986). To generate the initial solution will be used GRASP method as specified above. As can be seen in the Figure 4, the GRASP method is responsible for generating the initial solution *s*, which is refined in advance by VND method. After completion the initial solution generation, the ILS method is triggered to start the deep refinement in order to search for better solutions. This stage is characterized by explore, as much as possible, the search space of this problem looking for even better solutions. To escape the regions of great places and go to other regions of the search space, it uses the relocation movements to change the order of one or more surgeries. In addition to these movements is also used the exchange the order of scheduling surgery, with the intention of evaluating greater possibilities solutions. The VND and Tabu Search methods are used as local search, the Tabu Search being activated only after a certain number of iterations without any improvement of VND, given by *iterMaxVND* parameter. Thus, after the VND is heavily exploited, the Tabu Search is thrown with the intention of refining the solutions. This last step is responsible for going through regions of the search space that have not been explored previously. As in VND, the Tabu Search also has a set number of iteration: *iterMaxTS*.

```
SC-ILS Algorithm
    γ ← random number between [0.0, 0.7];
    s ← GRASP (γ, Time);
    s ← VND (s);
    iter ← 1;
    While ( iter ≤ maxIter ) do
        s' ← Perturbation (s);
        If ( iter ≤ IterMaxVND ) then
            s'' ← VND (s');
        Else
            Tabu_Search ( s', Tabu_List, IterMaxTS);
        End If

        If ( f(s'') < f(s) ) then
            s ← s'';
            iter ← 1;
        Else
            iter ← iter + 1;
        End If
    End While
    Return s;
```

*Figure 4 - Proposed methodology for elective surgeries sequencing problem*

According to Andrade (2012), solving the surgeries sequencing problem means finding solutions that minimize the surgeries total processing time in a given interval that could be a day, a week or a month. The most common of them that has been discussed in the literature is minimize the total processing time for one day. Therefore, the programming is done every day. Another factor, which also seek to minimize is the preparation time of the operations resource, such as cleaning the operating room and preparing the equipment. Therefore, according to the mathematical formulation proposed by Kim and Horowitz (2002) for sequencing machines, the proposed algorithm is using the Equation 1 as the objective function. This objective function is responsible for guiding the search algorithm, it is responsible for calculating processing time of each solutions found. To the extent that the algorithm performs the search in the solution space, the objective function delivers the processing time used to evaluate the current solution, saying if it is better or not in relation to the earlier one. As this is a minimization problem, the solution improves accepts must have a shorter processing time than the last found and so on. Thus, it is possible to reduce the waiting time of the patient, as well as maximize the use of hospital resources, since it will be possible to perform more surgeries without the need for investments in infrastructure and overtime.

$$Z = C_{max} + \beta \sum_{i=1}^{n} S_i \tag{1}$$

The objective function thus represents the sum of terms of carrying out the surgery. The first part is characterized by the longest surgical time according to the number of surgeries to be performed. The second part is the time duration for each surgery, where the factor $\beta$ is responsible for focus in the short surgeries, i.e., they are executed before the longer ones. With the time duration of each surgery, the sum of the equation is able to promote the processing total time taken to complete all of them.

To validate the algorithm proposed is intended to use two techniques proposed by Essafi et al. (2008). The first is to measure the variability of the solutions produced by the proposed algorithm. Because it is a heuristic, there is a possibility of the algorithm produce final solutions with different objective function values than those found in other iterations, since the solutions thus generated may vary from one implementation to another. Therefore, the algorithm will only be efficient if the variation of the solution generated does not exceed the rate of 1% to a sample 1000 plays. The second technique is to compare the efficiency of the algorithm proposed in relation to the real data from a large public hospital in São Paulo, Brazil.

# RESULTS

The SC-ILS algorithm was programmed into the computer language C++, using as a compiler GCC (GNU Compiler Collection), Eclipse editor (Eclipse IDE for C/C++) and Windows 8.1 operating system on an Intel Core I5 computer with 8GB RAM. In order to verify the efficiency of the proposed algorithm, we used a set of instances drawn from real data from a large hospital in São Paulo.

Table 1 shows the results of the algorithm, as well as the total time of surgery programming prepared by hospital analysts. The intention is to compare which one is able to produce better results, whether the proposed algorithm or manual programming by hospital. The first column has the names of all eight instances; each one has a different type of surgery used to validate the proposed algorithm. As already specified, these instances were created based on data provided by a large public hospital in São Paulo, Brazil. The second column, called "Analyst Time (h)" represents the total processing time in hours used for each type of surgery, taking into account the use of the medical staff (surgeons, nurses, anesthesiologist, etc.) and the completion of eight surgical procedures. It is worth noting that this program was made by the operations management analysts working at the hospital to perform the daily surgical program. The column labeled "Time Alg. (H)" shows the time in hours for the same eight surgical procedures, but as a result of computer optimization program. The column called "Gain (%)" shows the gain of computational algorithm in relation to the result obtained manually by hospital analysts. The column called "Variability (%)" shows the variability degree of the results found. As this is a heuristic algorithm, the results can change from one run to another. Therefore, it is important to present this information as a way to characterize the algorithm. The smaller this number, the better the algorithm, namely, shows that this is able to produce good results without variations.

It may be noted that the proposed algorithm achieve better results for all instances presented, producing gains in relation to all results obtained by the hospital analysts. It is also important to note that the results obtained by the proposed algorithm showed improvements only using the heuristic combinatorial techniques of the search space exploitation, with no need for investments in infrastructure or overtime.

*Table 1 - Results of the Proposed Algorithm*

| | | SC-ILS Algorithm | | |
|---|---|---|---|---|
| **Instances** | **Analyst Time (h)** | **Time Alg. (h)** | **Gain (%)** | **Variability (%)** |
| Hospital_1 (Arrhythmias) | 6,4 | 5,7 | 10,94% | 0,02% |
| Hospital_2 (Congenic Cardiopatics) | 7,5 | 6,9 | 8,00% | 0,04% |
| Hospital_3 (Coronary) | 14,6 | 12,6 | 13,70% | 0,00% |
| Hospital_4 (Endomyocardial) | 16,3 | 11,7 | 28,22% | 0,01% |
| Hospital_5 (Hemodynamic) | 6,9 | 5,2 | 24,64% | 0,06% |
| Hospital_6 (Cardiomyopathies) | 7,3 | 7,1 | 2,74% | 0,02% |
| Hospital_7 (Pericardium) | 5,8 | 5,3 | 8,62% | 0,00% |
| Hospital_8 (Vascular Heart) | 11,8 | 10,4 | 11,86% | 0,01% |

## CONCLUSION

This work is focused on the development of a computational algorithm optimization to solve the sequencing problem of elective surgeries in order to improve hospital performance indicators. The objective is to reduce the waiting time of patients, as well as maximize the use of hospital resources, i.e., more patients without the need for investment in infrastructure and overtime payments.

It is noted, however, that the proposal for this work had been answered successfully, since it is possible to reduce the total time used to perform all six daily operations for each of the eight specialties of the created instances. With the minimization of this time, it is possible to perform more operations with the same resources and, consequently reduce the waiting time of the patient, as it can allocate more surgical procedures.

Therefore, the use of computational optimization methods is an important tool to assist the hospital operations management analysts in decision-making. With these algorithms, they are able to perform the sequencing operations efficiently and effectively at the same time, contributing directly to the improvement of the performance indicators of healthcare organizations.

According to Jung and Jacques (2006), the use of computational optimization methods in hospital organizations is still not a very common practice, since only a few hospitals in Europe have addressed such techniques as an innovative and continuous improvement proposal. There is no history of hospitals in the Brazilian scenario using such tools. Therefore, this is a great opportunity to use this proposal to improve the indicators quality.

For future work, there is a plan to test the algorithm proposed on a larger number of test-problems available in the literature, as well as use it to solve real problems in other large hospitals. It stands the need to improve the algorithm with even more robust optimization techniques, such as using mathematical methods.

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