Optimal Workflow Scheduling for Radiology Unit

Group 15

Federica Aresu
aresu@kth.se

Blanca Bastardés Climent
blancabc@kth.se

Blanca Cabrera Gil
blancacg@kth.se

Osheen Sharma
osheens@kth.se




Abstract

Time management is one of the biggest challenges faced by all the organizations and industries these days in order to efficiently deliver the assigned work. Healthcare is one of the organizations which needs optimal time planning to deliver better health facility to the patients. In hospitals, the radiology department plays an important role in the early diagnosis and treatment of diseases. It is essential to have a smooth workflow to avoid any bad consequences, in terms of delivering low quality healthcare to the patients or having stressful workloads for the doctors. Additionally, poor time management affects financial healthcare resources. Taking these factors into consideration, this project focuses on the implementation of two planning algorithms for better management and easy work scheduling in the radiology unit. The two methods used for solving the problem were: Linear Programming (LP) and Genetic Algorithm (GA). The main aim of the algorithms was to minimize the cost in terms of working hours for the doctors. The solutions obtained from both the algorithms were compared and it was observed that for large combinations of patient the results were same but for small combinations GA performed better than LP.

1 Introduction

With the arrival of Artificial Intelligence (AI), many industries have experienced changes in their daily routines. Healthcare, it is no different. By means of the introduction of AI in this field, everyday activities like diagnosis, treatment planning, medication management and repetitive tasks scheduling have been improved and optimized.

One of the main problems that healthcare institutions need to overcome on a daily basis is the scheduling of the different appointments, interventions and activities that take place every day. This is especially difficult due to the complexity of healthcare organizations, the costly infrastructures, the difference between the severity in patients and the need for a prompt reaction to emergencies [12]. Being in hospital environment where uncertainty is always present, one of the most important ability is to be able to adapt to the rapidly changing environments [10]. Doctors, nurses and healthcare practitioners in general play a key role in delivering high quality healthcare. Therefore, if the workers of healthcare institutions suffer from high workload and stress will lead to wrong diagnosis, incidents and fatal results for the patients. Hence, the planning task is of high importance so that the workload is balanced and healthcare professionals as well as patients get the best outcome from the healthcare institutions.

In this project, a comparison of the planning performance between two optimization algorithms applied to a particular test case is presented. The compared techniques are Linear Programming (LP) and Genetic Algorithm (GA) with constrains. The particular test case is a 8 hour shift in an X-Ray diagnosis unit where the schedule of appointments for 70 patients must be planned. The test case is described in more detail in section 3.

In this report, planning is defined as the process of putting in a sequence or partial order a set of activities to fulfill temporal and resource constraints in order to achieve a certain goal [12].

2 Related Work

It is important to mention related-work using genetic algorithm and linear programming in scheduling problems as a significant way to compare and evaluate this project. One can refer to [5] as an application of the GA algorithm in medicine, specifically in radiology as well as neurology, rehabilitation medicine and many more. A representative case mentioned in this paper regards mammograms analysis for which the border of breast parts are easier and quicker detected by the GA. Besides, in the study [11] it has been used a Hybrid Genetic Algorithm HGA which optimizes the results from the general GA algorithm and heuristic function for workflow scheduling issues. In this project, the authors obtained better results in less amount of time.

Regarding Linear Programming, a well-known application of this optimization algorithm is in general care and ICU days planning. For instance, in [9] LP algorithm has been implemented in the case of optimization of resource distribution within an all Department of Surgery. The main goal and benefit on the usage of LP optimization is the application of constraints which better takes into account real-world situations. Furthermore, in [6] and [7] the application of simulation methods combined with Linear Programming algorithm are tested in their optimization performance in patients' admission scheduling problems. It is noticeable that, the study conducted in [6] affirmed that a patient waiting time reduction (41%) is established. Meanwhile, in the [7] work, Linear Programming algorithm has been used to control the patient admission workflow without considering a real-situation case of emergency priority code.

The [8] is an example of a comparison of genetic algorithm and linear programming in order to assess which optimization process is most efficient in real-world situations. The conclusion given from this study is that the Genetic Algorithm is found to be the most efficient one, along with easier to implement in more complex systems.

3 Test case

The problem used to compare both optimization methods is the one of scheduling a 8 hour shift in a radiology unit of a diagnostic center. In the diagnostic center it is necessary to have an efficient workflow so that all the patients are attended without elevated waiting times to have the highest patient satisfaction rate. In addition, it is important to keep adequate workloads for doctors so that no doctor works overtime and avoid burn outs. Finally, the diagnostic center wants to attend as many patients as possible so that to have the maximum income.

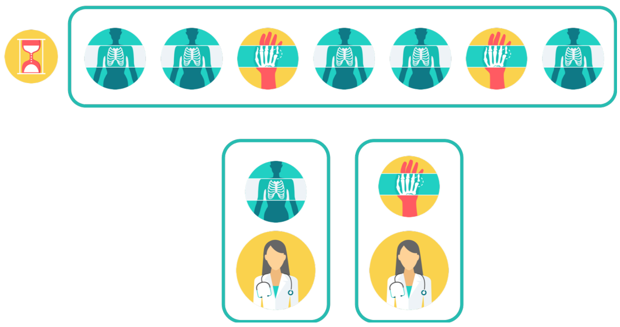


Figure 1: Graphical representation of the stated test case

Our test case scenario has been defined as the patient schedule of a day in the X-Ray unit in a diagnostic center which is represented in Figure 1. The characteristics of the scenario are the following:

- 2 Doctors: 1 specialized in chest scans, 1 specialized in bone scans.
- 70 patients having bone or chest related problems.
- hour shifts: the doctors cannot work more than 8 hours a day.
- Each patient must be assigned to one and only one doctor.

	Bone Patient	Chest Patient
Bone Doctor	15	20
Chest Doctor	12	10

Table 1: Cost relationship between doctor and patient

- Each doctor must visit at least one patient.
- Doctors can attend patients regardless of their condition but a mismatch of doctor and pathology leads to a cost penalization.
- Time cost of an appointment where doctor specialization matches the patient condition is 10 min for chest condition and 15 min for bone condition.
- Time cost of an appointment where doctor specialization does not match patient condition is 12 min for chest patient and 20 min for bone patient. Table 1 shows the time cost for each kind of assignment.
- Goal: minimize the working time of the doctors.

The initial sequence of patients to be scheduled is described in table 2, where *pc* is a patient with a chest pathology and *pb* is a patient with a bone pathology.

pc1	pb2	pb3	pc4	pc5	pc6	pb7	pb8	pb9	pb10
pc11	pc12	pb13	pc14	pb15	pc16	pb17	pb18	pc19	pb20
pc21	pc22	pb23	pc24	pb25	pb26	pb27	pc28	pb29	pc30
pc31	pb32	pb33	pb34	pb35	pc36	pc37	pc38	pb39	pb40
pb41	pb42	pc43	pb44	pc45	pb46	pc47	pc48	pb49	pb50
pb51	pc52	pb53	pb54	pc55	pc56	pc57	pc58	pb59	pb60
pc61	pc62	pc63	pb64	pb65	pc66	pb67	pc68	pb69	pb70

Table 2: Initial patient sequence.

The optimization goal is to minimize the doctors workload, being the total cost the maximum workload between two doctors.

4 Methods

To be able to asses which is the planning algorithm that fits better the test case, two main methods were chosen to be compared. On an early stage of the project it was decided to compare the planning capabilities of using PDDL and evolutionary methods like GA. However, after analyzing how to develop a PDDL model for our problem, it was clear that *durative-actions* had to be used as well as a *metric* to evaluate the total cost. These last statements were introduced in PDDL 2.1 version. The problem faced when exploring this method was the difficulty of finding appropriate compilers that supported PDDL 2.1. Most of them just supported previous versions of the language and the ones that supported 2.1

version required Linux as OS or other requirements that did not mach the environments of our computers. For this reason, it was decided to change the methods towards a comparison between Linear programming against Genetic Algorithm.

4.1 Linear Programming

The first optimization technique that it is presented is Linear Programming. This is a computational technique that uses algebraic relationships to decide the best possible solution from a set of parameters related by a linear relationship. It is most widely used to find the best way to distribute finite resources [1]. In this method, the statement constraints are defined as a set of inequalities or equalities that the model must satisfy. The direction of the optimization is defined by the objective function. This is a mathematical function of the decision variables which evaluates the provided solution.

One of the main benefits of LP is the flexibility to adjust and adapt to changes in objective function, decision variables, change of goals and constraints. They generally deliver the best possible planning and scheduling solution [3]. On the other hand, one of the main disadvantages of this method is the linear relationship between the variables. In the real world, not all applications can be modelled by means of linear relationships. LP is not suitable for problems with too many possibilities to be mathematically modelled.

To fit our test case to the LP approach, two main variables were used, Doctors (*D*) and Patients (*P*). The first one contained the two possible doctors, d_i, with chest and bone specialization respectively; the second one contained the sequence of 60 patients, p_i, each one with the type of condition assigned. Also, a third variable *cost* containing the mapping of the relationship of costs between the doctors and the patient's pathology is declared. The decision variable, *assignment* in this case, is the binary assignation table of the patients to the doctors. The constraints used to build our LP optimization model are that each doctor must have assigned at least one patient, each patient must be assigned to only one doctor, the total cost of all the patients should not be higher than 720 hrs, and the cost is defined as the maximum time when comparing the time assigned to each doctor. The equations describing these constrains can be found in 1-3 and the objective function in 4:

$$\forall D \sum_{i=1}^{P} assignment[d_i][p_i] \geq 1 \tag{1}$$

$$\forall P \sum_{i=1}^{D} assignment[d_i][p_i] = 1 \tag{2}$$

$$\sum_{j=1}^{D} \sum_{i=1}^{P} assignment[d_j][p_i] \times cost[d_j][p_i] \leq 720 \tag{3}$$

$$\begin{aligned} max(&\sum_{i=1}^{P} assignment[d_c][p_i] \times cost[d_c][p_i], \\ &\sum_{i=1}^{P} assignment[d_b][p_i] \times cost[d_b][p_i])) \end{aligned} \tag{4}$$

To code the LP method, Python 3 was selected as programming language and PuLP library was used to perform the optimization task.

4.2 Genetic Algorithm

A Genetic Algorithm (GA) is an evolutionary method used to solve constrained and unconstrained optimization problems. This algorithm mimics biological evolution process by repeatedly modifying a population of individual solutions. The GA selects successively the individuals with the best fitness value from a population to become the parents of the following generation. Over a set of generations the algorithm evolves to an optimal solution.

One of the main advantages of using GA is that it can address problems that are not well suited for optimization algorithms in which the objective function is discontinuous, non-differential, stochastic, or nonlinear. Unlike other linear optimization approaches, it can improve a set of solution or hypotheses of a population [2] by means of the random exploration of a wide range of possibilities and combinations. However, on the other hand, GA does not guarantee to always converge as it depends on randomness and on the choice of model parameters [4]. In addition, the algorithm is much slower than the classical ones, specially when the optimization problem size scales up. Moreover, it has no concept of 'optimal solution', it works with comparisons between previous results. Therefore, it is difficult for the algorithm to know where to stop. One way to overcome this issue is to set an heuristic function to stop when the best solution has not improved for a long time.

Genetic algorithms use three types of rules to create the next generation from a current population:

- Selection rules: To assess the fitness of each individual and select the parents for the next generation.
- Crossover rules: How to combine the genes from the two parents to create the child chromosomes.
- Mutation rules: When to apply random changes.

The problem constraints were introduced in the GA by means of the way the fitness function was built. The method used to evaluate the fitness of the chromosomes in each population is described in Algorithm 1, where *dBCost* is the cost assigned to the doctor specialized in bone fractures and *dCCost* is the cost assigned to the doctor specialized in chest pathologies.

The code for the GA was written in Python 3, and Pandas and Numpy libraries were used.

Algorithm 1 Genetic Algorithm

procedure FITNESS FUNCTION
  if ($patient.type == Bone$) **then**
    if (*dBCost* + *15* $\leq$ *dCCost* +*20)* **then**
      $dBCost \leftarrow dBCost + 15$
    else if *(dBCost* + *15* $>$ *dCCost* +*20)* **then**
      $dCCost \leftarrow dCCost + 20$

  if *(patient.type* == *Chest)* **then**
    if *(dBCost* + *12* $<$ *dCCost* +*10)* **then**
      $dBCost \leftarrow dBCost + 12$
    else if *(dBCost* + *12* $\geq$ *dCCost* +*10)* **then**
      $dCCost \leftarrow dCCost + 10$
  totalCost $\leftarrow \max(dBCost, dCCost)$

5 Results

A small difference in the performances between GA and LP has been obtained. Specifically, from the first population, before the implementation of the algorithms and therefore with a simple first-come first-served approach, the cost functions are at **480** min.

During the test performed on the GA performances, the elite population size has been changed from 10 to 20, out of 1000 generations. These different configurations led to no substantial differences on the final cost. However, it has been assessed that for larger population size could be of relevance.

Finally, the following configuration is the one that was selected to perform the comparison as had the best trade-off of results-computation time.

- Population: 2000
- Elite: 20
- Mutation rate: 0.01
- generations: 50

The evolution graph showing the final convergence for the GA can be found in Figure 2.

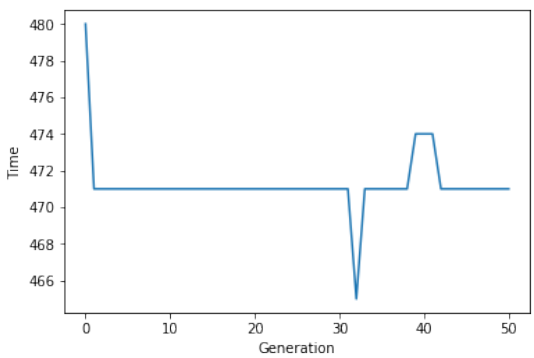


Figure 2: Evolution of GA along generations.

After running both methods, two behaviours have been observed. For small sequences, 60 patients, the GA obtained a best optimization result with a total final cost of 402 minutes. On the other hand, the LP result was 405 minutes. Contrarily, for greater sequences, 70 patients, both GA and LP reached the same final cost value of **465** minutes, which is the equivalent time to 7 hours and 45 minutes.

The difference in the total cost obtained from both algorithms lies in the different final schedule they provide. In Figure 3a and Figure 3b it can be observed the patient-doctor workload in terms of time for the GA and LP respectively. Likewise, the amount of patients assigned to each doctor can be found in figures 4a and 4b.

6 Conclusion

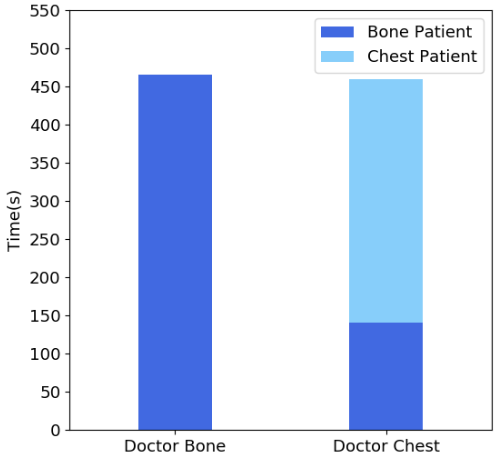
Time planning is an important aspect of healthcare management to provide the best service delivery to patients as well as guarantee adequate healthcare efficiency and cost care. In this work, the usage of optimization algorithms, such as GA and LP was reported and their performance was compared for addressing this issue. It was observed that the cost in terms of time was reduced from 480 minutes to 465 minutes. Although there were few mismatches between the doctors and the patients, it was addressed by giving more time to the doctors for attending patients of different modality. However, it is more convenient to have mismatches and add time penalization so that all the patients will receive attention, assuming the patients do not have extreme severe conditions. This way, the optimization balanced the workload and reduced 15 minutes the working time of the doctor with maximum workload. Hence, reducing the stress at work and improving the practitioners mental health.

Although it was observed that both methods had similar results, their performance varies depending on the sequence of patients given as the input. This sequence will be different every day in real world. For small sequences of patients, the optimal solutions from GA were better than the ones found with LP. For our determined sequence of 70 patients, both methods led to the same results. Although GA results depend on randomness, the best optimal value reached was the same as the one obtained with LP.

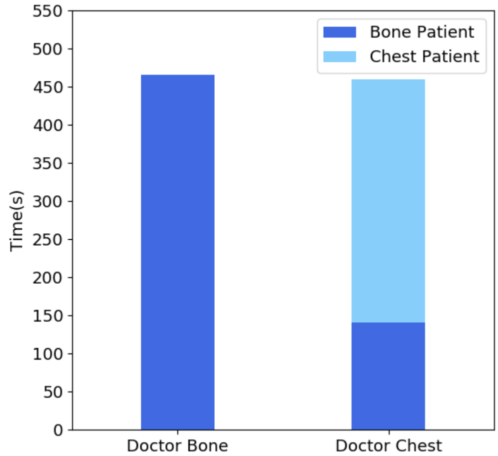
7 Future Work

Throughout this project the total cost has been defined as the total work-time that would take a doctor to attend a patient. However, this scenario is not that common in real-life situations. Therefore, there is scope for improvement related to defining the cost in financial resources and constraints. Some of the financial resources that would condition the test case are energy-cost consume of X-ray machines, working hours of staff members and expenses given by the usage of medical supplies. In such a scenario, it should be pointed out the possible impact on the running time efficiency of these algorithms.

Furthermore, another improvement to explore in the future would be the one of considering emergency situations. Thus, not only considering the time-cost but also prioritizing depending on the emergency of the patient's condition. Along the

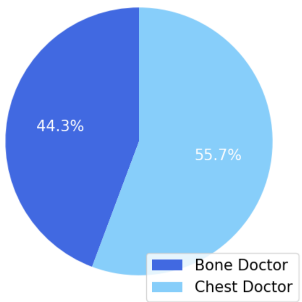


(a) GA result.

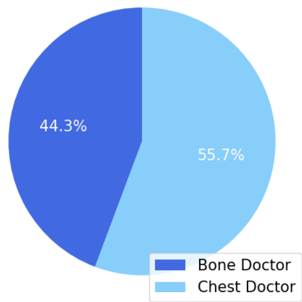


(b) LP result

Figure 3: Distribution of workload per doctor and type of patient assigned.



(a) GA assignation.



(b) LP assignation.

Figure 4: Assignation of patients per doctor.

development of the project, this improvement has been implemented for GA as further test, with an emergency priority of 3 for the most urgent conditions and 1 for the less important ones. Yet, it has not been implemented for LP as it was not in the project scope. In addition, it is possible to consider cases of patients that need to be scanned in more than one part of the body, i.e. bone and chest.

References

[1] Definition - what does linear programming (lp) mean? URL: https://www.techopedia.com/definition/20403/linear-programming-lp.

[2] Genetic algorithms. URL: https://www.sciencedirect.com/topics/engineering/genetic-algorithm.

[3] Optimization vs. heuristics: Which is the right approach for your business? URL: https://icrontech.com/blog_item/optimization-vs-heuristics-which-is-the-right-approach-for-your-business/.

[4] What is the genetic algorithm? URL: https://www.mathworks.com/help/gads/what-is-the-genetic-algorithm.html.

[5] Mohammad Naderan Ali Ghaheri, Saeed Shoar and Sayed Shahabuddin Hoseini. The Applications of Genetic Algorithms in Medicine. , November 2015.

[6] Filipe Janela Joo Seabra Conceio Granja, Bernardo Almada-Lobo and Adlio Mendescorresponding author. An Optimization based on Simulation Approach to the Patient Admission Scheduling Problem: Diagnostic Imaging Department Case Study. , August 2013.

[7] J.M.H. Vissers I.J.B.F. Adan. Patient mix optimisation in hospital admission planning: a case study. , April 2002.

[8] H.Md. AzamathullaaFu-ChunWubAminuddin AbGhaniaSandeep M.NarulkarcNor AzaziZakariaaChun KiatChang. Comparison between genetic algorithm and linear programming approach for real time operation. , Dec 2008.

[9] Vinita Bahl Michael W Mulholland, Paul Abrahamse. Linear Programming to Optimize Performance in a Department of Surgery. , July 2005.

[10] Christoph-Eckhard Heyde Sandra Kuwatsch Marco Bohn Mohamed Ghanem, Jrg Schnoor and Christoph Josten. Management strategies in hospitals: scenario planning. *GMS Interdiscip Plast Reconstr Surg DGPW*, Jun 2015.

[11] Ehsan Ullah Munirb Tan FongAnga Samee U. Khan. Saima Gulzar Ahmada, Chee Sun Liewa. A Hybrid Genetic Algorithm for Optimization of Scheduling Workow Applications in Heterogeneous Computing Systems. , October 2015.

[12] Constantine D. Spyropoulos. AI planning and scheduling in themedical hospital environment. *Artificial Intelligence in Medicine 20*, May 2000.