Extended Abstract to obtain the Master of Science Degree in Industrial Engineering and Management

Optimization of Patient Centered Processes - The Oesophageal and Stomach Reference Center at Portuguese Institute of Oncology Lisbon Francisco Gentil

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Abstract: The oncology department is a complex environment requiring multiple professionals and departments coordination, and the limited budget create a complex decision for administrators in the healthcare field to increase efficiency with the existent resources. This isolated process structure in each service hinders the timely treatment of the patient and, in the case of disease situations with oncological pathology, this out-of-time treatment can significantly worsen the patient's health condition and undermine recovery. The largest hospital in Portugal specialized in oncology is the Portuguese Institute of Oncology Francisco Gentil, and its center located in Lisbon (IPOLFG) is the hospital in analysis in this study. Due to the complexity of processes in the hospital environment the research focus on the reference center of oesophagus and stomach cancer, being one of the most severe pathologies and with a more aggressive diagnosis for the patient. Thus, the aim of this dissertation is to implement a Multi-Priority Integer programming model for the referenced organization to optimize the patient flow and the process time of the operations in the RCOS providing an increased patient satisfaction and serving patient's wait time targets. The results obtained with the present study provide sufficient evidence that addressing priorities through the demand of patients in the department is more efficient than the patient scheduling method that is currently used in the department and the present implementation could improve the results in terms of care delivery and the consequent improvement in the patient health status.

Keywords: Oncology, Patient Flow, Multi-Appointment, Patient Priorities, Optimization, Mathematical Model

1. Introduction

Cancer is considered the second leading cause of death globally and is responsible for an estimated 9.6 million deaths worldwide (World Health Organisation, 2018). In Portugal, cancer is the second most common cause of death. Providing optimal and effective methods to optimize this dangerous condition is a major challenge to healthcare organisations. The oncology is a multi-disciplinary department in charge of the research and treatment of cancer, and due to the severity and mortal condition of this disease methods to optimize the healthcare delivery in this department have been under research in the recent years. This multi-facility environment creates a difficult decision for clinical administrators to improve efficiency, since the coordination of these services and resources is critical for timely and efficient treatment of patients. A critic analysis focused on the patient path and the scheduling and timing of activities are necessary tasks to increase the potential results and meet the expectations of the patients. For that purpose, the dissertation focusses on the implementation of a mathematical model of optimization in order to fulfil patients scheduling priorities. In the case of Portugal, the biggest hospital in this field is Intituto Português de Oncologia, and for the purpose of the dissertation the center positioned in Lisbon (IPO Lisboa Francisco Gentil, IPOLFG) is the main motivator and supporter of the work. IPOLFG receives around 14.000 new patients/year and has currently in the system more than 57.000 patients (IPOLFG,2020). These numbers tend to increase due to the increasing number of cancer patients worldwide (World Health Organisation, 2018). Nevertheless, due to the complexity of processes in IPOLFG and the many departments it is important to focus the work on a reference center in order to obtain more concise and patient directed results. The one debated with the IPO Administration and selected under conditions such as priority and necessity for the IPOLFG is the oesophagus and stomach reference center (RCOS). This institution receives the highest volume of patients with oesophagus and stomach cancer in the country (120 new patients/year for oesophagus and 100 new patients/years for stomach), providing responsibilities to the area in the implementation, development, and divulgation of strategies in the approach and treatment of patients. Furthermore, an analysis in the hospital ground is developed to understand the patient path with the purpose of identifying difficulties in the flow of the patients and give insights to the present study. In this context, the usage of sophisticated methods to support de decision-making in the hospital environment could potentially lead to more effective and efficient solutions and enhance the procedures and processes in the IPOLFG always aligned with the patient's expectation and performance levels that are a standard of excellence in this organization.

The main goal of this study is to develop and use Operations Research (OR) methods to optimize the IPOLFG operations with focus in the oesophagus and stomach reference center. The model must allow understanding on the patient path, aligning with his/her expectations in the process. Must also manage effectively all the relevant scheduling process of consultations, coordinate all the multidisciplinary resources involved in the patient path and provide insights in the impact of the alternatives in the systems performance

The paper is structured as follows: in the section 2 the problem context is defined where the IPOLFG and the Oesophageal and Stomach department are introduced. In the section 3 relevant literature on patient flow, multi appointment scheduling, patient priorities and patient selection from a waiting list is presented. In Section 3, the problem statement is identified. The mathematical models are presented in section 4. In Section 5 the input data of the model is presented for two different scenarios and in chapter 6 the results of each scenario are shown and compared. A sensitivity analysis is conducted to study the influence of the variation of certain parameters, in section 7. Finally, in section 8 conclusions are drawn.

2. Problem Context

The Portuguese Institute of Oncology Francisco Gentil (IPOLFG) is a public multidisciplinary oncologic centre under the surveillance of the Portuguese National Health Service (Serviço Nacional de Saúde, SNS). IPOLFG is responsible for the delivery of healthcare services in the field of oncology, with further activity in the areas of research, education, prevention, diagnostic, treatment and rehabilitation making sure that each patient is addressed with properly care that reach his necessities and the usage of best clinical practices with efficient utilization of the available resources.

2.1 The reference center: Oesophageal and Stomach Department

Due to the complexity of processes in IPOLFG and the numerous existences of departments is necessary to focus the work on a reference center: the one chosen is the oesophagus and stomach.

The oesophagus is a part of the digestive tube that transport the aliments from the mouth to the stomach. The oesophagus carcinoma is a type of cancer with one of the most severe prognostic, with a global survivance rate of 15-30% in 5 years, being the 8th most common in the world (World Cancer Observatory,2018). The patients diagnosed with this disease generally are already in an advanced state. Approximately 50% of the patients in the diagnosis process show metastasizing advanced and 25% will develop metastasizing (PAI Oesophagus and Stomach,2018). Regarding the treatment of this disease, it could be involved by different therapeutic modalities. In the most cases chemotherapy and radiotherapy is needed to reduce the size of the tumour and then a surgery is often required. The IPOLFG receives 120 new patients/year with oesophagus pathology diagnosis (corresponding to 1/3 of the cases identified in the south region of Portugal (Registo Oncológico Regional, ROR)).

The stomach cancer or gastric cancer is the 5th most common cancer worldwide (World Cancer Observatory,2018). Early-stage stomach cancer rarely causes symptoms, making early detection very difficult. The overall 5-year survival rate is 29.3% (PAI Oesophagus and Stomach,2018). Stomach cancer is treated with surgery, chemotherapy, radiation, or a combination of these. Surgical options depend on the extent of cancer within the stomach and include partial or total gastrectomy (removal of the stomach). IPOLFG receives 100 new patients/year with gastric cancer diagnosis all followed in this reference area (Pai Oesophagus and Stomach,2018)

The flow of patients involves the sequential activities for the diagnosis, staging, treatment, and monitoring of the patient with oesophagus or stomach cancer. The flowchart of the patient flow within the oesophagus and stomach reference center can be observed in the Figure 1.

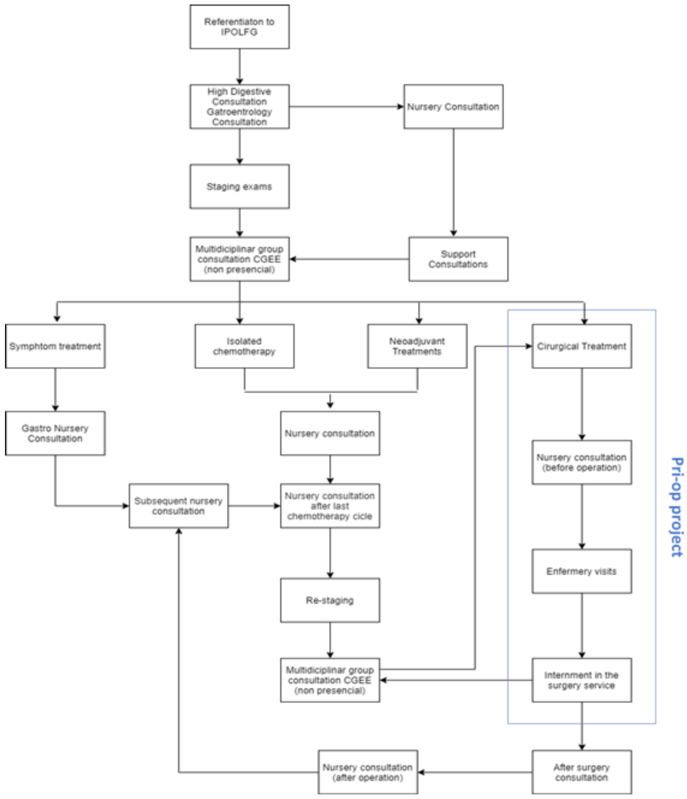


Figure 1 Flowchart of the patient on both oesophagus and stomach area, (OSRC,2019)

The optimization of the processes in this system is a challenge to the organisation since the IPOLFG is the national center that receives the highest volume of patients with oesophagus and stomach cancer, providing responsibilities to the area in the implementation, development, and divulgation of strategies in the approach and treatment

3. Literature review

3.1. Patient Flow

Long waits, delays, cancellations and resource overloads have become commonplace in healthcare (Hall et all, 2006). In the recent years, the purpose of the healthcare providers was simply to add more resources to solve this problem, but this approach has become impractical due to the shortage of human resources and the limited finances available. Nowadays, healthcare providers are forced to look at different approaches to solve this problem and evaluating the patient flow is a procedure that is increasingly gaining importance.

In the early 2000's, in order to analyse the patient flow and helping the decision maker to identify bottlenecks through a cancer treatment centre (Sepulveda et al.,1999) developed a discrete event simulation to determine the impact of alternative layouts, number of patients scheduled per day and new building plan for this purpose. Additionally, (Baesler and Sepulveda,2001) also used discrete event simulation to find the best combinations of control variables (resources) to meet the predetermined goals of patient waiting time, chair utilisation, clinic total working time and nurse utilisation. Another distinct model using multi-objective integer programming model contemplating discrete event simulation to allocate all patients considering the nurse capacity with the objective of satisfying patient's time preferences, pharmacy capacity, balance workload between nurses and the workload throughput the day and assigning clinical trial patients to specialised nurses was conducted by Santibáñez et al. (2012). The study by Hahn-Goldberg et al. (2014) use constraint programming to develop a template schedule based on historical data and update the template dynamically, when appointment requests that don't fit those of artificial appointments already scheduled in the template. Furthermore, the authors Turkcan, Zeng, and Lawley (2012) contributed to develop integer programming models to address chemotherapy problems that consider acuity levels of patients, with the goal of minimizing treatment delays, reducing staff overtime and maximizing staff utilization. In a similar study, Condotta and Shakhlevich (2014) proposed creating multi-level templates to accommodate patient requests for chemotherapy appointments. Another relevant study was developed by Liang and Turkan (2016) that strive to address the daily flow of patients considering nurse assignments. Another level of study and regarding more recent technology was developed by Heshmat, Nakata, and Eltawil (2018) that considered the patient appointment and proposed an approach inspired on cellular manufacturing that involved creating clusters of patients using a mathematical programming model.

3.2 Multi-Appointment Scheduling

Multi-Appointment Scheduling Problems in Healthcare (MAPSPHs) are design to act as an umbrella for both combination appointments: those which patients need multiple appointments, preferably in the same day and appointment series in which patients need to revisit the same set of resources several times (Hulshof et al.,2012). This definition fits in the oncology research field due to the complex network of treatments that the patient need and the various resources and departments coordination that are in the patient path through the system. Therefore, each patient need to be assigned a specific path over a subset of the considered resources and each step needs to be scheduled in order to obtain a timely care (Marynissen & Demeulemeester, 2019). This is an important issue in healthcare delivery because delayed diagnosis and treatment may result in adverse effects in the patient health and with the application of this methods the hospitals could increase the patient satisfaction and reduce the patient visits to the hospital. Regarding the study of multi-appointment scheduling problems in the oncology field, there is a vast number of techniques used and very heterogeneous and with different optimization purposes. Introducing this problematic, the authors Sadki, Xie, and Chauvin (2011) studied the scheduling of patients for chemotherapy treatments and oncologist consultations simultaneously using a mixed-integer programming (MIP) model. In another study Shashaani (2011) determined the appointment schedule using a deterministic integer programming model and then it is used as input to the simulation model in order to evaluate the impact of variability in the service time in key performance measures such as patient waiting times. Another example was conducted in radiation therapy (Sauré et all, 2012) using an approximate dynamic programming to solve a mainly deterministic multi-day problem with the only uncertainty on the number of new requests for each type of radiotherapy treatments. In the same models Gocgun and Puterman (2014) also proposed formulating a problem as a Markov decision process model (mathematical framework for modelling decision making in situations where outcomes are partly random and partly under the control of a decision maker) and proposing approximate schemes to solve instances of real size. More work in this field were conducted by Liang, Turkcan, Ceyhan, and Stuart (2015) and Liu et al. (2019) that used simulation and optimisation models to analyse the scheduling, staffing, and flow process stages inside an oncology clinic and to identify bottlenecks where improvements can be made for a single day but not for a planning horizon. Dobish (2003) proposed a two-day treatment process to reduce patient waiting time in a cancer treatment centre, since the patients were examined by their oncologists and then were given appointments for chemotherapy treatment for the following day. Another simulation was conducted to evaluate the impact of different patient arrival rates, resource levels (nurses, doctors) and queuing policies (Matta and Patterson,2007). Ramos, Cataldo, and Ferrer (2018) studied two sequential decision problems: a capacity planning problem for assigning a date to appointment requests, and a daily patient-scheduling problem for allocating a chair and time slot for each patient on each day. In the recent years Garaix, Rostami, and Xie (2019) proposed a heuristic that uses a greedy randomized adaptative search procedure algorithm to solve the multistage problem of scheduling patient appointments for chemotherapy and consultation and considering drug preparation times. Furthermore, Benzaid, Lahrichi, and Rousseau (2019) consider a distinct three-stage procedure problem through the examination of chemotherapy appointment scheduling problem, a nurse planning problem, and a daily nurse-patient assignment. The goal of the first stage was to determine a date and start time for each new patient with the aim of maximizing the number of patients starting their treatments. Further, in the second stage they try to assign patients to nurses in a way that the required staffing level and length of waiting list were minimized. Finally, in the third stage, after simulating last-minute changes including cancellations and nurse absences, the daily assignment problem was executed for the final set of patients and nurses.

3.3 Patient Priorities

Particularly in medical facilities problems with heterogeneous patients is usual to determine priorities for various patient groups. There are two major types of patient priorities, which may be called hard and soft. A common method to define soft priorities is to assign a different weight to each patient group to reflect its relative importance. In most studies, these weights are represented by waiting-time penalty coefficients (Saure et al., 2012). Is important to notice that, both hard and soft priorities can be considered simultaneously. Although priorities have a significant impact on patient waiting time and on resource utilization (Kortbeek et al., 2012), no optimization study has focused on determining patient priorities. The allocation of different patient priorities in the hospital environment is under analysis in the present dissertation.

3.4 Patient Selection from a Waiting List

For some problems in the literature, there are more patients on the waiting list than the available capacity, even with overbooking. In such a case, the number of patients to serve should be selected in terms of various criteria, such as the capacity allocated to each patient group, the patient waiting time, and the patient priority levels. Some authors assume that the priority initially assigned to each patient does not change, but in the real world the patient's condition may change during that time (Min & Yih, 2014).

A variation of this decision occurs in some hospital diagnostic facilities (such as magnetic resonance imaging (MRI) and computed tomography (CT)) that serve both inpatients and outpatients. These clinics face the challenge of selecting, in real time, who will be served next when demand comes from three patient groups: inpatients, emergency patients, and pre-scheduled patients, which based on our terminology could be referred to as regular walk-ins, urgent walk-ins, and scheduled patients, respectively (Gocgun et al., 2011). This problem can be also considered a type of dynamic capacity allocation problem for a diagnostic facility. The selection of patients from a waiting list is also a critical aspect that is relevant for the further model implementation.

3. Problem Statement

In the present scheduling method of the oesophageal and stomach department there are no rules in the appointment booking since the department receives a waiting list and the first patient that is contained in the waiting list is booked for consultation according to the multidisciplinary group consultation. That method may not be the optimal way to increase the efficiency of the patient flow and neglecting patient priorities that could lead to catastrophic results due to the condition of the disease in analysis. Considering that problematic, the purposed Multi-Priority Integer Programming model aims to add a step in this process. Instead of considering no rules in the appointment booking, the model considers different levels of priorities (P) for different patients in a planning horizon (T). Instead of selecting the patient with higher priority the model first minimizes the total wait time for all the priorities of patients, then books appointments for the higher priority patients until a certain service level that the hospital compromises to achieve is fulfilled and assuring that the wait time target of the patient is met according to the total service time available in the hospital.

4. Mathematical Formulation

In order to solve the problem defined, in this section is presented the mathematical formulation.

Sets

t ∈ T set of all time periods

p ∈ P set of all patient priorities

n ∈ T number of days that a patient is waiting to receive treatment

Parameters

dpt Number of patients with priority p who require a service in period t

ct Total available time for service in period t

sp Service time of patients with priority p

wp Wait time target for patients with priority p

αp Fraction of priority patients served within their wait time target (service level)

h (n,p) Penalty cost for delaying patients of priority p for n days

Variables

Xptn number of priority p patients served in period t after waiting for n periods.

Iptn number of priority p patients not yet served in period t after waiting for n periods.

Objective Function

$$\text{Min} \sum_{p=1}^{P} \sum_{T=1}^{T} \sum_{n=1}^{t} h(p,n) I_{ptn} \quad \textbf{(1)}$$

Constraints

$$I_{ptn} = d_{p,t,n+1} \sum_{i=0}^{n-1} x_{p,t-i,n-i} \; \forall \; \mathrm{p} \in \mathrm{P}, \mathrm{t} \in \mathrm{T}, \mathrm{n} \in \{1, \dots, \mathrm{T}\} \quad \textbf{(2)}$$

$$\sum_{i=0}^{n-1} x_{p,t-i,n-i} \leq d_{p,t-n+1} \; \forall \; \mathrm{p} \in \mathrm{P}, \mathrm{t} \in \mathrm{T}, \mathrm{n} \in \{1, \dots, \mathrm{T}\} \quad \textbf{(3)}$$

$$\sum_{p=1}^{P} \sum_{n=1}^{T} s_p x_{ptn} \;\leq\; c_t \;, \forall \; \mathrm{t} \in \mathrm{T} \quad \textbf{(4)}$$

$$\sum_{n=1}^{wp} \sum_{t=1}^{T} x_{ptn} \geq \; \alpha\mathrm{p} \sum_{t-1}^{T} d_{pt} \;,, \forall \; \mathrm{p} \in \mathrm{P} \quad \textbf{(5)}$$

$$Xptn \geq 0 \text{ integer } \forall\, p \in P, t \in T, n \in \{1, \ldots, T\} \qquad \textbf{(6)}$$

The objective function (1) minimizes a weighted sum of total wait times of all patients and allow different penalty costs h(p,n) for wait time of different priorities (p) and is a function of the number of days the patients have been waiting (n). The objective is to balance the number of patients that receive treatment according to the different priority levels as stated previously, in order to obtain a balanced schedule for patient admission. The constraint (2) captures the number of patients of each priority (p) that are still waiting to receive treatment. This function depends on the number of patients with priority (p) who require a service in period (t). The constraint (3) ensures that are only schedule past patients, not considering future demand. With that constraint we restrict the patient flow since the waiting list isn't dynamic. The constraint (4) restricts the total daily number of patients who receive service based on the available capacity in each period. The constraint (5) ensures that desired service level αp, for serving patients within their wait time targets is met for each priority The constraint (6) ensures that the number of served patients is a non-negative integer, which is captured in the sign constraint.

5. Input Data

5.1 Scenarios

In order to analyse the study, two samples of data are going to be addressed to the model. Firstly, the model is going to be addressed with the data that simulates most reliably the hospital environment when considering patient priorities. Additionally, and with the purpose of examine the efficiency of the model, an alternative scenario is going to be tested depreciating the patient priorities, and the same priority for all the group of patients is going to be addressed. This scenario is relevant since it is the present patient scheduling method of the department, and trough comparing these two scenarios it is possible to identify the pertinence of the present work for the oesophageal and stomach cancer departments of the IPOLFG hospital.

5.1 Base Model Scenario

5.1.1 Planning Period (T)

In line with the current practice, and to support the formulation of IPO's yearly patient scheduling plan, a 12-month planning horizon is analysed, representing 365 days (T={T1,…,T365}).

5.2.2 Patient Priorities (P)

The principal differentiator that the model proposed to address in the department is priority levels for different category of patients. Regarding that, there are 4 types of priorities for patient scheduling being the level 4 the most severe and the level 1 the less (Diário da República, Maio 2017).

- Priority of level 4 - considers patients with known or suspected cancer where there is risk of life with progressive change in the state of consciousness.
- Priority of level 3 - considers aggressive neoplasms, situations with rapid progression, without immediate risk of life.
- Priority of level 2 - considers neoplasms without characteristics that fall into any of the other categories, corresponding to most neoplasms.
- Priority of level 1 – considers indolent neoplasms (causing little or no pain).

Regarding that the model is going acquire these 4 types of priorities with the purpose of addressing them to the patients that enter in the oesophageal and stomach department and analyse how categorising the patient by them affect the department scheduling performance (P= {P1,..., P4}).

5.2.3 Demand of Patients with Priority (dpt)

The demand of patients in the IPOLFG is majorly irregular and due to confidentiality and data protection policy that kind of information is difficult to estimate and obtain. Although it is stated in the PAI that the IPOLFG receives 120 new patients/year with oesophagus and 100 new patients/year of stomach cancer diagnosis. It is important to consider also that the department already has patients in the system. Considering that statement a sample of 300 patients/year is going to be under analysis in the present model. The implementation of the present model works with that sample of demand and is static.

5.2.4 Total Available Time for Service (ct)

The total available time for service is a parameter from the model that intends to restrict the hours that a patient must receive treatment. It is stated by the department that the available time for consultation is 2 shifts per day with 4 hours each. Regarding that information, the total available time for service that is going to be considered in the model is 8h per day.

5.2.5 Service Time for Patient Priority (sp)

In the current department environment, there is no distinction in the service time between patients, however when considering patient priorities, it is feasible to assume that patient with higher priority require a longer service time than patient with lower priority and as stated before that kind of reality is being used in other departments of the hospital. In light of this assumption, the model is going to consider that patients with higher priority (level 4) have higher service time than patients with lower priority (level 3, level 2 and level 1). The service time for patient priority considered are specified in the table 1.

Table 1 Service Time for Patient Priority

Patient Priority	*Service Time for Patient Priority*
Level 1	2h
Level 2	4h
Level 3	6h
Level 4	8h

5.2.6 Wait time targets (wp)

Considering the severity of the cancer disease an important parameter to be under evaluation is the wait time target for patient scheduling. This parameter is important because allow the model to include patient expectations in the process, but it should be also realistic in terms of the hospital capacity and resources to attend the patients. Since the IPOLFG is a public hospital, the maximum number of days that a patient should be waiting to receive treatment are standardized in the legislation Diário da República, 1.ª Série N. º 86 4 de Maio de 2017 and described in the table 2

Table 2 Patient Priorities for Surgery (Diário da República, Maio 2017)

Patient Priority	*Maximum nº of days to receive treatment*
Level 1	60 days
Level 2	45 days
Level 3	15 days
Level 4	3 days

5.2.7 Service Level (αp)

The service level is stated as the fraction of patients that are served within their wait time target. When allocating patients for treatment and with the purpose of obtaining a balanced patient scheduling without a strict policy of allocating first the patients with higher priority and compromising lower priorities the service level can address this problematic and allow flexibility to the model. For a certain priority, the service level (αp) is going to restrict the number of patients that must be scheduled within their wait time targets. It is feasible to consider that high priority of patients must have a higher service level when comparing with lower priorities of patients. The distribution of the service level per priority is presented in the table 3.

Table 3 Service Level per Patient Priority

Patient Priority	*Service Level*
Level 1	60%
Level 2	70%
Level 3	80%
Level 4	90%

5.2.8 Penalty Cost for Delaying Patients (h(p,n))

In order to regulate the time that a patient is waiting to receive treatment, the present model allows a penalty cost h(p,n) in the objective function. A penalty cost h(p,n) is the cost the model incur if a patient of priority p waits for n days in the system. If the penalty cost is 1 per day for all priorities, the objective would be the average waiting time for all patients. Intuitively, it would be reasonable to consider a higher penalty cost for patients of a higher priority. The objective function compromises to minimize this penalty cost. For that purpose, for each priority, the penalty cost is going to be considered as (1) until reached the patient wait time target, after achieving that time the penalty cost increases one unit until the end of the horizon, for example the penalty cost for priority level 4 is going to be 1 until n=3, after that it increases 1 unit until n=365.

5.3 Alternative Scenario Data

The planning period is similar (T=365) as the demand of patients (300 patients) and the total available time for service (8h). Although, with the purpose of achieving response in the model the weight of the patient's priorities was modified through the parameters service time for patient's priority (sp), wait time targets (wp), service level (αp) and penalty cost for delaying patients (h(p,n)). The principal assumptions of the alternative scenario are presented in the table 4.

Table 4 Alternative Scenario Data Input

Parameter	*Value*
Planning Period (T)	365 days
Patient Priorities (P)	P1=P2=P3=P4
Demand of Patients with Priority (d_{pt})	300 patients
Total Available Time for Service (c_t)	8h
Service Time for Patient Priority (s_p)	4h
Wait time targets (w_p)	35 days
Service Level (α_p)	90%
Penalty Cost for Delaying Patients (h(p,n))	1 until n=35, increasing 1 unit until n=365

6. Results

The present section presents the results of the presents study. The proposed model was implemented in GAMS language, in a computer equipped with an Intel® CoreTM i5-8250U with 1.80 GHz and 12 GB of RAM.

The main assumptions needed to be taken in consideration are:

- Patients that are not served at the end of the horizon must be served in the next planning horizon.
- The demand is known in advance for the entire horizon.
- Patients do not choose between appointment dates. In the purposed model it is just defined considering the maximum expected appointment time.
- Additional resources availability as nurses, doctors are not being considered in the model.
- No-shows and unpunctuality are not being considered in the model.

6.1 Base Model Results

In the purposed model the demand that is being considered is 300 patients, and the results were able to schedule 299 patients with the parameters considered, the distribution of the patients scheduled per priority level is represented in the figure 2.

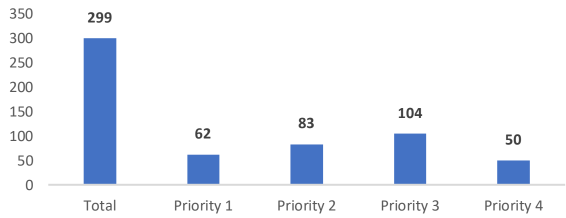


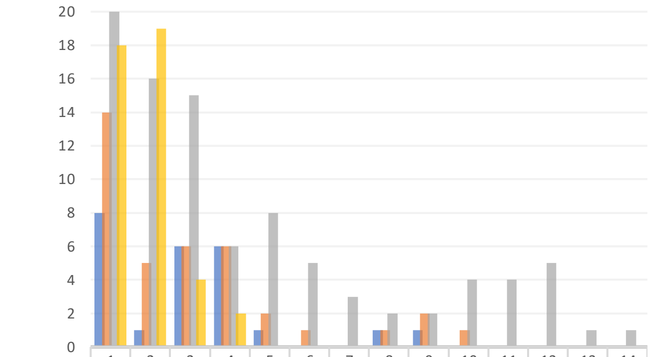
Figure 2 Number of patients attended (Base Model Scenario)

Although the principal objective of the model is to obtain a balanced patient scheduling attending to the patient wait target levels and with that add patient preferences to the model. The current results were effective since from the demand sample 102 patients were attended with 0 days of waiting time. The distribution of patients attended with 0 waiting time per priority is described in the table 5. When considering the results, the solution provided were able to decrease the wait time to 0 for 14% of the patient demand for level 4 of priority, 11% for priority level 3, 54% for priority level 2 and lastly 61% for priority level 1.

Table 5 Number of patients with 0 waiting time (Base Model Scenario)

Patient Priority	*Nº of patients with 0 waiting time*
Level 1	38
Level 2	45
Level 3	12
Level 4	7

Another relevant data is the number of days that the patients is waiting to receive treatment per priority. In the present solution the maximum number of days of wait time achieves is 14 days (n=14). The distribution of the wait time per priority level is described in the figure 3. In the data provided it is relevant to state that for priority level 4 98% of the patients were attended within the wait time target of 3 days, with only 2 patients with 4 days of waiting time. Despite that conclusion, the acuity level was 90% so that restriction was achieved. For the rest of the priority levels the wait time target was achieved (100%) for all the patients.



	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Priority 1	8	1	6	6	1	0	0	1	1	0	0	0	0	0
Priority 2	14	5	6	6	2	1	0	1	2	1	0	0	0	0
Priority 3	20	16	15	6	8	5	3	2	2	4	4	5	1	1
Priority 4	18	19	4	2	0	0	0	0	0	0	0	0	0	0

Figure 3 Number of patients waiting to be scheduled per priority (Base Model Scenario)

6.2 Alternative Scenario

In the purposed model the demand that is being considered is 300 patients, and the results were able to schedule 295 patients with the parameters considered, the distribution of the patients scheduled per priority level is represented in the figure 4.

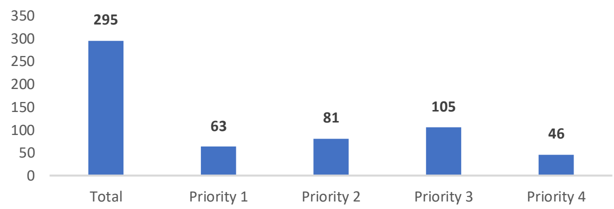


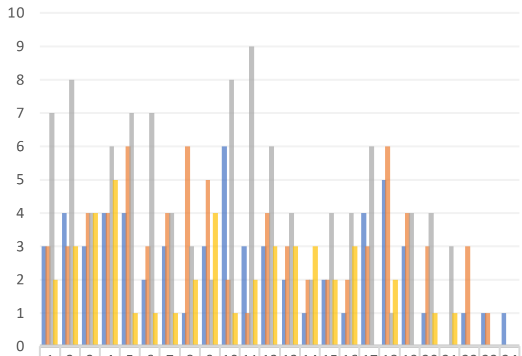
Figure 4 Number of patients attended (Alternative Scenario)

The distribution of patients attended with 0 waiting time per priority is described in the table 6. When considering the results, the solution provided were able to decrease the wait time to 0 for 2% of the patient demand for level 4 of priority, 2% for priority level 3, 8% for priority level 2 and 3% for priority level 1.

Table 6 Number of patients with 0 waiting time (Alternative Scenario)

Patient Priority	*Nº of patients with 0 waiting time*
Level 1	2
Level 2	7
Level 3	2
Level 4	2

As stated before, another relevant data under study is the number of days that the patients are waiting to receive treatment per priority. In the present solution the maximum number of days of wait time achieves was 24 days (n=24). In the data provided it is relevant to state that for the current's scenario the wait time target for all the patients were increased to 35 days, and it is visible that the model is able to schedule all the patients within this time for the required service level (90%). Although and as is going to be analysed in the next chapter and due to the severity of the cancer disease depreciation the patient priorities could have negative effects in the condition of the patients, and it is visible that for higher priority level of patients the waiting time is larger than the expected and this could be a high conditioner for the timely treatment of the patient and his health status. The distribution of the wait time per priority level is described in the figure 5.



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Priority 1	3	4	3	4	4	2	3	1	3	6	3	3	2	1	2	1	4	5	3	1	0	1	1	1
Priority 2	3	3	4	4	6	3	4	6	5	2	1	4	3	2	2	2	3	6	4	3	0	3	1	0
Priority 3	7	8	4	6	7	7	4	3	2	8	9	6	4	2	4	4	6	1	4	4	3	0	0	0
Priority 4	2	3	4	5	1	1	1	2	4	1	2	3	3	3	2	3	0	2	0	1	1	0	0	0

Figure 5 Number of patients waiting to be scheduled per priority (Alternative Scenario)

6.3 Scenario Trade-Off

In this section, it is presented the principal comparisons of both scenarios under analysis. The purpose is to be able to compare the effect that introducing patient priorities has in oesophageal and cancer department scheduling performance. To simplify the analysis the base model scenario is going to be addressed as scenario A and the alternative scenario (absence of priorities) is going to be addressed as scenario B.

The first consideration is that in the scenario A, we were able to schedule more patients than in the scenario B. This states that the scenario A is more effective when minimizing the objective function and balance the number of patients that receive treatment according to the different priority levels as stated previously, in order to obtain a balanced schedule for patient admission.

Furthermore, another relevant consideration is the number of patients with 0 wait time per priority. For all the priority levels it is visible that the number of patients that are scheduled without wait time are superior in the scenario A than in the scenario B (as shown at the figure 6). With that consideration is feasible to say that addressing priorities within the different patients could help the department to decrease the wait time for all the demand of patients.

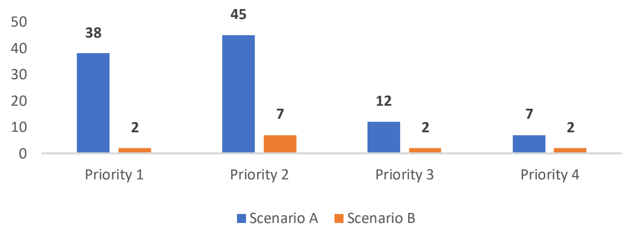


Figure 6 Nº of patients with 0 wait time per priority (Scenario A vs Scenario B)

When analysing the maximum number of days that a patient is waiting to receive treatment, once again in the scenario A we were able to decrease in 10 days the overall waiting time for the overall patient demand. The figure 7 shows the evolution of the number of patients per waiting day. This indicator is especially important to consider, because when considering patients with higher priority for the scenario B we could observe that (figure 22) for example for the priority of level 4 there are 35 patients waiting for more than 3 days for treatment, representing 76% of the patients of this priority and for level 3 there are 9 patients waiting for more than 15 days for treatment representing 8% of the patients of this priority. This scenario provides a solution that could be threatening for the patient health status.

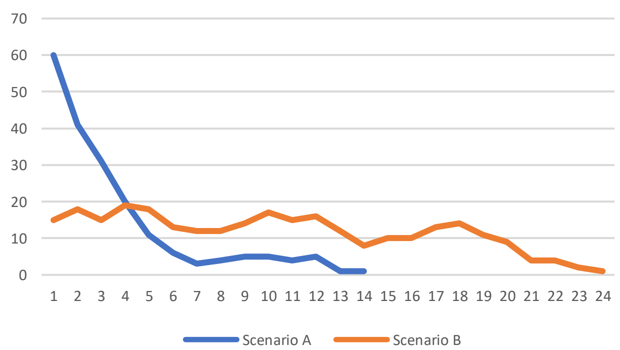


Figure 7 Nº of patients waiting for n days per scenario

The evidence the present chapter provide valid conclusions to say that the performance of the scenario A is better than the scenario B.

7. Sensitivity analysis

After considering the results for both scenarios, it is relevant to test the effect that the variation of the different parameters has in the model performance. For that purpose, through the following sections the service time for patient priorities, wait time targets and service level for the base model scenario are analysed with the purpose of evaluate the model performance. In the case of the service time and the wait time target for patient priorities the values were variated 20% and in the case of the service level it was variated 1 percentual point.

7.1 Service Time for Patient Priorities (s_p)

The principal results for the variation of the service time for patient's priority is presented in the table 7. When analysing the results, we can conclude that when decreasing the service time for patient priorities could be an additional improvement in the model. When decreasing 20% of the service time for each priority we were able to decrease 2 days the wait time target and increase the number of patients with 0 wait time for almost the priority levels. Although this could be an improvement in the model this need to be articulated with the oesophageal and stomach cancer department, because reducing the service time may not be feasible in the real context.

Table 7. Sensitivity Analysis Service Time for Patient Priorities (sp)

Variation	-20%		Base model scenario		+20%	
	Nº of patients with 0 wait time	Max. nº days waiting	Nº of patients with 0 wait time	Max. nº days waiting	Nº of patients with 0 wait time	Max. nº days waiting
Priority level 4	8	4	7	4	8	4
Priority level 3	26	12	12	14	9	15
Priority level 2	41	9	45	8	24	17
Priority level 1	57	2	38	5	20	13
	SUM (132)	MAX (12)	SUM (102)	MAX (14)	SUM (61)	MAX (17)

7.2 Wait Time Targets (w_p)

The principal results for the variation of the wait time target is presented in the table 8. Therefore, it is important to state that it is infeasible to decrease 20% of this parameter for the patients with priority level 4, since it's impossible to attend the demand of this patients with less than 3 days. For the case of this parameter, we can state that for the variation considered, the wait time target doesn't have much effect in the model solution.

Table 1 Sensitivity Analysis Wait Time Targets

Variation	-20%		Base model scenario		+20%	
	Nº of patients with 0 wait time	Max. nº days waiting	Nº of patients with 0 wait time	Max. nº days waiting	Nº of patients with 0 wait time	Max. nº days waiting
Priority level 4	6	4	7	4	4	4
Priority level 3	14	15	12	14	12	15
Priority level 2	44	9	45	8	49	10
Priority level 1	38	10	38	5	39	7
	SUM (102)	MAX (15)	SUM (102)	MAX (14)	SUM (104)	MAX (15)

7.3 Service Level (α_p)

The principal results for the variation of the wait time target are presented in the table 9. It is also stated that when variating in 1pp the wait time target the solution provided don't change much and neither increasing nor decreasing the service level provides a better solution than the base model scenario.

Table 9 Sensitivity Analysis Service Level

Variation	-1 pp		Base model scenario		+1pp	
	Nº of patients with 0 wait time	Max. nº days waiting	Nº of patients with 0 wait time	Max. nº days waiting	Nº of patients with 0 wait time	Max. nº days waiting
Priority level 4	4	4	7	4	9	3
Priority level 3	14	15	12	14	11	15
Priority level 2	47	9	45	8	42	11
Priority level 1	38	9	38	5	35	9
	SUM (103)	MAX (15)	SUM (102)	MAX (14)	SUM (97)	MAX (15)

8. Conclusions

In the present dissertation is developed a mathematical model to help the IPOLFG to optimize the patient flow and the process time of the operations in the RCOS providing an increased patient satisfaction and serving patient's wait time targets. With that in mind, a Multi-Priority Integer Programming model is developed in which patients are prioritized based on their acuity level, assuming that there is a wait time target for each acuity level to ensure that patients of lower acuity do not wait for an unreasonable amount of time while higher acuity patients are being served and through that achieving a balance scheduling for all patients. It was also stated that in the present hospital patient admission there are no rules in the appointment booking since the department receives a waiting list and the first patient that is contained in the waiting list is booked for consultation according to the multidisciplinary group consultation. As concluded in the present dissertation, that method is not the optimal way to increase the efficiency of the patient flow and neglecting patient priorities could lead to catastrophic results due to the condition of the disease in analysis.

Furthermore, the results obtained with the present study provide sufficient evidence that addressing priorities through the demand of patients in the department is more efficient than the patient scheduling method that is currently used in the department.

Despite the dissertation present resolute solution for the hospital patient scheduling, some future work considerations that were not possible to be covered need to be addressed. The first consideration is that the integration of multiple healthcare providers with different levels of expertise must be addressed. It is feasible to consider that the demand of patients requires different type of resources, physical and human. This consideration could help the model to obtain more robust results.

Another future consideration is the condition of patient availability. As presented in the literature review, the demand of patients is not static, and several factor as the punctuality and assiduity of patients could affect the optimal patient scheduling. This uncertainty has not been addressed in the present research and such factor could be an important addition when simulating a model that strives to reflect the real context of the hospital patient flow.

In sum, this study reflects that there is space for increasing the efficiency in the oesophageal and stomach department of the IPOLFG. The principal conclusion is that addressing patient priorities within the scheduling methods decrease the waiting time for the overall demand of patients. Also, it is possible to attend the overall yearly demand of patients with the present resources available, and that consideration is important for the department. Finally, balancing the hospital service time capacity and the patient's wait time expectation is able to bring benefits for both parts since the hospital is able to balance the resources in a more balanced way and with increased efficiency and for the patients it is able to increase the satisfaction without compromising their health status, and in a disease as cancer with the mortal condition that is well known, this could help to save lives.

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