

CASE STUDY

# Discrete-event simulation applied to a radiotherapy process: a case study of a cancer center

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## ABSTRACT

**Goal:** This research aims to investigate how to maximize the throughput and reduce the waiting time for oncological patients of a radiotherapy process.

**Design / Methodology / Approach:** A case study was conducted to develop a simulation model integrated with optimization techniques, including an expert system to support everyday decision making in the operation.

**Results:** The experiments demonstrated that the approach was able to identify better configurations of the process, improving productivity without deteriorating quality. Results also considered the future acquisition of a new linear accelerator allowing the operation to plan its ramp up accordingly. Another result is the devised tool to allow the operation to run its own simulation studies.

**Limitations of the investigation:** The results are valid for processes with similar characteristics of the one studied in the present paper, closing the scope at the treatment stage.

**Practical implications:** This work demonstrates the possibility of applying modern simulation techniques in radiotherapy, not only enabling improvements for the present situation but also integrating the model to the operation to support everyday decision making.

**Originality / Value:** The number of details captured by the model is significantly higher than others studies. The integration of the methodology to the treatment process makes possible for the operation to continue benefiting from the model in a long term.

**Keywords:** Discrete Event Simulation; Radiotherapy; Scheduling; Optimization; Cancer Clinics.

## 1. INTRODUCTION AND BACKGROUND

More than 14 million new cases of cancer are diagnosed globally each year, and among other types of treatment, radiotherapy (radiation therapy) has the potential to improve the rates of cure of 3.5 million people and provide palliative relief for an additional 3.5 million people (Jaffray and Gospodarowicz, 2015). The patient waiting time from the point of referral to the point of starting treatment is a major concern considering its relationship with the patient's overall survival and quality of life. In this context, there have been studies in the literature applying Operational Research techniques such as discrete event simulation techniques (DES) to find ways of reducing patient waiting time.

Radiotherapy is a treatment that uses radiation to destroy or prevent the growth of tumor cells, control bleeding and pain, and reduce tumors that are compressing other organs. It is a treatment modality that uses ionizing radiation to eliminate the abnormal cells of a tumor or,

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at least, to prevent its proliferation. During radiation therapy, some normal cells can also be damaged, but in this type of treatment, normal cells have a better ability to recover from radiation damage. External-beam radiation therapy is the most common type of treatment where a linear accelerator machine (linac) is used to aim high-energy rays at the tumor from outside of the body.

Zubizarreta et al. (2017) report that the actual coverage of needs to provide full access to radiotherapy globally ranges from 34% in Africa to over 92% in Europe. There are more than 7500 radiotherapy centers worldwide, and over 7000 additional centers needed which is evidence that maximizing the throughput of the existent centers has a great social and economic appeal, especially to developing countries where high gaps are found.

In this context, this paper proposes a discrete-event simulation model for the treatment stage of a local radiotherapy center in Brazil. The objective is to understand through simulation and optimization techniques the relationship of the variables that impact the throughput and, consequently, the waiting time of the patients.

The main contributions of this paper are:

1. A higher number of details captured by the modeling of the treatment stage when compared with the related literature.
2. The utilization of optimization techniques with simulation to better evaluate the process.
3. The development of an expert system for the operation to support everyday decision making.

Our literature review showed that a vast majority of papers modeling radiotherapy processes focus on modeling the whole process, which is a plausible attempt because it may provide insights about issues in any part of the process. On the minus side, we have identified flaws in these models that potentially affect their validity and reliability. Among many reasons, we quote the lack of precise data to properly represent the behavior of all steps (for instance, the duration time of all tasks and doctors' shifts) and the lack of a rigorous statistical analysis both regarding the input and output data. By closing the scope in the treatment stage, we favor to capture in details all the nuances of the operation, not only analyzing the current situation and possible scenarios but also building a friendly tool that stays in the operation for its day-to-day routine, reinforcing the legacy of the present work.

The paper is structured as follows. We give a literature review in Section 2 specifically related to radiotherapy, followed by the description of the simulation model in Section 3. Next, in Section 4, we present experiments and results regarding the validity of the model, tested scenarios, variables relationship, and optimization. We also explain the expert system built for the operation. Finally, the main findings and conclusions are highlighted in Section 5.

## 2. LITERATURE REVIEW

Operational Research and Production & Management techniques have been largely applied to hospitals operations (Chang Junior et al., 2019). In radiotherapy, simulation techniques have been applied over the years and the related literature is listed in Table 1 showing a classification based on the problem characteristics and situating this paper in the literature.

Table 1 presents five categories where the first identifies the simulation technique used to model the process: DES (Discrete Event Simulation), SD (System Dynamics), MCS (Monte Carlo Simulation). The second category refers to the platform or software used to apply the simulation technique. The third category gives information about the scope of the studies where it is found that most of them (9 out of 16) approaches the whole radiotherapy process comprising the planning and treatment stages. Four papers are tackling the planning stage that includes the steps preceding the execution of the treatment as mentioned in Section 1. There are also studies approaching specific steps of the process: consultation step by Joustra et al. (2010), quality assurance by Pooya et al. (2014) targeting the verification points of the process, and the treatment stage by the current paper.

The fourth category refers to the main output metrics used by the authors to assess different scenarios of the process, where 11 studies used directly the RTTT emphasizing their

concern with the patient waiting time to start radiotherapy sessions. The other studies focus on metrics that assess one specific part of the process but still related to the RTTT. Joustra et al. (2010) use the waiting time for the first consultant, and naturally, the longer it is, the longer it takes for the patient to start treating. Analogously, Pooya et al. (2014) study the time interval between incidents (TIBI) which is directly related to the RTTT. Also, the current paper by proposing solutions to maximize the throughput of the treatment stage contributing then to the reduction of the RTTT.

**Table 1:** Literature classification based on the study characteristics

Reference	Technique	Platform	Scope	Main outputs	Main variables
Munro and Potter (1994)	MCS	Excel	planning & treatment	RTTT	demand
Thomas et al. (2001)	MCS	C++	planning & treatment	RTTT	demand; machine quantity
Thomas (2003)	MCS	C++	planning & treatment	RTTT	demand; machine quantity
Proctor et al. (2007)	DES	Simul8	planning & treatment	RTTT	demand, # oncologists, # technicians, # other resources
Kapamara et al. (2007)	DES	Simul8	planning & treatment	RTTT	demand, # oncologists, # technicians, # other resources
Werker et al. (2009)	DES	Arena	planning	planning time	capacity; # resources (therapists; physicists)
Joustra et al. (2010)	DES	not mentioned	consultation	first consultant time	# consultations; # regular and urgent patients
Morgan et al. (2011)	DES & SD	not mentioned	planning & treatment	RTTT	# oncologists, # technicians, # other resources
Oddiraju and Mutic (2011)	DES	Arena	planning	RTTT	incident stage; demand
Pooya et al. (2014)	DES	Arena	quality assurance	TIBI; throughput	incident stage
Morgan et al. (2016)	DES & SD	not mentioned	planning & treatment	RTTT	# oncologists, # technicians, # other resources
Babashov et al. (2017)	DES	Simul8	planning & treatment	RTTT	# oncologists, # technicians, # other resources
Saberi and Awasthi (2019)	DES	Arena	planning & treatment	RTTT	# oncologists, # technicians, # other resources
Vieira et al. (2019)	DES	Siemens PLM	planning	RTTT	# patients; push/pull scheduling
Bauza and Chow (2019)	MCS	Matlab	planning	workload balance	physicist on call schedule
Current paper	DES	Arena	treatment	treatment waiting time; throughput	scheduling; # technicians; demand; slot length for treatment

Finally, the last category of Table 1 lists the main variables used in the experiments in which values have been changed to study their impact on the output variables. The level of demand (number of patients) and the number of resources such as therapists, physicians, technicians, and linacs are the most common variables studied.

Among more recent papers, Morgan et al. (2016) give a valuable contribution by studying how SD can be used to support the DES model. While the SD model captures the dynamics of how the radiotherapy department responds to increasing referral to first treatment times, the DES model was used to provide more representative insights into the knock-on impact of altering the treatment time or the number of treatment fractions for different groups of patients.

Babashov et al. (2017) analyzed the radiotherapy planning process at the London Regional Cancer Program to determine the bottlenecks and to quantify the effect of specific resource levels with the goal of reducing waiting times. It was found that increasing the number of dosimetrists by one, reduced the mean RTTT by 6.55%, leading to 84.92% of patients being treated within the 14-calendar day target. Adding one more oncologist decreased the mean RTTT from 10.83 to 10.55 days, whereas a 15% increase in arriving patients increased the waiting time by 22.53%.

Saberi and Awasthi (2019) is an extension of Werker et al. (2009) providing a broader view of the process. They suggest including palliative and radical priority patients at the beginning of the process helps to start the process treatment sooner for the patients who are palliative and close to the highest stages of cancer.

Vieira et al. (2019) study the planning stage, especially the effect of two scheduling policies for the first irradiation session: pull strategy and push strategy. In the first strategy, the first session is set right after consultation; in the second, it is set after the planning stage has been completed. Results showed that increasing the pull strategy reduces the average number of patients starting treatment after their due date.

Bauza and Chow (2019) applied Monte Carlo Simulation to study a specific variation of the problem that refers to the emergency radiotherapy in a cancer center. The objective was to improve the scheduling of the physicists by maximizing the workload generating fairer planning among the physicists.

The literature review has also identified significant limitations in these works. Morgan et al. (2016) does not provide details of the simulation model and the software used to run the simulation. The input data is not listed, as well as the data collection method, and task times are estimated by interviews. Babashov et al. (2017) provide few details of the simulations model, using descriptive statistics but without the support of inferential statistical analyses such as hypothesis tests and regressions. According to the authors, because task times were not available through the tracking database, the staff was interviewed to estimate the duration of several tasks. Additionally, other data estimates were obtained through model calibration. Saberi and Awasthi (2019) utilize triangular distributions for many input data which suggests that these data are estimated from interviews. Experiments report results from only three replications, and no hypothesis test has been provided to validate the model. An optimization problem is solved with no justification for the objectives and constraints.

From the aforementioned, the inattention to the application of the best simulation practices may affect the validity and reliability of the studies. It is expected to properly list the input data of the model as well as the probability distributions functions used to approximate the random variables supported by a goodness of fit statistical test. The model should be validated by using proper statistical tests as well as the number of replications used in the experiments. Whenever possible, time studies should be preferable over interviews. The attention to points like these is one difference between our paper and others.

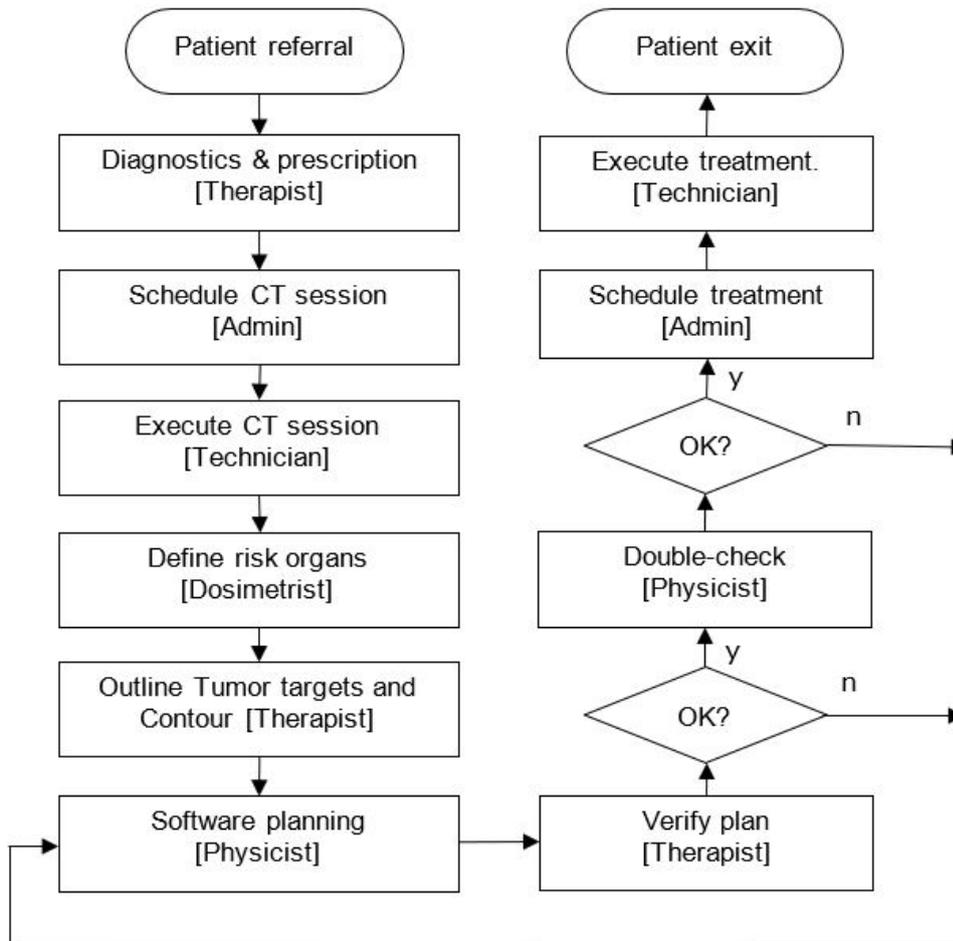
Another difference is that the current paper closes the scope on the treatment stage, capturing details of the operation such as the existence of unscheduled patients; patient absences; dropouts; scheduling; queue policies, and many others; improving the representativity of the model when emulating the real system. An optimization with simulation model is solved to study scenarios that a human would unlikely think by himself. We also build a friendly tool that has been used by the operation, cementing the legacy of the present work.

### 3. SIMULATION MODEL

This section describes the developed discrete-event simulation model. The modeling consists of firstly developing a conceptual model through an Activity Cycle Diagram (ACD), flowchart, and causal diagram. Next, we describe the data collection process, statistical treatment, and modeling of the input data; and finally, the development of the computational model used to carry out the experiments.

### 3.1 – Conceptual Modelling

During the conceptual modeling, it is appropriate to map the process and understand its context. A radiotherapy center that works with external-beam radiation therapy is mainly comprised of human resources (administrative staff, therapists, dosimetrists, medical physicist, technicians) and machine resources (linear accelerators, mold apparatus, computed axial tomography).



**Figure 1:** Process Flow Chart of a typical radiotherapy process

Figure 1 presents a basic flowchart with the main tasks performed by the human resources, where initially the patient has a consultant with the therapist to have a diagnostics and prescription; next a member of the administrative staff schedules a session for a computed axial tomography (CT) scanner that generates 3D images of the tumor and its neighborhood; then a technician performs the scanning. Still in this step, depending on the tumor (head and neck for example), before going to the CT, the technician goes to a mold room to produce a mask for the patient. Hereafter, a dosimetrist imports such images to draw the organs of risk using specific software. After that, a radiation therapist is responsible for prescribing the radiation dose, number of sessions, and for drawing the target areas around the tumor using the images previously processed by the dosimetrist. In the next step, a medical physicist performs the treatment planning using a specific software where it is defined the method to be used in the treatment, the linac configuration such as machine and table positions, number of radiation fields, and others parameters aiming to deliver the prescribed dose by the therapist. The therapist checks if the treatment plan holds all medical constraints, and if approved, a physicist (usually one who did not perform the treatment plan) makes a final check. In both verifications, if there is something wrong, the physicist performs the

necessary adjustments. Finally, the administrative staff can schedule the treatment sessions that are performed by the technicians using a linear accelerator.

A typical performance metric of the process is the elapsed time from the patient referral until the first session of treatment, and sometimes this metric is referred to as ready-to-treat to treatment (RTTT) à la Babashov et al., 2017. It is common to split the process into two stages: planning and treatment, where the first refers to all steps preceding the execution of the treatment, and the second the treatment itself.

Differently from the first stage, the treatment stage is repeated many times over the days for the same patient. The treatment is comprised of fractions, where a fraction is the base unit of treatment during a visit to the radiotherapy department, delivered at daily intervals. A phase of radiotherapy treatment comprises several treatment fractions and a single course of treatment is designed around a single treatment regime of one or more phases, requiring one or more treatment plans to be created by the therapist and physician. Note that the complexity of these plans can vary for the different cancer types and the characteristics of the patient’s disease (Morgan et al.,2016).

Because the treatment stage is a repetitive task, where it is common to have a plan lasting more than 20 sessions, it usually has the largest number of employees, in this case, technicians. It also utilizes the linear accelerator which is the most expensive resource of external-beam radiation therapy. Because of the high volume of sessions, this operation must work with high productivity levels, otherwise it becomes a bottleneck of the whole process, affecting the waiting time of the patient (RTTT). These reasons make this stage particularly important, so it is the focus of the present work.

During the modeling, it is also appropriate to identify what is important in the system in order to bring its effects to the model. The nature of the problem is summarized by the causal diagram in Figure 2 which helps to understand relevant variables of the process and their relationship with each other.

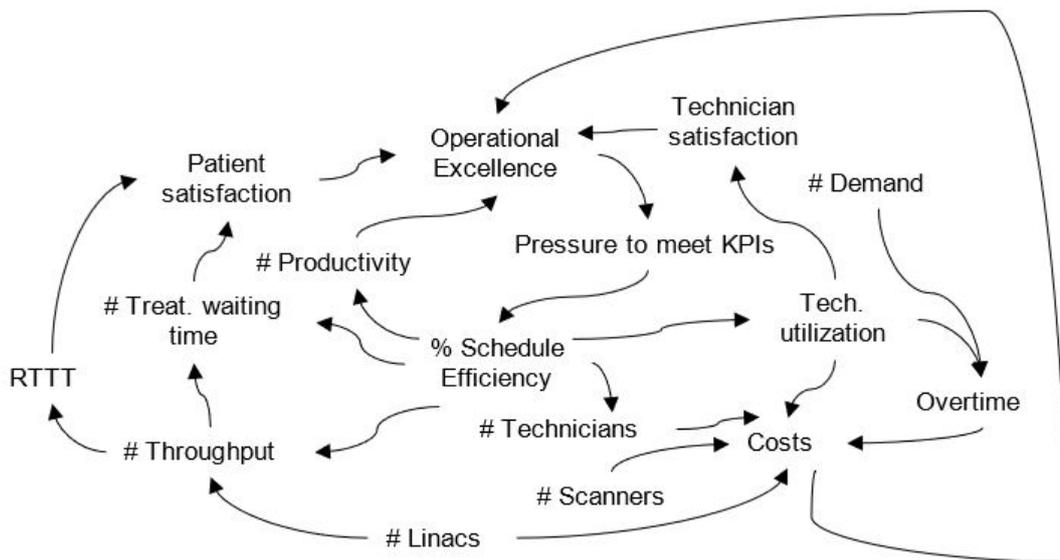


Figure 2: Causal Diagram

In Figure 2, by aspiring operational excellence, the process creates pressure for meeting KPIs, encouraging higher scheduling efficiency that may result in higher utilization of the technicians, reducing overtime, and consequently, costs. It is also possible to see, among many other relations, that the better the scheduling, the higher the throughput, the smaller the RTTT, the higher the patient satisfaction.

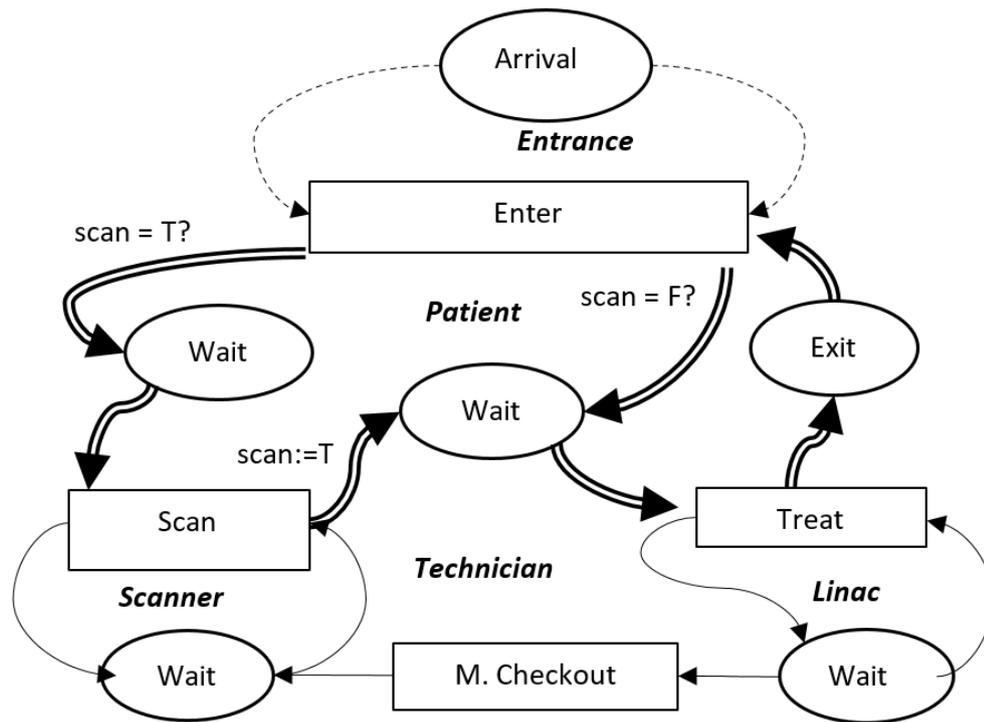


Figure 3: Activity Cycle Diagram

Figure 3 presents the ACD of the model with the life cycle of the main entities and resources. The double arrows refer to the life cycle of the patient, once into the process, if the patient has been already scanned by the CT machine, the patient goes to treatment, otherwise, the patient goes for scanning. Therefore, in the perspective of the patient, considering the scan is performed only once and the number of treatment sessions is numerous, in a typical day, the patient arrives at the radiotherapy department, stays in the waiting room until being called by the technician, then entering the linac treatment room, receiving the treatment and finally leaving. Still, in Figure 3, it is seen in the life cycle of the technicians that this resource is shared between the activities “Scan”, “Treat” and “Morning Checkout”, therefore despite the fact that the CT is in the planning phase of the process, it has to be included in the model of the treatment stage.

Figure 4 is a process flowchart that focuses on the technicians considering they are the ones who provide the service for the patient during the treatment sessions. The first activity performed by the technician at the beginning of the day is the “Morning Checkout” to confirm that the machine is ready for utilization. The counters  $r$  (number of patients treated in the current day) and  $q$  (number of available technicians for treatment) are initialized. If there are at least two technicians available, then the treatment session is performed with duration time  $t_2$ ; if there is only one technician, the session is performed with duration  $t_1$ , where  $t_2 < t_1$ ; otherwise the activity waits for the technician. Although the ideal number of technicians in the treatment room is at least two, there might be situations along the day where a technician leaves temporarily the treatment room, such as attending to a CT session, where may remain only one technician to perform the treatment. In this case, the technician takes longer to position the patient on the linac table, operate the machine, and remove the patient from the table. This behavior is also showed in the flowchart, where if there is a call from CT station, one technician goes to the CT (decrementing  $q$ ) while the remaining technicians perform the treatment session (if all planned patients  $p$  have not yet been treated).



**Table 2:** Input data

Input	Expression	Measure Unit
Duration of Treatment session (T2) ( $\geq 2$ tech.)	$5 + 12 * BETA(1.02, 2.69)$	minutes
Duration of Treatment session (T1) (1 tech.)	$5 + LOGN(6.18, 4.24)$	minutes
Number of scheduled patients (Q)	$round(N(92.1, 2.65))$	units
Time between unscheduled patients (TBUP)	$EXP(3.9)$	units
% of absence	4%	units
Dropouts	Conditional Probability	units
Process working time (WT)	912	minutes
Shift working time	288	minutes
Technicians start time (scheduling)	Schedule1	minutes
Lunch time	48	minutes
Duration of Morning Checkout (DMC)	$N(14.9, 2.1)$	minutes
Duration of CT session (DCT)	$N(12.1, 3.2)$	minutes
CT working time	[8:00 – 12:00; 14:00 – 17:00]	HH:MM
Time between CT session calls (TBCT)	$EXP(1.5)$	hours
Process interruptions (uptime)	$EXP(2.5)$	hours
Process interruptions (downtime)	$N(8.2, 2.9)$	minutes
Slot length (SL)	10.0	minutes
Number of slots with duplicated schedules	$round(GAMM(5.78, 0.964))$	units
Arrival time deviation from scheduled time ( ATD )	$-20 + GAMM(19.7, 2.3)$	minutes

The scheduling refers to the start time of the technicians. Because it is not possible to attend the demand in one technician shift of 288 minutes, the technicians have to be spread along the day. Table 3 provides the current scheduling.

**Table 3:** Scheduling

Technician ID	Start time	Lunch time	End time
ID1	06:30	-	11:18
ID2	06:54	-	11:42
ID3	08:06	-	12:54
ID4	10:30	12:06	16:06
ID5	12:06	-	16:54
ID6	12:54	-	17:42
ID7	14:06	-	18:54
ID8	16:54	-	21:42
ID9	16:54	-	21:42

There are also many situations where the operation is paused such as machine problems, doubts where the technicians consult the physicists, room cleaning, hospital events, etc. We found it possible to group all these interruptions by generating one event every  $EXP(2.5)$  hours of duration  $N(8.2, 2.9)$  minutes.

### 3.3 – Computational model

The computational model is presented in Figure 5 and Figure 6. It was implemented using the commercial simulation software Arena™, on a desktop computer with two Intel™ Core processors i7™3, 1GHz with 8GB of RAM and Windows™ 10 operating system. The model simulates workday events of the treatment stage, where the patients are the entities that flow through the system, and the technicians, linac and CT are the resources.

For the sake of organization, we have labeled the modules of the model by row and column to facilitate references in Figure 5. The main attributes of the entity “patient” are: arrival time, start time of treatment, scheduled time, treatment time, patient delay, process delay, process anticipation.

The main flow starts at module R3C1 that generates  $Q$  scheduled patients to be treated at the day. Next, in R3C2, it is assigned the scheduled time of the patients. In R3C3, if the patient is absent (4% probability), it leaves the system (R4C5), otherwise it moves on to R3C4 that imposes a delay to the entity. The entity leaves this module at the time equivalent to the arrival time of the patient in the waiting room of the facility. Note that  $Scheduled\ Time(ST) - Arrival\ Time(AT) = Deviation(ATD)$ , therefore the delay in R3C4 is  $AT = ST - ATD$ , where  $ATD$  is the random variable listed in Table 2. This is important because the patient can arrive before or after the scheduled time impacting the queue order when called by the technicians. That is the reason we don't simply use the time between arrivals but the deviation from the scheduled time. Following, the arrival time is captured in R3C5. Next, R3C6 seizes the resources “technicians” and “linac”, with queue policy of type “Lowest Attribute Value” for the attribute “arrival time”. By doing so, the patients that already arrived in the waiting room are ordered by scheduled time, allowing to properly calculate the waiting time of the patient.

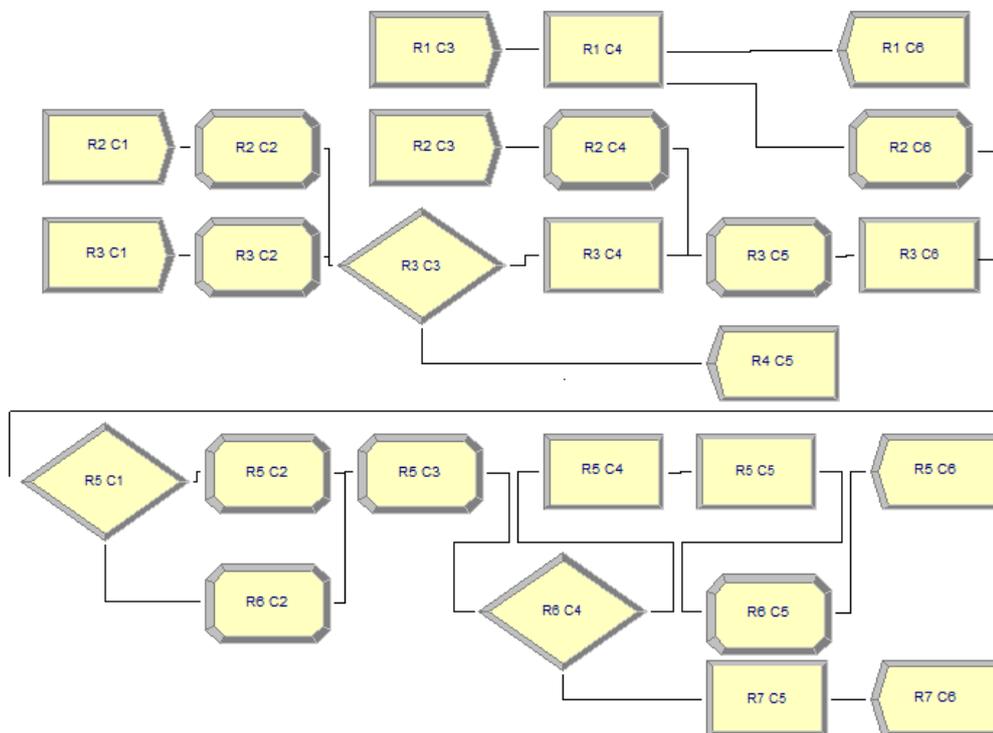


Figure 5: Computational model

In R5C1, if the patient is not late, it goes to R5C2 where the attribute “process delay” is computed by the expression:  $(TNOW - ST) * ((TNOW - ST) > 0) + (0) * ((TNOW - ST) \leq 0)$  where  $TNOW$  refers to the simulation time the entity entered into the module. Otherwise, it goes to R6C3, where the attribute “patient delay” is computed by the expression:  $AT - ST$ . Module

R5C2 assigns value  $TNOW$  for the attribute “start time of treatment” and the attribute “process anticipation” is updated with value:  $(ST - TNOW) * ((ST - TNOW) > 0) + (0) * ((ST - TNOW) \leq 0)$ . In module R6C4, if the entity refers to a patient dropout, it goes to R7C5 (read & write module) that writes into an Excel file statistics of the entity and after that the entity leaves the system. Otherwise, it goes to R5C4 (delay-release module) that delays the resources “technicians” and “linac” by  $T1$  or  $T2$  minutes and releases them. Module R5C5 writes into an Excel file attributes values of the entity, R6C5 updates auxiliary variables such as the time of the last patient, and finally, the entity leaves the system.

Another flow is started in R2C1 that generates entities related to the patients scheduled in slots already busy. This is a practice of the operation where, for example, instead of reducing the slot length to have more slots for scheduling, they double schedule one slot a certain number of slots. R2C2 assigns the schedule time picking a slot using a uniform distribution  $U[a,b]$  where  $a$  is the completion time of the morning checkout and  $b$  is the planned process closing time. There is also a flow starting at R2C3 regarding the unscheduled patients that creates an entity every  $TBUP$  hours, and R2C4 assigns the schedule time (value  $TNOW$ ) then moving to the main flow. The last flow models the dropout, where R1C3 creates an entity every 1 minute that triggers the “search & remove” module R1C4 that checks the linac queue according to the criteria already explained. If any entity (patient) in the linac queue meets such criteria, the entity is removed from the queue and goes to R2C6 where it receives an attribute  $dropout = true$ , it is separated from the flow in R6C4 and its statistics collected in R7C5.

There are other separated modules to create CT call, the activity morning checkout seizing “linac” an “technician”, a VBA module with an algorithm to initialize variables and replicate the logic used by the operation to assign lunch time for the technicians.

## 4 – EXPERIMENTS AND RESULTS

### 4.1 – Preliminary experiments and validation

Firstly, preliminary experiments were executed to determine the appropriate number of replications to be used in further experiments. The system is said terminal, where each replication of the model emulates one workday of the operation, with a given start time, including the events and statistics under transient regime. The number of replications has been calculated based on Law et al. (2000) by a rearrange of the confidence interval formula. The results for 10 initial replications, 95% confidence level, for the metrics “exit time of the last patient” ( $ET$ ) and “process delay” ( $PD$ ), determined 24 replications to be used in the following experiments.

In order to validate the model, we have performed one experiment using the current values of input data of the operation to compare the model output with the real system output for the responses  $ET$  and  $PD$ . We performed a t-test assuming equal variances to compare the means (after Levene’s test), with 95% confidence level. Table 4 and Figure 6 shows that there are no significant statistical differences for both responses evidencing that the model behavior reflects the real world.

**Table 4:** Comparison with the real system

	$ET$ (model)	$ET$ (real system)	$PD$ (model)	$PD$ (real system)
Mean	871.55	869.42	11.47	12.77
Standard Deviation	16.84	18.65	6.51	6.93
$p$ -value (variance)		0.183		0.540
$p$ -value (mean)		0.810		0.535

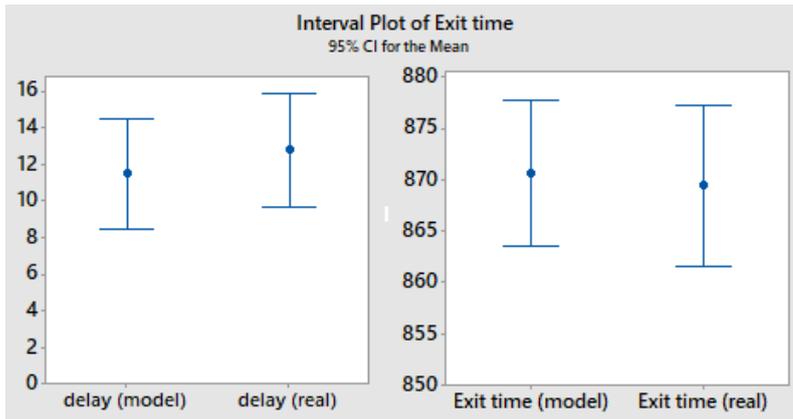


Figure 6: Interval plot for means

### 4.2 – Factorial experiments

In this section, a factorial experiment is conducted with two responses ( $ET$  and  $PD$ ) and three factors: number of scheduled patients ( $Q$ ), slot length ( $SL$ ) and slot duplication ( $D$ ); with factor levels  $[80, 90, 100, 110]$ ,  $[8.5, 9.0, 9.5, 10]$  and  $[true, false]$  respectively; totaling 32 experiments which results are given in the Appendix section, so here we focus on the analysis of the results.

Figures 7 to 10 show the main effects plot and interactions plot for  $SD$  *false* and *true*, where each dot is the mean result for its respective case. In Figure 7, we see that  $ET$  increases substantially when  $Q$  increases from 80 to 110, and that this increase is less significant for changes in  $SL$  and  $D$ . Regarding the interactions (Figure 8), the change in  $ET$  is similar for different levels of  $SL$ . For moves in  $SD$ , the effect of changes in  $Q$  is similar within the range  $80 \leq Q \leq 100$  and significantly higher for  $Q = 110$ ; and the effects of changes in  $SL$  is small for  $D = true$ .

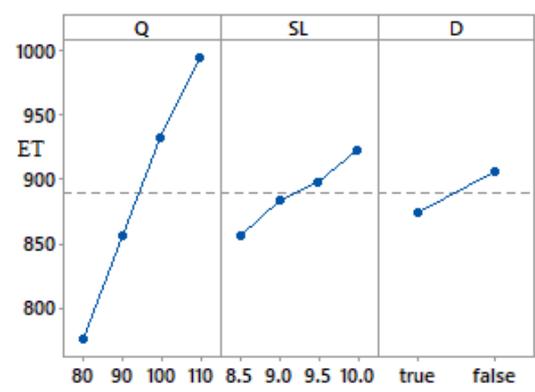


Figure 7: Main Effects Plot for ET

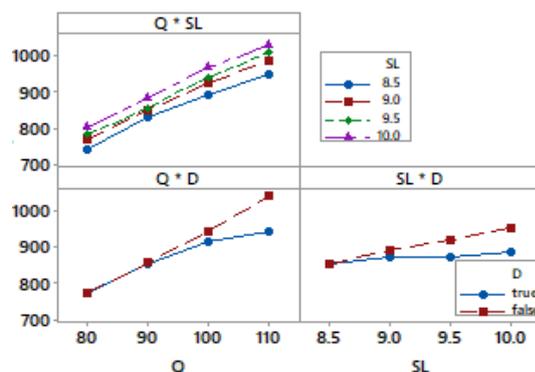


Figure 8: Interactions Plot for ET

With respect to the response  $PD$ , in Figure 9, the patients have to wait much more when  $Q$  moves above 90 and much less when  $SL$  is increased; for changes in  $D$ , there is a slight difference. Regarding the interactions (Figure 10), the changes in  $PD$ , when  $Q$  moves to higher levels, are different depending on the  $SL$  value; and there are also differences for changes in  $D$ . Figure 11 offers another visualization of how changes in the factors  $SL$  and  $D$  affect the responses  $ET$  and  $PD$ , for  $D=true$ . It is also seen that changes in the factors have opposite effects in the responses.

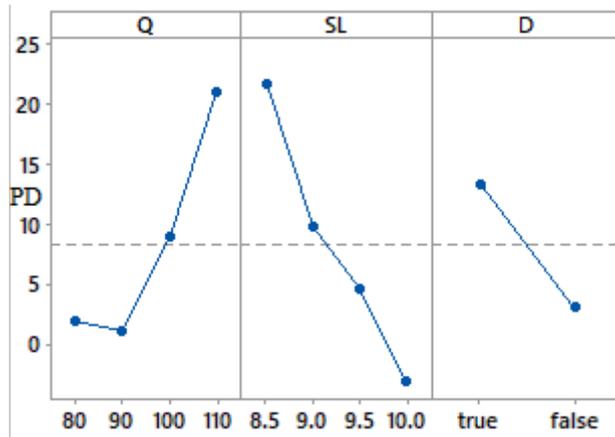


Figure 9: Main Effects Plot for PD

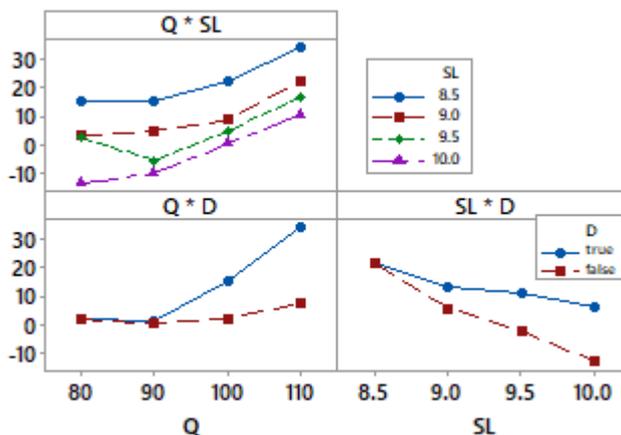


Figure 10: Interactions Plot for PD

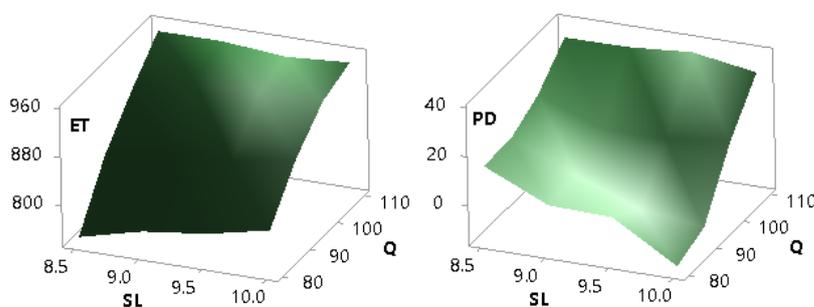


Figure 11: Surface Plot; Slot Duplication = true

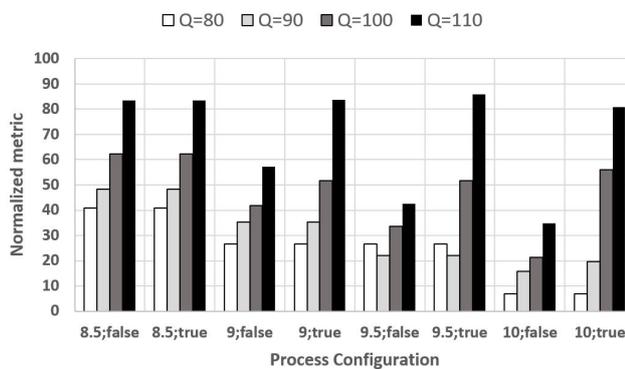
Elaborating on the results, Table 5 provides multivariate regression equations that makes possible for the operation to predict the responses for any values of the factors within the tested ranges. A Backward elimination procedure with  $\alpha$  (significance level) equal to 0.1 has been applied

to remove not significant terms. The high values of the adjusted and predicted  $R^2$  indicate that the predictors  $SL$  and  $D$  explain most of the variance in the responses  $ET$  and  $PD$ ; and because the adjusted and predicted  $R^2$  are close, the model does not appear to overfit and has an adequate predictive ability. No issues have been found regarding the residuals.

**Table 5:** Multivariate Regression

D	Regression Equation	$R^2 (adj)$	$R^2 (pred)$
False	$ET = 1688 - 14.56Q - 176.5SL + 2.543Q * SL$	98.93%	98.25%
	$PD = -57 + 1.30Q + 19.7SL + 0.01563Q^2 - 0.441Q * SL$	93.75%	86.26%
True	$ET = -2212 + 43.01Q + 148.7SL - 0.1303Q^2 - 1.346Q * SL$	99.03%	98.83%
	$PD = 963 - 13.69Q - 67.9SL + 0.04800Q^2 + 0.614Q * SL$	94.51%	92.40%

Considering all these analyses, in practical terms, it is useful to provide the operation a mean of selecting the best configuration in terms of  $SL$  and  $D$ , for different scenarios of  $Q$ . Figure 12 aims to make it possible. Because of the different order of magnitudes of the responses, the values for the results of the 32 tested scenarios have been normalized to a standard scale from 0 to 100 equivalent to the minimum and maximum values respectively, using linear interpolation. Remind that, also in this scale, the lower the values of the responses, the better. Because of the conflicting nature of the responses, we have weighted both of them, with 30% for  $ET$  and 70% for  $PD$  after alignment with the operation manager. By doing so, for example, if the operation plans to work with a volume of patients close to 110, by looking at Figure 12, for  $Q = 110$ , it is seen the configuration with  $SL = 10$  and  $D = false$  is the one that provides the best performance.



**Figure 12:** Performance for different scenarios

### 4.3 – Space search experiments

The previous experiments have considered three decision variables ( $Q, SL$  and  $D$ ). Another decision variable that can impact the performance of the operation is the scheduling of the technicians, i.e., the entrance time of each of them. Considering there are 9 technicians working in the operation, that represents additional 9 decision variables. For this case, the number of possible combinations among the variables is too high, characterizing a combinatorial problem, where optimization techniques are required to select the best values for these variables.

By doing so, the optimization model consists of a problem which objective (Equation 1) is to maximize the throughput ( $Q$ ) subjected to the constraints described in Equations 2 to 6; where  $PD$  must not exceed 15 minutes; the number in queue  $NQ$  (patients in the waiting room) must not exceed 8 patients; number of dropouts  $ND$  must not exceed 2 patients; and the exit time  $ET$  must not exceed 927 minutes which means up to 15 minutes of overtime, considering 912 minutes of process working time.

- $Max Q$  (1)
- s.t. (2)
- $PD \leq 15$  (3)
- $NQ \leq 8$  (4)
- $ND \leq 2$  (5)
- $ET \leq 927$  (6)

The decision variables are described in Table 6, where  $ST_i$  refers to the start time of the technician  $i$  where  $i \in \{1, 2, \dots, 9\}$ .

**Table 6:** Decision variables for the optimization model

Variable	Type	Lower Bound	Upper Bound	Increment
$SL$	discrete	8.0	10.0	0.25
$D$	Boolean	false	true	-
$ST_i$	discrete	0	624	24

The problem has been solved using the solver OptQuest™ that is a module of the simulation software Arena™ combining the metaheuristics of Tabu Search, Neural Networks, and Scatter Search into a single search heuristic. For each run of the optimization, 24 replicas of the simulation model are executed and the average values among the replications are calculated to check the constraints. The results are showed in Table 7 where, in simulation time, minutes 0 and 912 are equivalent to the operation starting time 6:30 and closing time 21:42, respectively. It is seen that when compared with the original values used by the operation, some technicians are scheduled to arrive earlier and the slot length changed from 10 to 9 minutes. The output  $Q$  and its 95% confidence interval are showed at the bottom of the table.

**Table 7:** Opt. Results

Dec. Variables	Original	Opt.
$ST_1$	0	0
$ST_2$	24	24
$ST_3$	96	96
$ST_4$	240	192
$ST_5$	336	312
$ST_6$	384	360
$ST_7$	456	456
$ST_8$	624	600
$ST_9$	624	624
$SL$	10	9
$D$	true	true
$Q$	98.4	107.1
95%CI	[95.5;101.3]	[104.2;110.0]

#### 4.4 – Space search experiments for two linacs

The operation is acquiring a second linear accelerator, and the manager has expressed his concern about the configuration of the operation, including the number and scheduling of technicians. We have modified the model described in Section 3 to operate with two machines, where each machine has its own scheduled patients. It has been decided to have both

machines in the same model instead of individual models for each machine because there is a relationship between the machines. For example, when a technician is called to a CT session, the technician of the linac with the lowest number of patients in the queue is the one to attend the session.

The optimization model is described in Equations 7-12, where  $j \in \{1,2\}$  is the linac index. The decision variables are:  $SL_j, D_j$  and  $ST_i$  where:  $i \in \{1,2,\dots,I\}$ ,  $I$  is the number of technicians. The problem has been solved for  $I = 9, 10, \dots, 14$ .

$$Max Q_1 + Q_2 \tag{7}$$

$$s.t. \tag{8}$$

$$PD_j \leq 15, \forall j \in \{1,2\} \tag{9}$$

$$NQ_j \leq 8, \forall j \in \{1,2\} \tag{10}$$

$$ND_j \leq 2, \forall j \in \{1,2\} \tag{11}$$

$$ET \leq \max(ST_i) + 15 \tag{12}$$

In Table 8, it is possible to see how the throughput ( $Q_1 + Q_2$ ) increases with the number of technicians. There are a few differences in the schedule for different values of I. It is observed that it is possible to schedule 196 patients using 14 technicians which represents a substantial productivity increase when compared with the current operation scenario with 92 patients using 9 technicians. It supports the usefulness of the optimization model that provides more flexibility in terms of configuration to better adjust with the stochastic behavior of the operation.

**Table 8:** Opt. Results for two linacs

Dec. Variables	I=9	I=10	I=11	I=12	I=13	I=14
$ST_1$	0	0	0	0	0	0
$ST_2$	24	24	24	24	24	24
$ST_3$	192	168	192	192	264	264
$ST_4$	312	312	360	360	312	312
$ST_5$	336	360	504	504	528	528
$ST_6$	0	0	528	528	600	600
$ST_7$	24	24	0	0	624	624
$ST_8$	240	192	24	24	0	0
$ST_9$	288	312	168	216	24	24
$ST_{10}$	-	360	312	360	216	240
$ST_{11}$	-	-	360	528	360	288
$ST_{12}$	-	-	-	528	528	528
$ST_{13}$	-	-	-	-	528	600
$ST_{14}$	-	-	-	-	-	600
$SL_1$	9	8.5	8.5	9	8.5	9
$SL_2$	9	9	9	9.5	9	9
$D_1$	1	0	0	1	0	1
$D_2$	1	1	1	1	1	1
$Q_1 + Q_2$	133.1	140.2	159.1	178.3	188.2	196.3
95%CI	[129.1;137.1]	[136.1;144.3]	[154.4;163.8]	[173.2;183.4]	[182.2;193.9]	[190.4;202.2]

#### 4.5 – Developed tool

The operation is situated in the hospital Hélio Angotti, city of Uberaba, state of Minas Gerais, Brazil, where patients from an area covering more than 30 cities are treated, as

illustrated in Figure 13. Nowadays, the Hospital has about 45 physicians and 433 employees, contributing to the social impact of the region by offering outpatient services, diagnostic imaging (installed capacity to perform more than 7,000 tests / month), nuclear medicine (about 800 tests / month), chemotherapy (approximately 400 consultations / month) and radiation therapy (over 1800 sessions per month).

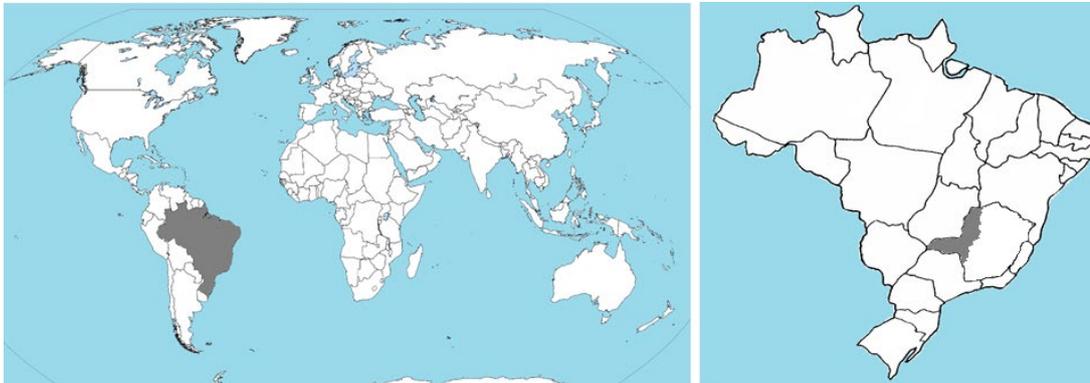


Fig 13: Geographical region covered by the hospital

Building on all the analyses from the experiments, we have devised a simulation tool with a friendly interface that can be used by the manager to simulate the operation for any values of  $Q, SL, D$  and technicians scheduling, for one or two linacs. By doing so, the operation is free to make its own studies, gathering information to support decision making in everyday business.

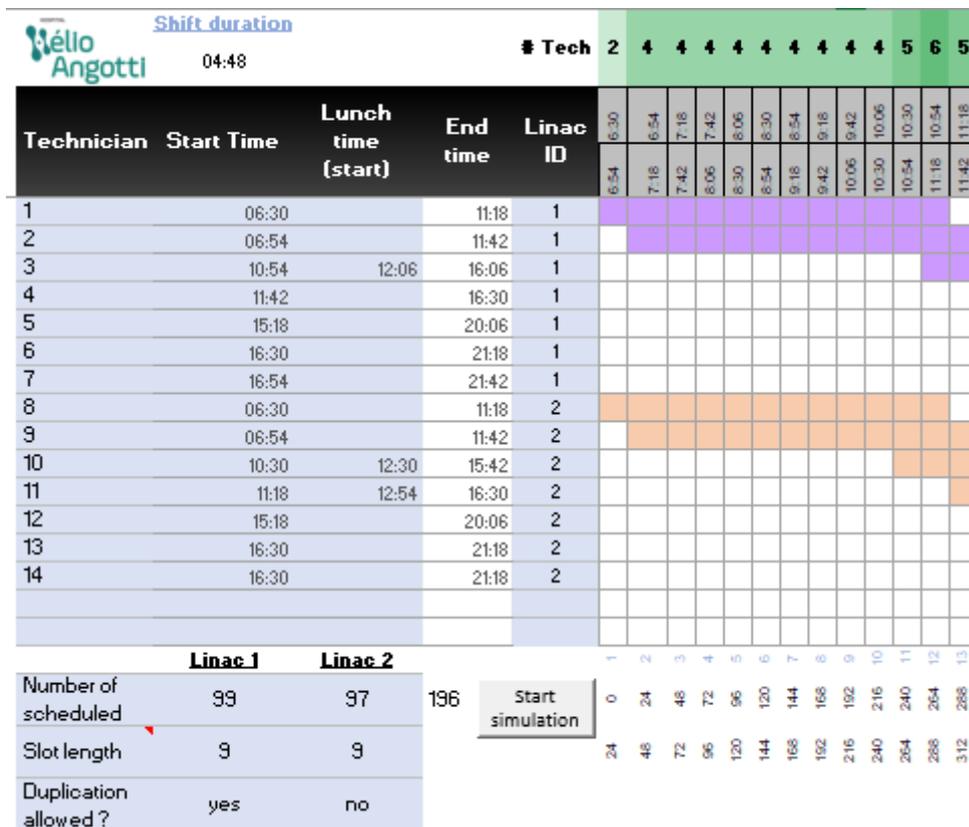


Figure 14: Tool interface

The interface is an Excel file as illustrated in Figure 14, where the manager can set up values for the decision variables. The user clicks on a button, and a VBA macro is executed in the background, therefore not requiring simulation knowledge from the user. The macro calls the Arena model, execute the simulation and writes the statistics into a .csv file, finally it reads the .csv to compute a summary of the relevant statistics, writing the summary in another tab of the initial Excel file (Figure 15). The results table is comprised of many statistics such as % of patients waiting up till 30 minutes, allowing the operation to analyze the pros and cons of the simulated scenario.

### Simulation results

	Overall	Linac 1	Linac 2
Start time HH:MM	06:30	06:30	06:30
End time (plan)	21:42	21:42	21:18
# Number of treated patients (total)	557	437	120
# Simulated days	5	5	5
# Number of treated patients (avg)	196.5	99.4	97.1
Exit time (avg)	21:23	21:35	21:12
Over time (minutes)	00:00	00:00	00:00
% Patients treated in advance	42.37%	43.71%	37.50%
% Patients treated in time	1.62%	0.92%	4.17%
% Patients waiting < 30 minutes	34.47%	36.61%	26.67%
% Patients waiting [30,60] min.	6.46%	5.26%	10.83%
% Patients waiting > 60 min.	0.00%	0.00%	0.00%
% Patients arriving late	15.08%	13.50%	20.83%
Mean Waiting time (minutos)	13.04	10.97	21.45
Mean Overall Waiting time (minutos)	-2.95	-3.26	-1.34

Figure 15: Tool results

## 5 – CONCLUDING REMARKS AND FURTHER RESEARCH

We presented an application of a discrete-event simulation model in a real radiotherapy process. By concentrating on the treatment stage, we were able to include many details of the operation in the model, increasing its capacity to emulate the real operation. Our experiments initially studied a suitable number of replications to have reliable results in further experiments. In order to also have valid results, a second experiment compared the real-world results with the simulation results for two critical responses (exit time of the last patient and process delay). After confirming that the model is able to provide valid and reliable results, we executed a set of experiments to explore a number of possibilities to analyze, understand and identify improvements, which returned some interesting findings.

In Section 4, we performed factorial experiments testing different values for the number of scheduled patients, slot length and duplication admission; identifying the main effects and interactions for these variables. We also found regressions equations to estimate results for any values within the tested range; additionally, the graph in Figure 12 allows the operation to find the best configuration for different values of  $Q$ .

Recognizing the combinatorial nature of the problem when including the scheduling of the technicians, we performed space search experiments which results suggested changes in the original setup. Going further, still in Section 4, considering the operation is acquiring another linac, we provided results of optimization models with two linacs for different numbers of technicians, so the operation can plan its ramp up accordingly. The results also showed a substantial productivity increase when using the solution from the optimization model. Finally, we devised a friendly tool to allow the operation to run its own simulation studies.

In a future study, we plan to include in the simulation model other steps of the radiotherapy process in order to complement our findings.

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**APPENDIX**

Table A1 provides the results for the 32 experiments mentioned in Section 4.2.

**Table A1:** Results of Factorial Experiments

StdOrder	RunOrder	Q	SL	D	ET	PD
17	1	100	8.5	true	895.2	22
2	2	80	8.5	false	743.5	15.1
5	3	80	9.5	true	782.1	2.5
8	4	80	10	false	804.5	-13.2
21	5	100	9.5	true	924.5	12.4
22	6	100	9.5	false	960.4	-2.8
27	7	110	9	true	949.5	34.5
7	8	80	10	true	804.5	-13.2
14	9	90	9.5	false	856.8	-5.3
26	10	110	8.5	false	949.6	34.3
18	11	100	8.5	false	895.2	22
9	12	90	8.5	true	833.8	15.3
31	13	110	10	true	947.7	32.4
3	14	80	9	true	769.5	3.3
29	15	110	9.5	true	940.6	36.5
13	16	90	9.5	true	856.8	-5.3
19	17	100	9	true	927.1	12.3
20	18	100	9	false	922.6	5.3
23	19	100	10	true	928.1	15.4
12	20	90	9	false	851.7	4.8
10	21	90	8.5	false	833.8	15.3
32	22	110	10	false	1116.8	-11.2
6	23	80	9.5	false	782.1	2.5
11	24	90	9	true	851.7	4.8
4	25	80	9	false	769.5	3.3
25	26	110	8.5	true	949.6	34.3
28	27	110	9	false	1029.9	10.4
1	28	80	8.5	true	743.5	15.1
15	29	90	10	true	878.3	-8.3
16	30	90	10	false	890.4	-11.7
24	31	100	10	false	1008.7	-14.7
30	32	110	9.5	false	1079.9	-3.3