Using of Optimal Simulation Modelling to Reduce Radiotherapy Cancer Waiting Time and Improve Survival

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Abstract

Standard indicators of the quality of cancer radiotherapy treatment not only includes accuracy of treatment process, but also the patient wait time to go under treatment. A common cause of anxiety for patients who are diagnosed with cancer and prescribed for radiation therapy is how long they should wait for their radiation sessions to begin. This waiting time estimation either remains unclear or is longer than it is originally planned. One of the major attempts for radiotherapy cancer centers to improve their quality of services is to try to keep the patient waiting time under control and as low as reasonably possible. In this paper, the aim is to understand the magnitude of bottlenecking in the fundamental steps of the radiation therapy treatment process in order to simulate a model that can be used further on by cancer centers to develop their quality program. The result of this optimal simulation model would be a reduction of the delay between the time that the oncology recommends a patient for undergoing radiotherapy and the time that patients actually starts the radiation treatment sessions.

Keywords
Radiotherapy Treatment Process, Patient Wait Time, Cancer Center Quality Program and Optimal Simulation Model.

1. Introduction

Radiotherapy involves the use of radiation to treat cancer tumors while minimizing damage to healthy tissue. The radiation may be delivered in different methods from a source at a distance from the patient's body in or near the tumor. These methods involve several steps before the actual treatment commences.

Oncology centers aim to immediately treat patients recommended for radiotherapy. However, some patients wait for a long time before undergoing treatment. These prolonged waiting times has negative impacts on immediate cure or palliation of the disease. An estimated 120 000 people lose their lives to cancer annually in England (The NHS cancer plan 2000). Thus, several waiting time standards have been framed by the Joint Council for Clinical Oncology (JCCO) and the Department of Health (DH) to reduce further loss of life through the disease (Burke et al. 2011), (Kapamara et al. 2007). These standards are difficult to meet because of bottlenecks created by the interactions between the patients and human or machine resources in the treatment system. Oncology centers face the challenge of reducing these patient waiting times to improve their quality of service. Their aim is to reduce waiting times and maximize patient throughput while utilizing their available resources to full capacity. This could be difficult to achieve because of disturbances in the system like patients not attending sessions, staff shortages, unavailability of doctors, machine breakdowns, and or continual surge in cancer patients. Therefore, a simulation model of the treatment system would help to understand the magnitude of bottlenecking in the fundamental steps of the process. The simulation model is developed with this respect, and as a first step towards development of radiotherapy patient scheduling algorithms.

1.1 Objective of Simulation

Waiting times for radiation therapy (RT) are of a global concern. Emerging evidence indicates that a wait for RT may be a threat to patient outcomes, and that waiting times for RT should therefore be as short as reasonably achievable (Mackillop 2007), (Chen et al. 2008). In some cases, additional resources are required to reduce waiting times while in other cases, process changes or better use of existing resources will be enough. Therefore, waiting times may be

improved by the application of modern management techniques such as mathematical programming, simulation modelling, and statistical analysis aimed at improving processes.

The patient treatment time allocation of the radiation therapy treatment process within oncology cancer department is always crucial and essential in-patient care pathway but nevertheless contains room for improvement which effect both on tumor growth as well as survival outcome. The purpose of this study is to show how different simulation and optimization models can be used to represent this complex process and to suggest improvements that may reduce the cancer patient treatment time and ultimately reduce overall waiting times which effect on patient quality care. In this paper, the application of discrete-event simulation (DES) modelling of cancer radio therapy planning processes is described, and how such a model can be constructed, validated and used to recommend improvements to waiting times is also demonstrated.

2. Literature Review

Simulation is a problem-solving methodology that resembles a real-world system over a period of time (Banks 1998). Literature has considerable spectra of real-world problems analyzed and solved using simulation models. These models provide invaluable information for decision making and also increase the problem solver's understanding of the system through experimentation (Chen et al. 2002), (Pidd 2004). Simulation models can be continuous or discrete event. Discrete-event simulation involves modelling a system whose state changes instantaneously whereas in continuous simulation, state changes continuously with respect to time (Chen et al. 2002), (Pidd 2004).

This paper discusses a discrete-event simulation of patient radiotherapy treatment at a cancer center. Numerous articles have been published on the application of discrete-event simulation on healthcare problems. There is different literature on simulation of single or multi-facility health care clinics. However, it seems a few researchers have attempted to model cancer clinics. The radiotherapy treatment processes could be viewed as a multi-facility healthcare environment that shares key resources such as doctors and radiographers.

Lowery (1996) presents an introduction to simulation in healthcare and clearly outlines the barriers to modelling in this environment. One important issue is how the simulation model would be developed and implemented. Numerous computer simulation software packages are available on the market. Some of these include Arena, eM-Plant, Micro Saint, ProcessModel, SimScript, Simul8, and or Visual Simulation Environment (McGinley 2005). In this paper, Arena, a discrete-event simulation computer package, is used in the development of the model.

2.1 Statistic Review

The report of Barua et al. (2015) shows that many Canadians are waiting for some form of medical treatment. In particular, Canadian cancer patients have experienced long waiting times in radiotherapy for many years (Kavanagh et al. 2008), (Mackillop et al. 1995). Lengthy waiting times for radiation treatment may have a negative clinical impact. For example, delayed radiation treatment may increase the risk of local recurrence (Hebert-Croteau et al. 2004), (Chen et al. 2008) and poor survival (Do et al. 2000), (Dahrouge et al. 2005).

Several population-based studies have been conducted to investigate waiting times for radiotherapy and to determine the predictors of long waits. A higher incidence of cancer, together with an increase in the demand for radiotherapy, insufficient resources and certain patient characteristics represent some of the predictors for longer waiting times (Fortin et al. 2006), (Benk et al. 1998). Conversely, radiotherapy waiting times decrease with an increase in the number of radiation therapists, medical physicists, radiation oncologists and radiation planning and therapy equipment (Cooke et al. 2009).

Discrete-event simulation (DES) is a valuable tool for investigating system capacity and throughput. The use of DES models with healthcare application includes hospitals, outpatient clinics, emergency departments and pharmacies (Günal and Pidd 2010), (Jacobson et al. 2006). DES can help decision makers to carry out a 'what- if?' analysis to determine good policies for scheduling patients, optimising resources, reducing waiting times of patients in clinics and improving workflows (Santibanez et al. 2009), (VanBerkel and Blake 2007). DES models have also been used to investigate patient scheduling challenges (Everett 2002), waiting time bottlenecks, overall system throughput and

system configuration in emergency rooms (Duguay and Chetouane 2007), optimal intensive care unit size (Kim et al. 1999), as well as staffing levels and bed requirements (Akkerman and Knip, 2004) in various healthcare settings.

Simulation modelling has been applied in the field of radiation therapy to explore target waiting times through varying capacities (Munro and Potter 1994), (Thomas et al. 2001) and to analyse the number of linear accelerators to achieve shorter waiting times (Thomas 2003). Kapamara et al. (2007) and Proctor et al. (2007) used DES modelling to understand the treatment process, complexities, patient flow and bottlenecks at the radiotherapy unit. More recently, Werker et al. (2009) modelled a portion of the planning process of the radiation therapy at the British Columbia Cancer Agency, with the aid of a DES model.

In this paper, the work extends the study of Werker et al. (2009) by modelling the entire radiation therapy planning process, from patient arrival to treatment completion. This is a model to analyse the entire radiotherapy planning process at a cancer treatment facility. The primary objectives are to understand how to improve the radiotherapy planning process, to understand which resources are the most important in decreasing waiting times, and to provide an optimal strategy for deploying existing and new resources.

3. Input Modelling

In order to create a simulation model, a number of inputs are needed. For this model, data describing the arrival process, the task times, and the resource availability is required. Arena suggests that a Poisson distribution is the best fit for the daily arrivals. Using a Chi- squared good- ness-of-fit test confirms this result. Also, the validity of the Poisson distribution can be seen visually in Figure 1, which shows the distribution of arrivals plotted against the corresponding Poisson distribution.

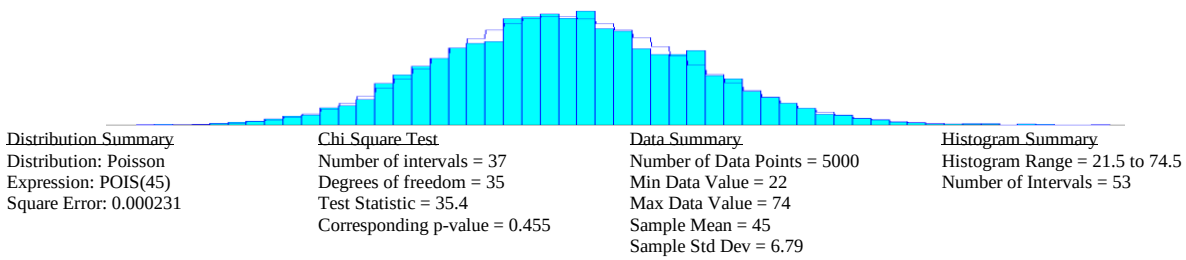

Figure 1. The validity of the Poisson distribution

3.1. Input Description

The inputs used in the model along with their description are given below:

- Number of Oncologist Consultant:

Patients first meet the oncologist to get consultation to start their treatment.

- Number of CT machines:

The treatment will begin with imaging patient and for that a CT machine is needed

- Number of CT Technician:

The technicians who do the CT process will be assigned here.

- Number of Medical Physicist (MD):

They will work almost everywhere in the process to plan and check the treatment.

- Number of Dosimetrist:

They calculate the radiation dose which is needed for each treatment.

- Number of Mould Room Technicians:

These technicians work in mould rooms to prepare mask for patients.

- Number of Linac Machines:

These machines are being used to deliver the radio to tumor in patient's body.

- Number of Therapists:

They work with MDs to smooth the process of delivering the radio dose to tumor cancers.

- Number of Contour Technicians:

For outlining the tumor these technicians will work with MDs and Therapists.

- Different Waiting Time for each Process Task:

Table 1 shows how tasks are timing.

Table 1. Different Waiting Time for each Process Task

Task Name	Dealy Type	Units	Min	Value	Max
Meet Oncologist Consultant	Triangular	Minutes	60	90	120
Prepare Mask in Mould Room	Triangular	Hours	5	5.5	6
Outline Tumor and Contour	Triangular	Hours	1	2	3
OAR Outline	Triangular	Hours	1	3	5
Check Outline	Triangular	Hours	2	3	4
Dose Calculation	Triangular	Hours	2	3	4
Physics QA	Triangular	Hours	3	3.5	4
Schedule Patient for Treatment	Expression UNIF (90,120)	Minutes	40	60	80
Treatment	Triangular	Minutes	30	45	60
CT and Chemo	Triangular	Minutes	80	90	100

4. Model Design

4.1. Simulation Method: Discrete Event Simulation using Arena

Discrete Event Simulation Parameters:
Entities: Patients
Attributes: Waiting time, Service time
Queues: Patients wait in various queue to meet the specialists
System State variables: Patient wait time, Total time spent by patients in the system, Resource utilization
Events: Arrival and Departure of Patients
Resources: It is shown in Table 2.
Activities and Delays: The various activities/process and the corresponding delays are given in Table 3.

Table 2. Resources

Resources Used	Capacity	Resources Used	Capacity
Oncologist Consultant	1	Technician	2
CT machine	1	Therapist	2
Linac machine	2	CT Technician	1
Medical Physicist	2	Contour Tech	2
Dosimetrist	2	Technician	2

Table 3. Activities and Delays

Name	Action	Delay Type	Units	Min	Value	Max
Meet Oncologist Consultant	Seize Delay Release	Triangular	Minutes	60	90	120
Prepare Mask in Mould Room	Seize Delay Release	Triangular	Hours	5	5.5	6
Outline Tumor and Contour	Seize Delay Release	Triangular	Hours	1	2	3
OAR Outline	Seize Delay Release	Triangular	Hours	1	3	5
Check Outline	Seize Delay Release	Triangular	Hours	2	3	4
Dose Calculation	Seize Delay Release	Triangular	Hours	2	3	4
Physics QA	Seize Delay Release	Triangular	Hours	3	3.5	4
Schedule Patient for Treatment	Seize Delay Release	Expression UNIF (90,120)	Minutes	40	60	80
Treatment	Delay	Triangular	Minutes	30	45	60
CT and Chemo	Seize Delay Release	Triangular	Minutes	80	90	100

4.2. Process Map

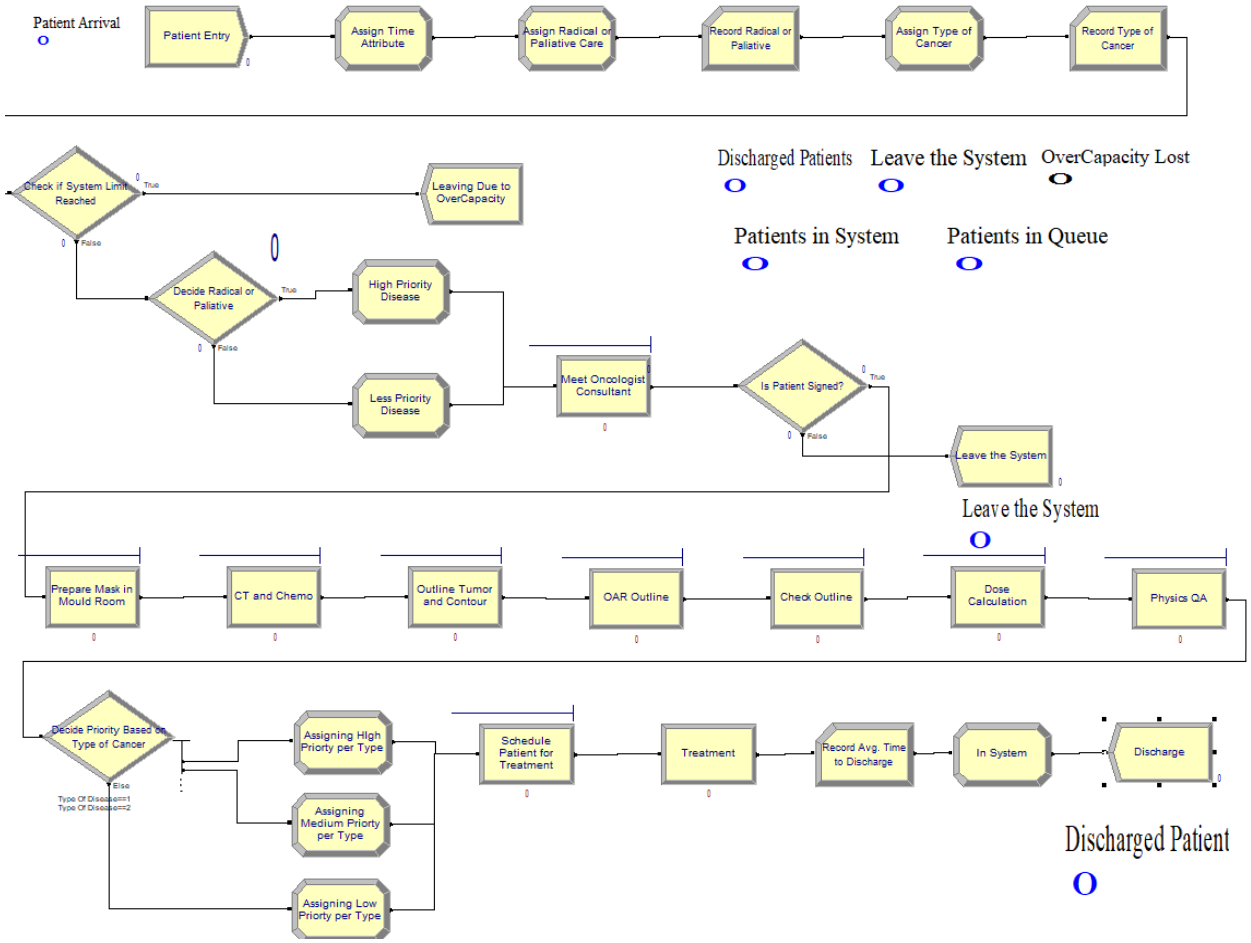

Figure 2. Process Map

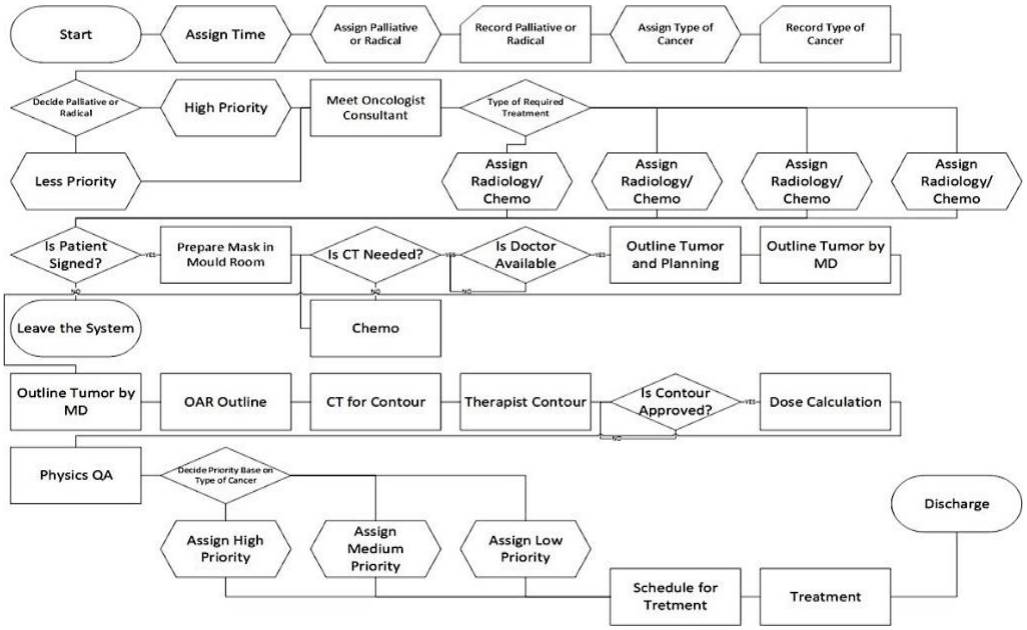

Figure 3. Flow Chart

Process map is represented in Figure 2. The purpose herein is to understand how series of action in a cancer center are taking place from the time patients are coming to the center until they are discharged. Through brainstorming the idea of how the process works, before drawing a process map a flow chart given in Figure 3 is drawn. By looking at the activities, it is found that the state of the system changes at a discrete set of points. All the process in order to prepare the treatment plan were completed at discrete times. For example, the first activity which is "Meet the Oncologist Consultant" is getting done between 60 to 90 minutes. The further activities are going to be completed in the same manner.

4.3. System Visualization

To help visualizing how every and each components of the systems are related, Causal-Loop Diagram, Stock Flow Diagram, Class Diagram, and Sequence Diagram were generated by software. These diagrams are respectively shown in Figure 4, 5, 6, and 7. The principal of accumulation is very important to such a complicated system so that these diagrams are illustrated to have a reasonable output.

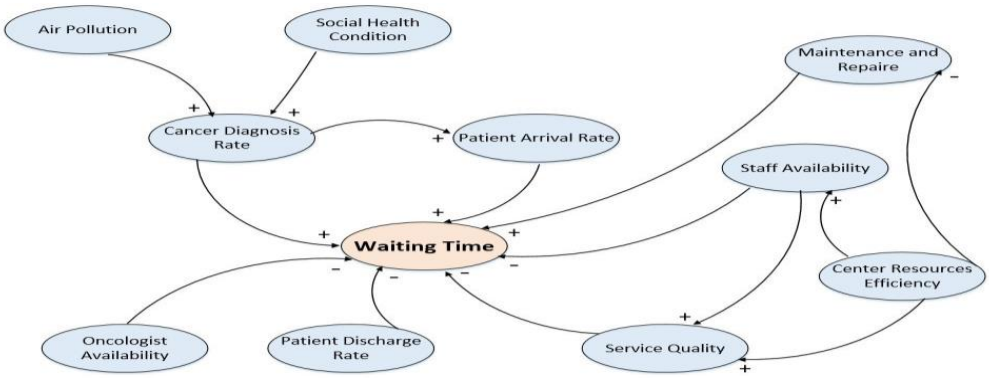

Figure 4. Causal-Loop Diagram

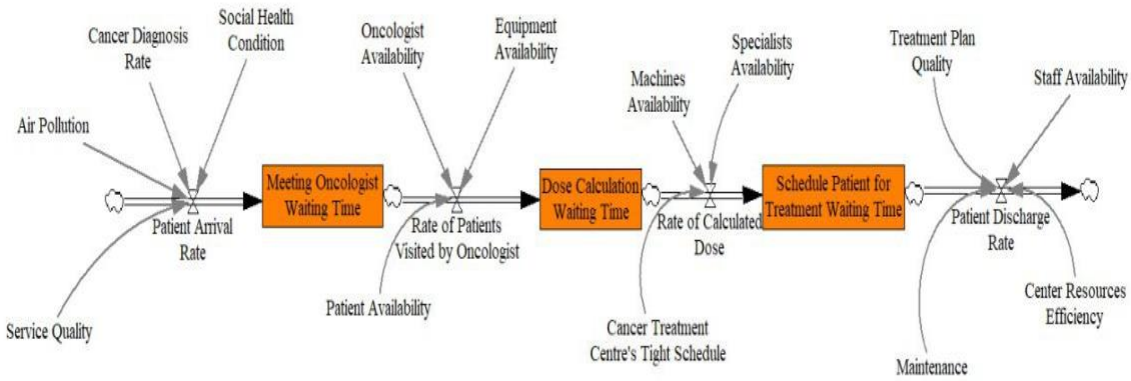

Figure 5. Stock Flow Diagram

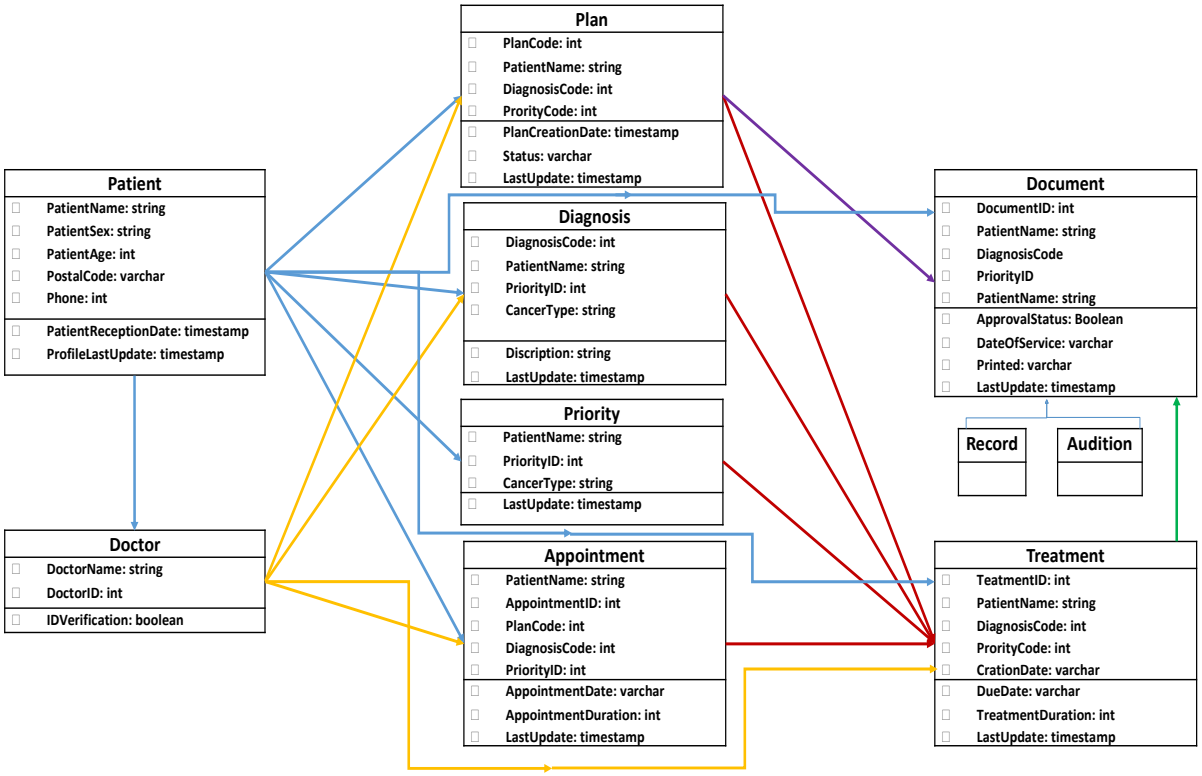

Figure 6. Class Diagram

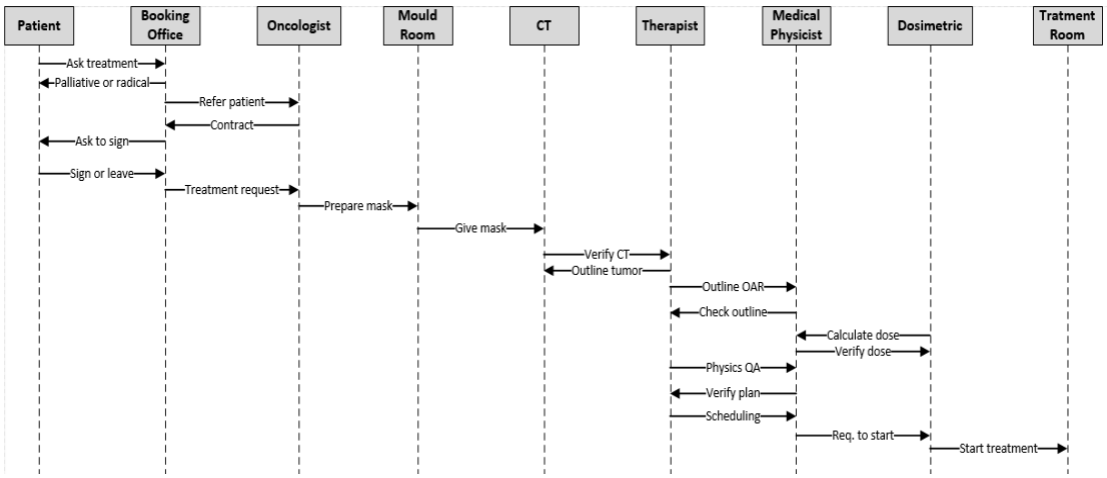

Figure 7. Sequence Diagram

5. Output Analysis

Output analysis is the process of analyzing output results generated by the simulation model. The Arena output result description is represented in Figure 8. The responses to Sensitivity analysis (Monte Carlo analysis) by considering six scenarios are shown in Figure 9. The sensitivity analysis is used to see the stability of result to the input parameter variations.

Values Across All Replications

Simulation Modelling for Patient Radiation Therapy Treatment

Replications: 3 Time Units: Hours

Time

VA Time	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Patients	14.3142	23.61	3.6553	21.9075	0.00	26.5037

Wait Time	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Patients	23.2602	25.82	12.8049	33.5927	0.00	104.53

Total Time	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Patients	37.5743	45.97	16.4602	50.9724	0.00	108.46

Resource

Usage

Instantaneous Utilization	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Contour Tech	0.7879	0.10	0.7578	0.8351	0.00	1.0000
CT machine	0.5486	0.01	0.5461	0.5507	0.00	1.0000
CT Technician	0.5486	0.01	0.5461	0.5507	0.00	1.0000
Dosiometric	0.3143	0.06	0.2983	0.3406	0.00	1.0000
Linac machine	0.1325	0.02	0.1231	0.1399	0.00	0.5000
Medical Physicist	1.0000	0.00	1.0000	1.0000	0.5000	1.0000
Oncologist Consultant	1.0000	0.00	1.0000	1.0000	0.00	1.0000
Technician	1.0000	0.00	1.0000	1.0000	0.5000	1.0000
Therapist	0.4061	0.07	0.3828	0.4399	0.00	1.0000

User Specified - Patient Discharge Time

Tally

Interval	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Total time taken	73.2146	63.18	46.8169	97.5588	36.1551	108.46

Figure 8. Arena Output Result Description

	Scenario Properties				Controls									Responses				
	S	Name	Program File	Reps	Oncologist Consultant	Contour Tech	CT machine	CT Technician	Dosiometric	Linac machine	Medical Physicist	Technician	Therapist	Discharge Time	Patients.WaitT ime	Patients.Total Time	Oncologist Consultant.Utilizatio	CT machine.Utiliz
1		Scenario 1	55 : INSE 691	3	1	2	1	1	2	2	2	2	2	73.215	23.260	37.574	1.000	0.549
2		Scenario 2	55 : INSE 691	3	2	4	2	2	4	4	4	4	4	77.142	34.707	52.185	1.000	0.544
3		Scenario 3	55 : INSE 691	3	1	1	1	1	1	1	1	1	1	82.496	27.227	36.556	1.000	0.271
4		Scenario 4	55 : INSE 691	3	3	2	2	1	2	4	2	2	2	78.208	19.690	32.241	0.541	0.273
5		Scenario 5	55 : INSE 691	3	3	3	3	3	3	3	3	3	3	78.105	28.716	43.264	0.649	0.270
6		Scenario 6	59 : INSE 691	3	2	3	1	1	2	2	4	4	2	75.490	35.031	52.913	0.995	1.000

Figure 9. Sensitivity Analysis (Monte Carlo Analysis)

5.3. Optimization Using Arena – OptQuest

Simulation optimization is defined as the process of finding the best input variable values from among all possibilities without explicitly evaluating each of the possibilities, Figure 10. The summery of the work done by optimization method is brought in figure 11.

Figure 10. Optimization-based Simulation

Objective:

Objectives Summary

Objectives Summary						
	Included	Name	Type	Goal	Description	Expression
	☑	Objective 1	NonLinear	Minimize		[Patients.WaitTime]

Constraints:

Constraints

Constraints Summary					
	Included	Name	Type	Description	Expression
	☑	Constraint 1	NonLinear		[Oncologist Consultant.Utilization] > 0.8
▸	☑	Constraint 2	NonLinear		[Technician.Utilization] > 0.8

Controls:

Controls

Controls Summary										
	Included	Category	Name	Element Type	Type	Low Bound	Suggested	High Bound	Step	Description
	☑	Resources	Oncologist Consultant	Resource	Discrete	1	1	5	1	
	☑	Resources	Technician	Resource	Discrete	1	2	5	1	

Best solution:

Best Solutions **Optimal solution found.**

Best Solutions					
Included	Simulation	Objective Value	Status	Oncologist	Technician
☐	18	8.461043	Feasible	2	5
☐	5	10.478124	Feasible	2	2
☐	10	11.4094	Feasible	2	4
☐	19	11.954758	Feasible	2	1
☐	20	13.8404	Feasible	2	3

Optimization 1*

Optimization **Running**

Minimize		
	Objective Value	Status
Best Value	10.478124	Feasible
Current Value	18.782599	Infeasible

Best Simulation 5
Running Simulation 14
Replication 1 of 1

Controls		
Control Name	Best Value	Current Value
Oncologist Consu...	2	3
Technician	2	1

Constraints		
Constraint Name	Type	Status
Constraint 1	Non Linear	Feasible
Constraint 2	Non Linear	Feasible

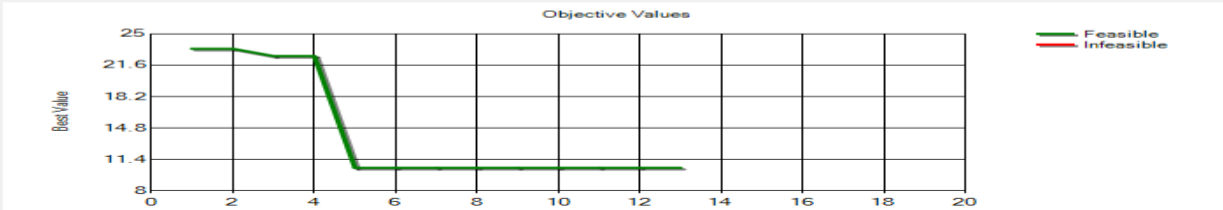

Figure 11. Optimization Process

6. Model Verification and Validation

The verification and validation are answers to the following questions,
Verification: "Was the model made right? "
Validation: "Was the right model made?"
There are different ways for performing verification and validation. From these different ways, four categories were defined namely a. Informal b. Static c. Dynamic and d. Formal Methodology Used: Informal Verification and Validation Methods. Informal verification is more qualitative in nature than quantitative. It also relies heavily on subjective human evaluation rather than detailed mathematical analysis. Experts will examine some of the artifacts of the simulation project and access the model based on the examination and their reasoning and expertise.

Validation method:
Face Validation, which is a validation method that compared the system behavior to the model results. In this method, observers who may be potential users or subject matter experts with respect to the system review or observe the results

of the system. By investigating through knowledgeable expert whose name are acknowledged in this paper, the face validity is done. They are asked whether the model and its behavior are reasonable in terms of the design and the results. This is the question to which the response is affirmative. Hence, the model is considered validated.

Verification method:
Inspection, which is a verification method that compares the project artifacts. In this method, the various project artifacts and results and analyzed and compared for its correctness. From the simulation model, it could be found that if the number of Oncologists (resources) are increased, then the overall time spent by patients in the system and the wait time decreases. Comparing the 2 graphs in Figure 12 and 13 says that the number of patients discharged increases.

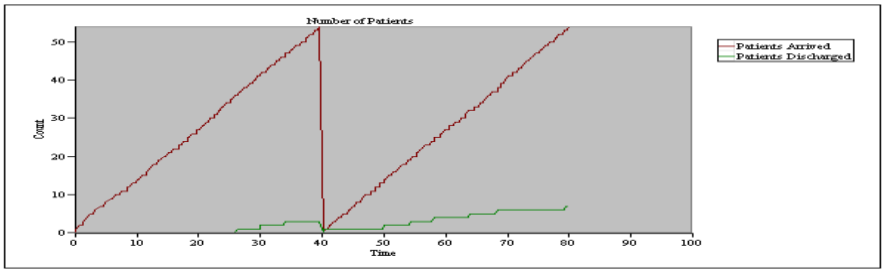

Figure 12. Verification

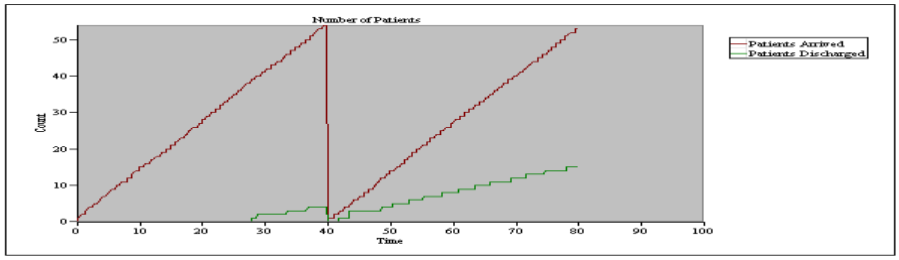

Figure 13. Verification Continuing

7. Conclusion

Waiting time for getting a treatment plan ready is an important standard within the subjects going on the research area in cancer radiation therapy. The numerous options can affect waiting time which would be the number of resources used in the system, the quality of care that a patient receives, the breakdown of machines especially Linac equipment, and the availability of patients. In this matter, there are too many examples of different waiting time in which a cancer treatment process can be defined. A typical cancer center considering that having 3 Linac machines, 4 to 5 Oncologists, 5 MDs, 7 Dosimetrists, 14 Therapists, 4 CT Technicians, and 1 CT machines would calculate the radio dose needed to go through patient's body in almost 2 weeks if the patient has breast cancer.

Werker et al., *Radiotherapy and Oncology*, vol. *92*, pp. 76-82

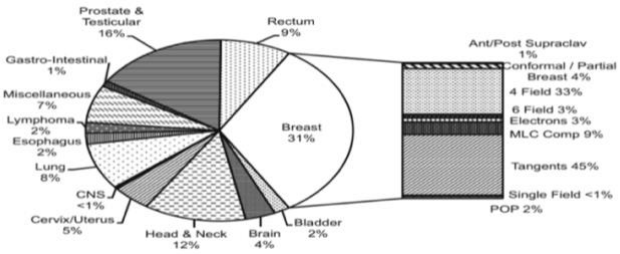

Figure 6. Cancer Category Breakdown; Breast Cancer Category Breakdown

One of the suggestions of this paper is the idea of including the Palliative and Radical priority in the beginning of the process, which helps to start the process treatment sooner for the patients who are palliative and close to highest stages of cancer. The other result which helped the project in Monte Carlo Sensitivity Analysis is considering the different types of cancer based on population. This gives higher priority to the patients who have the most diagnosed rate in a cancer category breakdown like one illustrated by Werker et al. (2009) shown in Figure 6.

As the idea of assigning priority to some patient is brought up by the authors, a big amount of time is spent on reading related papers and consulting with specialists to have a reasonable result, which is a positive point that the simulated result is close to a real true system as the average time gotten from the Arena process map to discharge a patient is almost 73 hours which is almost 9 days if the center works for 8 hours per day. However, by increasing the number of resources and availability of the machines, this even can go below one month as resulted in the sensitivity analysis. In patient scheduling algorithms, different factors can affect the patient waiting time to receive their radiotherapy treatment. The simulated model offered by this paper can be considered as an example model to find the bottlenecks of the treatment process in a cancer center to reduce the patient waiting time and get better service quality.

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