Simulation Analysis of Patients Flow in Oncology Clinics

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Abstract

With an ageing population and more efficient treatments, demand for cancer care is rising; leading to long waiting times and a significant increase in delays in chemotherapy clinics. Chemotherapy operations planning and scheduling is a multi-facet problem due to numerous aspects such as the variety of chemotherapy treatment plans, the flow of patients, and the interdependence between the departments. Patient flow is affected by many delays at different stages; doctors' and pharmacy's delay, referral to specialist, and waiting time for chemotherapy. The aim of this work is to improve the waiting time of chemotherapy patients by studying the flow of patients from the register time until departure time. The typical characteristics of outpatient chemotherapy are detailed in this paper based on a real-life case study in Alexandria, Egypt. The data collected showed that 66% out of 144 studied patients arrive earlier than scheduled, which results in a FIFO flow that affected the scheduling system. Hence, most planning and scheduling efforts are ineffective. A simulation model is built using the data collected to analyze the flow of patients. Two scenarios are proposed, tested, and compared to the base model and show that improvements can be attained by reducing unnecessary delays.

Keywords
Chemotherapy, Healthcare management, Outpatient clinics, Patient flow, Simulation analysis

1. Introduction

When people think of the deadliest diseases in the world, their minds jump to the fast-acting, incurable ones that grab headlines from time to time. But in fact, many of these diseases do not rank in the top 10 causes of worldwide deaths. Cancer, according to the World Health Organization, is the second leading cause of death globally; in Egypt, cancer rates are expected to increase three times the current status by 2050, according to the National Plan for Cancer Control (Ibrahim et al. 2014).

Cancer has several treatments including chemotherapy, radiotherapy, hormonal treatment, and surgery. Chemotherapy is one of the most important interventions in the cancer treatment, it can be proposed to the patient as a standalone treatment, in parallel or in sequence with radiotherapy or surgery (Lamé, Jouini, and Stal-Le Cardinal 2016). Due to the severe increase in the number of cancer patients subjected to either of the treatments, the demand for chemotherapy is increasing, and oncology clinics are experiencing higher workloads that can result in tremendous system delays.

In November 2018, a case study was performed in the oncology department in Hospital X in Alexandria, Egypt. The hospital started taking in an approximate of 45 patients per day in 2006 and increased up to 800 patients per day in 2018. Chemotherapy patients accounts from 60 to 70 patients per day. This study is focused on breast cancer patients who receive chemotherapy treatment which accounts for 20 percent of daily patients visiting the clinic.

Moreover, considering chemotherapy patients who come to the clinic according to their appointment times for chemotherapy treatment, and go through multiple stages (receptionist, oncologist visit, lab, pharmacy, and chemotherapy administration) require multiple resources (oncologists, nurses, chairs, and pharmacists). Each stage of the process exhibits uncertainties that occur during a typical clinic day, such as unpunctual arrivals, delays in laboratory and pharmacy areas, increase or decrease in treatment durations due to side effects or dose changes, cancellations, and add-ons. All these uncertainties affect patient flow and staff workload.

Hospital X Head of the nursing staff is the one responsible for scheduling the patients according to several factors such as the personal requirements according to the patients and the common treatments gathered at the same time to assess the pharmacy to batch several drug preparation for an objective of cutting down costs. However, the data

collected from Hospital X showed that 66 percent of the total observed patients that accounted 96 patients out of 144 patients come early to their scheduled chemo sessions, which results in a First In-First Out (FIFO) flow that affected the scheduling system. Hence, most planning and scheduling efforts are ineffective because although the schedules are set, large number of patients arrive earlier. Consequently, the focus of this paper is the study of the flow of patients rather than scheduling the patients' themselves.

A simulation model is built using ExtendSim™ v10.0.4, the simulation model is fed with real data collected from the hospital, which in turn was used to determine the distribution that resulted from StatFit v3.0. The model simulates the data collected to further understand, analyse the flow of patients, figure out the weaknesses of the system to understand the causes and sources of patients' delay and to propose an improvement that would affect positively the hospital objectives and patients' quality of health service received. Two different scenarios are proposed, tested, and compared to the base simulation model and showed that improvements can be attained by reducing unnecessary delays with improvements that will not need a high budget to implement using the resources available in the hospital as well as managing the resources utilization to be in an acceptable range. Hence, the aim of this work is to integrate the actual resource requirements into coordination of available resources to eliminate uncontrollable delays and improve waiting times for the chemotherapy patients resulting in a minimal length of stay. This is done with assuring that the utilization of the beds, nurses and doctors' load is acceptable and most importantly patient satisfaction is improved. This work contributes to the pool of discrete event simulations applied to healthcare in general and to oncology clinics in particular and ascertains the effectiveness of DES in analyzing and improving the patients' flow.

The remainder of this paper is structured as follows. Section 2 presents the literature review focusing on chemotherapy planning and scheduling, section 3 includes the case study description along with the structural data and analysis of patients' flow, section 4 demonstrates the simulation model with the simulation parameters, followed by section 5 that encompasses the experimentation scenarios and the results analysis, and finally the conclusions conducted at the end of this study in section 6.

2. Literature Review

Breast cancer is considered leading cancer among the female population worldwide, as well as in the majority of countries in Africa (Fribert et al. 2013). Moreover, it is the most common malignant tumor among women of reproductive age and is also the most costly according to European reports (Torres-Mejía et al. 2017). According to (International Agency for Research on Cancer (IARC) 2018), incidence data, available through 2018 revealed that 128,892 new cancer cases and 85,432 cancer deaths occurred in the Republic of Egypt; where, 17.9% of the new cancer cases, both males and females, are breast cancer; and 35% of the new cancer cases in females only is due to breast cancer.

For years Discrete-Event Simulation (DES) has been identified as an essential operational research technique that helps decision makers in assessing different "what-if" questions (changes in patients' flow, capacity of different resources, performance of resources, schedules of patients' arrival…) without interrupting the actual system (Jun, Jacobson, and Swisher 1999). The review conducted by (Jun, Jacobson, and Swisher 1999) showed that the application of DES in healthcare is wide spread due to the numerous successful studies that used simulation to address healthcare problems. (Brailsford and Vissers 2011) reviewed the application of operations research in general in healthcare. They stressed the need to take into account the impact of stochastic variation or differences in characteristics between different departments of a healthcare facility; in addition, when managing patient flows and resources there is a need to develop models for whole systems instead of developing models for isolated components of the hospital. Another more recent review by (Lamé, Jouini, and Stal-Le Cardinal 2016) stressed again the scarcity of models with multiple departments in healthcare with most models developed for single departments in healthcare; where, mathematical programming and simulation are among the very popular modeling techniques that could be applied to multi-department issues. Furthermore, (Lamé, Jouini, and Stal-Le Cardinal 2016) pointed out that outpatient chemotherapy is different from emergency departments; where, waiting time is a clinical variable and that system time is a better indicator of patients' satisfaction. (Vieira et al. 2016) also reviewed OR methods and their application in a more specific area of breast cancer treatment, which is radiotherapy treatment. Their review focused particularly on the logistics optimization in radiotherapy treatment and showed that machines' capacity dimensioning and throughput optimization are the most studied problems with computer simulation as the preferred technique. (Salleh et al. 2017) also reviewed simulation modelling techniques that have been used to support a wide range of healthcare decision problems. One of the areas reviewed in their work was the use of simulation modelling for resource management or system design to optimize patients' flow time by reducing queue or waiting time within healthcare departments.

Simulation has been used repeatedly to address different issues of cancer treatment such as patient flow, utilization of resources, and capacity analysis. (Sepúlveda et al. 1999) modeled and analyzed patient flow processes of real life full-

service cancer treatment facility using a simulation model. Simulation results analysis showed that potential improvements in patients' flow time could be achieved. (Coelli et al. 2007) developed DES models for the analysis of a real-life mammography clinic performance. Models tried to simulate changes in different input variables on key performance measures of the clinic. They concluded that the developed DES models were useful in defining the most adequate capacity configurations and equipment maintenance schedules. (Lamé et al. 2016) developed a DES model and validated it using real data of an integrated system of two interconnected departments, an outpatient oncology clinic for chemotherapy delivery, and the pharmacy unit that prepares the chemotherapy drugs. The objective was to identify sources of patient waiting times in the outpatient oncology clinic and to identify relevant corrective actions. Their study showed that the multi-department approach can yield significant results. Also, (Bernatchou, Bellabdaoui, and Ouzayd 2017) presented a case study of a cancer center; where, a simulation model of the chemotherapy department was developed to model, analyze, and improve the patient flow by reducing the patients' lengths of stay in the center. Simulation experiments show that the long waiting times are due to the variability in the patients' arrival, creating peaks in workload.

Furthermore, discrete-event simulation has been repeatedly reported in literature in conjunction with scheduling operations in a healthcare environment. (Yokouchi et al. 2012) developed a simulation model of an outpatient chemotherapy department at a general hospital and used it to identify optimal an optimal appointment schedule that shortens the mean of the waiting-time for all of the patients treated while maintaining the same bed utilization. (Dehghanimohammadabadi, Rezaeiahari, and Keyser 2017) focused on optimizing patient scheduling at a breast cancer center for follow up and consult patients who exhibit different service times and follow different care pathways. The objective of their paper was to sequence the patients such that minimum average flow time is achieved for each patient type. In a more recent work by (Alvarado et al. 2018) they stated that oncology clinics are often burdened with scheduling large volumes of cancer patients for chemotherapy under limited resources. To complicate matters further, each chemotherapy patients require a tailored treatment regimen that necessities a series of appointments prescribed by the oncologist. The timing of these appointments, that typically last several weeks or months, is critical to the effectiveness of the chemotherapy treatment. For that, they developed a DES model that can simulate scheduling of chemotherapy patients, clinic resources, and the arrival process of the patients to the clinic on the day of their appointment. This model simulates oncology clinic operations as patients receive chemotherapy treatments and thus allows for assessing scheduling algorithms using both patient and management perspectives.

Based on this brief review, the study presented in this paper focuses on analyzing the operations of a real-life chemotherapy clinic using a discrete event simulation model that is used to simulate and analyze the patients' flow. The model will present multi-department in an integrated approach. The performance measures selected are the average length of stay and utilization of the key resources required to serve the patients.

3. Case Study

This paper is motivated by the collaboration with Hospital X mentioned previously in the introduction section. It is a public non-profit comprehensive cancer center providing oncology, hematology, pediatric oncology, and radiotherapy services. The chemotherapy department in Hospital X is of limited area if compared to the increasing demand on chemotherapy treatments.

3.1 Structural Data and Resources Description

The Chemotherapy Department consists of treatment rooms, nurses, doctors, and a pharmacy. The treatment rooms consist of the following two main resources, treatment chairs/beds (as listed in Table 1) that are used to seat the patients during the treatment.

Table 1: Available chairs and beds in different stations

Station	Number of beds	Number of chairs
Station 1	2	4
Station 2	3	3
Station 3	4	2
Station 4	1	5
Station 6	3	3

The doctors' office consists of 2 doctors in 2 different shifts who examine the patients and decides whether the patient is in good health condition and ready for the chemo-session or the patient is not ready and should be dismissed to reschedule. The 1st shift starts from 9 AM to 2 PM, and the second shift starts from 3 PM to 6PM; noting that the two shifts ends when the last patient in queue is examined.
The pharmacy consists of two rooms; the first room includes administration and the second room consists of the laboratory/pharmacy which prepares the chemo drugs. The first room sorts out the patient files, and batch them to be sent to the pharmacy's 2nd room for drug preparation. Also the first room receive the drug from the pharmacy to be handed to the nursing staff to distribute it in order for the patients to start their chemo session.
Nurses are always available in the chemo rooms to handle the patients receiving his/her treatments to ensure high quality and self-care, each nurse is usually responsible for a maximum of 6 patients at a time (one station).
The clinic includes 4-6 nurses who usually work 12 hours shift from 8 AM to 8 PM. Moreover, the doctor's office has an assigned nurse to call for patients and to take their vitals. In addition, a specialized registered nurse, who works from 9 AM to 9 PM, is available to transport the drug from and to the pharmacy. This nurse receives the drugs from the pharmacy and distribute them among the stations according to the patients' name which is written on the drug. All treatment stations start at 9 AM and continue until the assigned nurse for each station completes her shift and/or the last patients scheduled for the day finish their treatment time. Table 2 summarizes shifts and working schedules of the available nurses in the chemotherapy department.

Table 2: Nurse Schedule in Chemotherapy Department

Number of Nurses	Shift Timing
4	8 AM – 1 PM
6	1 AM – 5 PM
4	5 PM – 9 PM

3.2 Analysis of Patients' Flow

On the patient's first appointment, the oncologist prescribes and assign the treatment plan based on different cancer types, stages, and patient's health. The treatment plan initiates when the responsible nurse schedules an available treatment schedule according to the protocol assigned to the patient upon the vacant days and times. Currently, the outpatient clinic schedules patients according to the cancer type, drug type used in protocol, the treatment duration and the social life of the patient, to keep the drug toxicity and to maximize the pharmacy utilization and thus cutting down costs when merging similar drug types in the same duration. By studying the current situation, the chemotherapy appointments are scattered throughout the day with no single peak time. However, more appointments are scheduled in the middle of the day compared with the rest of the day.
On chemotherapy day, the patient checks in, and wait for the doctor examination as shown in Figure 1. The patient is examined by an oncologist to check his/her condition (test results, vital signs, and drug dose) before the treatment can start. If the patient's health status is good enough to receive the treatment on that day, he/she is seated on a chemotherapy chair and pharmacy is informed for drug preparation. If the doctor decides that the patient is not fit for treatment (roughly 11% of patients), the patient is rescheduled. The oncologists allocate 1 to 12 minutes for examining the patients.
Patients are divided among rooms according to the cancer type and the duration of the patients' session. For example, the breast cancer patients, the scope of this study, are usually allocated in two stations from a total of six stations. Also those two rooms do not only include breast cancer patients.
While the drug is being prepared, the nurse starts an IV in the patient's arm and begins with a saline solution (line injection) through the IV. The nurse will then hang the bags of premedication on the IV stand and start it, followed by the chemotherapy drug. One reason that drugs can't be prepared in advance, is because they are too expensive or have too short stability delays, the oncologist confirms only after seeing the patient on chemotherapy day and at this time the drug is prepared.
Treatments are prepared by the pharmacy and the time taken to prepare the treatments is considered as constant delays and added waiting times in the study. Drug preparation is also different in all the cases according to the cancer stage, type of cancer and the session number. As soon as the chemo-drugs arrive, the responsible nurse transports the drugs from pharmacy to the infusion clinic and injection can start. The treatment time varies according to the patient's condition, which may take from 1 hour up to 4 hours.
Chemotherapy nurses administer the chemotherapy of the patient and the nurse leaves to check and admit another patient while monitoring other patients during their treatment cycle. At the end of the treatment, the nurse comes back,

removes the IV, make sure the patient's health is fine to be released and notifies the patient about the next appointment date and time which also takes few minutes (Delay before exit).

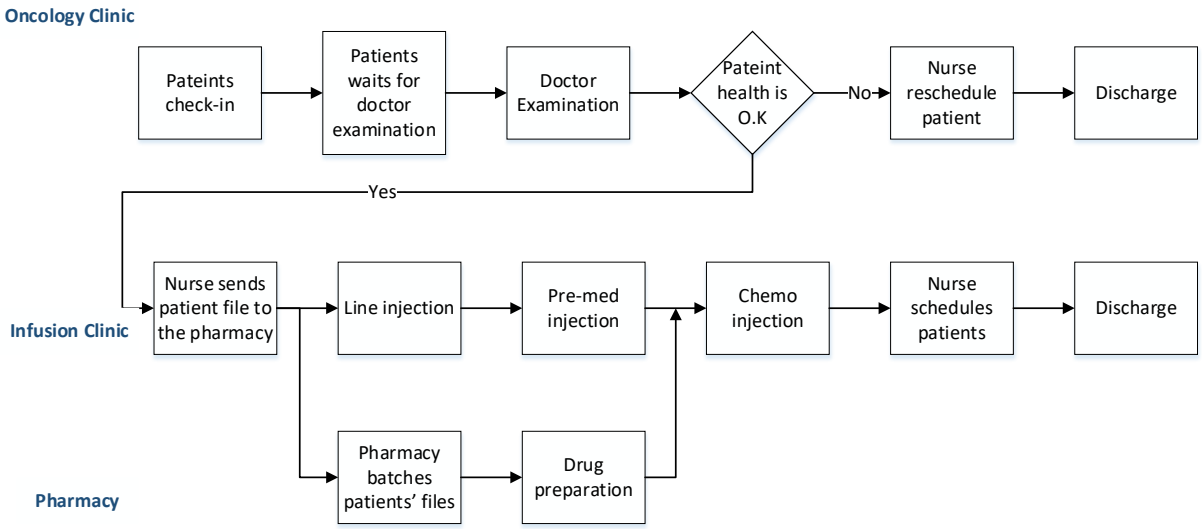

Figure 1: Illustration of the patient flow.

3.3 Problem Definition

Due to the poor coordination between the nurses and the pharmacy, the information card of the patients has a lead time to reach the pharmacy and to get back to the nurse with the prepared chemo dose. Also, the congestion of the patients at the nurse office responsible for the scheduling is an added problem that consumes time and can result in a dissatisfaction of the patients. This affects the waiting times and average length of stay of the patients in the chemotherapy clinic.
The study is undertaken to improve the overall performance of the chemotherapy outpatient clinic by reducing the patient's waiting time and average length of stay. Consequently, this will affect the closing time of the clinic and reduce overtime.

3.4 Numerical Data Collection

In Hospital X, appointment scheduling in the chemo clinic is complicated due to the huge number of patients and the diversity. Using the observation of 150 patients over 13 days of data collection, the duration of the treatment is categorized according to the cancer stage since the study's focus is only on breast cancer patients. Each specified activity is studied by monitoring different patients with different breast cancer treatment protocols and are divided into 3 groups according to the treatment duration and the type of protocol.
Data collected is analyzed and subjected to outlier analysis to exclude any number that is considered as outliers that resulted from any human error and is then fitted to a probability distribution using StatFit v3.0. The hospital serves the patients on a first-in-first-out basis regardless the schedule assigned. As a result, the average time between arrivals is noticed to be exponentially distributed with a mean of 27 minutes.
When the patient enters the doctor's clinics, the duration spent inside the clinic varied from 1 minute to 12 minutes of duration. Table 3 presents the probability distribution of the time spent in the doctor's office.

Table 3: Doctor's duration and its different frequencies

Time (minutes)	1	2	3	4	5	6	7	8	9	10	11	12
Prob. (%)	1%	2%	19%	19%	13%	18%	10%	8%	4%	2%	3%	1%

Each procedure that takes place on the treatment day is a separate activity and has its own distribution. Both, the line and premed injection, act as a queue before the chemo. By fitting the data after excluding the outliers resulted in various distributions. The table below (Table 4) demonstrates the distribution of each delay takes place in the system.

The division process performed during the data analysis is to divide the patients into three categories (types) by separating the chemo-duration into the three quartiles of the data. 1st quartile of which the data are present in the lower 25% of the data, this data is named under Group A. The data that lies in the top 25% is named under Group C. Finally, Group B is the Group that lies in between the two groups of the data.

Table 4: StatFit Analysis and distribution

Activity (arranged by sequence flow)	**Distribution**
Inter-arrival time	Exponential (1., 27)
Doctor waiting time	Weibull(0.859, 1.28, 8.97)
Doctor duration	Empirical Distribution
Delay before pharmacy (data entry and grouping files)	Pearson 6(1, 46.4, 1.81, 6.17)
Line injection waiting time	Weibull(1, 1.63, 14.8)
line injection duration	Triangular(0, 81.6, 0.587)
Premed duration	Beta(1, 54, 1.37, 1.69)
Chemo Group A	Weibull(5, 3.26, 19.6)
Chemo Group B	Triangular(30, 48.2, 32.3)
Chemo Group C	Empirical Distribution
Delay Before Exit	Beta(0, 20, 1.7, 2.27)

4. Simulation Model

The model considers multiple patient classes with varying routings and resource requirements, unpunctual arrivals, uncertainties in service and treatment durations, cancellations, and add-ons. The model will be used to evaluate the performance of a real chemo-department (As-Is model) and to test alternative operational decisions to improve system performance. Statistical data is produced by the model to validate it after comparing with the actual data collected in real life. The total number of the patients served during the day (throughput) is also compared with the actual output in the current situation. The model run length is ten months, which resulted 432,000 minutes plus the warm up period of 2,300 minutes resulting 434,300 minutes; each run is replicated for 30 times. The following performance measures are selected for this work:

- **Waiting time:** Waiting time is measured in minutes/patient.
- **Average length of stay:** ALOS is the sum of both the service time and the total waiting time per patient per visit. The average length of stay is sometimes referred as the cycle time (CT). The average ALOS of all patients regardless the patient type is considered since the improvements will take place in the system generally that will affect all patient types.
- **Utilization:** Utilization in the simulation model differs from the actual utilization in real life since the study is only focused on breast cancer. The acceptable range of utilization will be relative to the number of breast cancer that arrive per day divided by the total number of chemotherapy patients per day. Utilization will be acceptable if it ranges from 20-25 percent.

The activities are sorted descending according to their percentage in their contribution as shown in Table 5. It is shown that the top four activities that contributes about 83 percent of the average ALOS are considered to be non-controllable delays. The activities that can be considered as controllable activities are data entry procedures, delay before exit, and the doctor examination affect the ALOS by 15 % (31 minutes) as shown in Figure 2.

Table 5: Contribution of activities in ALOS

Activity	**Time (minutes)**
Pre-med injection	54.45
Chemo injection	45.85
Preparation of the drugs	31.38
Line injection	25.63
Data entry	16.62

Delay before exit	8.685
Doctor Examination	5.842

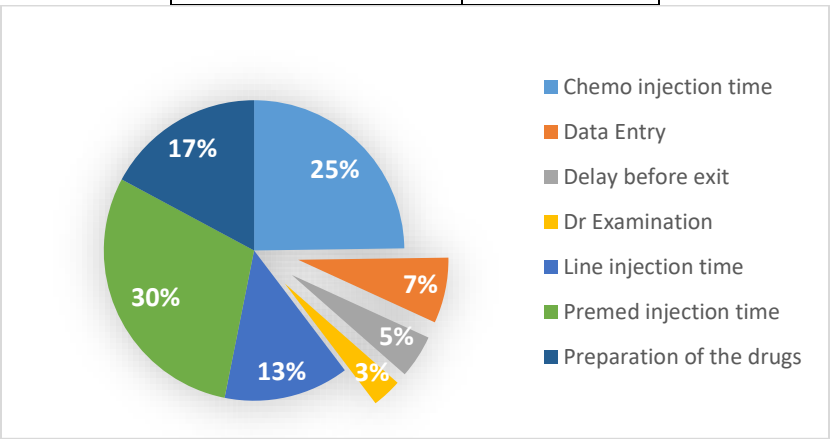

Figure 2: Contribution of activities in ALOS

Moreover, by studying the controllable activities, the following figure (Figure 3) is resulted. The top two delays in the controllable activities are data entry that contributes by 53 percent of the controllable activities percentage and delay before exit that contributes by 28 percent. Both activities contributes by 81 percent out of the controllable activities duration and 12 percent of the total ALOS.

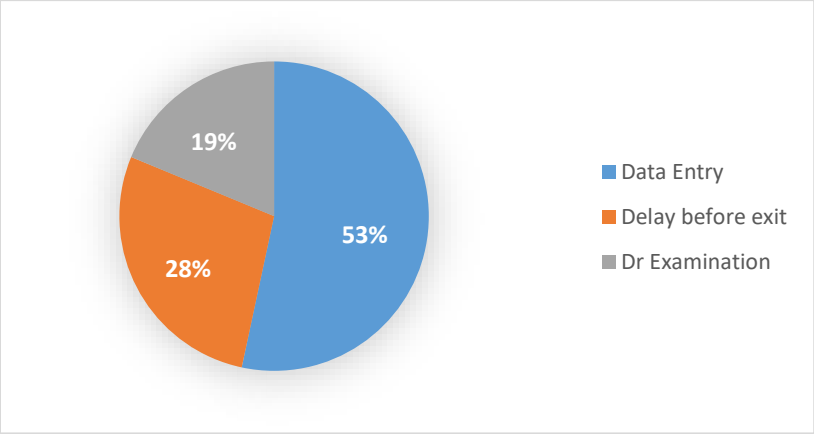

Figure 3: Controllable activities percentages

5. Experimentation and Analysis

First experiment includes change in the data entry process. Data entry includes entering the date of the session in the file, writing the summary of the patient health on the day of the session, putting doctor's notes inside the file and sending the file to the nurse office to batch multiple files and send it to the pharmacy administration. Afterwards, the data is entered again using the pharmacy's computer and batched to prepare the drugs.

The procedures are normally take an average of 17 minutes, a maximum of 56 minutes and a minimum of 1 minute. The delay may take place due to grouping files, writing the updates in the file manually and then re-writing the patient's information using computer in the pharmacy. Grouping takes place in the nursing staff to group multiple files to send it to the pharmacy in order to lower down the number of transportation cycles performed by the nurse. Whereas, the other grouping process takes place in the pharmacy in order to have a cost efficient process and to prepare the drug as efficient as they can. However, the pharmacy may not appear to be the focus of the paper but the data entry process will affect the pharmacy performance positively by starting the drug preparation process earlier.

The improvement will include adding a program that connects all three places to each other for faster data sharing. Once the patient is diagnosed to be healthy enough to receive the chemo-session, the update is sent from the doctor's clinic to the nursing department to update patients' files and to the pharmacy to start the dosage.

The patient's profile will be having every information concerning the patients. Since each patient should be unique on the system, barcode scanner can be used by placing it on the wrist of the patient so that the doctor or the nurse can find the patient's profile quickly without the need of adding a password etc.
Scenario 1 is modelled as the base model with a change in the data entry activity, the data entry is estimated and tested to be exponentially distributed with a mean of only 10 minutes.
On the other hand, the focus in the second proposed scenario will be on eliminating the delay before exit. It was observed the delay was mainly either from asking about precautions regarding the chemotherapy treatment journey, their diet, health condition, and general questions about cancer or because of the dizziness after taking the chemo-drug. However, the tiredness of the patients occurred only in 3 percent of the cases.
The solution proposal to the delay before exit is by different methods:

1. The nurse can pass by the patients in its idle time during the chemo-drug dosage duration to answer the patients' questions.
2. A full database that will aid patients regarding the healthy diet they need to follow and precautions before/after their chemo-session. Database can be accessed at a separate interactive board outside the clinic, a hotline that can answer all patient's questions or through the hospital's website.
3. Assigning 3 chairs for the patients that suffer from the chemotherapy side effects.

The main focus of the proposal is that the questions and answer take place during the chemo dosage since the patient is already waiting for the dosage to end. This will minimize the duration of the delay, which lasts for an average of 9 minutes and can reach up to 20 minutes, to only an average of 3 minutes.
The different scenarios proposed by the study includes multiple changes that produced consequently multiple results. Table 6 summarizes each improvement scenario with the proposed changes.

Table 6: Proposed scenarios

Scenarios	**Changes**
Scenario 1	Computerizing the data entry process that starts at the doctor examination till the pharmacy start preparing the drug
Scenario 2	Eliminating delays before exit.

Summarizing the outcomes of the base model and the two improvement scenarios, Table 7 is resulted. The results shows that both scenarios have improved the system performance in the average length of stay (ALOS). The waiting times and resources utilization is not that noticeable. On the other hand, the resources utilization act like an approval key that the improvement is acceptable since the utilization value lies between the acceptable ranges.

Table 7: Different scenarios affecting the current situation

Scenarios	**Main Effect**	**Average WT**	**Average ALOS**	**Avg. Chairs Utilization**	**Avg. Doctor Utilization**
Current Scenario	Represents the current working condition	9.967	173.653	20.34 %	20.34 %
Scenario #1	Improvement in the data entry system	9.247	168.330	19.98 %	19.98 %
Scenario #2	Eliminating the delay before exit	8.669	163.419	20.00 %	20.00 %

From the analysis above about the various improvement scenarios, it is concluded and proved that Scenario 2 provides the best system performance. Nevertheless, the cost of scenario 2 will definitely be less than that of scenario 1. Choosing the 2nd scenario and focusing more into the change in the different performance measures. Table 8 shows how Scenario 2 is differentiated from the current scenario.

Table 8: Summary of percentage changes in different measures

Performance Measure	**Percentage Change**
Waiting time	-13%
ALOS	-6%
Chair utilization	-4%
Doctor utilization	-2%

6. Conclusions

Long waiting time for chemotherapy patients occur frequently in oncology clinics and this does not only affect the patient satisfaction, but also affects the efficiency of the drug provided in the chemo and subsequently affects the whole treatment process. Operation Researchers have studied this field using assumptions due to the several number of departments that are involved in the process and the high variability. Simulation have been identified in literature as one of the key tools to address the complexity of these systems and to handle the stochastic nature of the different variables affecting the performance of healthcare processes in general.

A real life case study of an oncology department in a hospital located in Alexandria, Egypt has been selected. Actual data has been collected and analyzed for a considerable number of patients. Also, data about the different process, resources, and operation of the oncology clinic have been identified. Although the hospital treats patients with all sorts of cancer types; yet, the study has been limited to breast cancer patients only.

A base discrete event simulation model representing the current operation of the oncology clinic has been developed using ExtendSim^{TM} v10.0.4 and analyzed. The model included the different resources identified; in addition, the pharmacy and drug preparation time are considered in the model; however, without including the detailed operation of the pharmacy. Average length of stay of patients reported from the base model has been analyzed to identify its different constituents. The largest contributor to the ALOS that can be feasibly reduced are identified. Two different scenarios were developed to test the effect of the proposed solutions on the different performance measures. Results show that the different performance measures can be actually improved without the need to modify any of the current resources.

Furthermore, although other activities contributed to the ALOS of patients with greater values; however, these activities cannot be altered due to the fact that the duration of these activities is a clinical variable that cannot be changed, such as the chemotherapy, line, and the premed injection times. Drug preparation time was also one of the major contributors to the ALOS; yet, due to the restricted access to the pharmacy, detailed modelling of pharmacy operations and resources was not possible at this stage of the research. Hence, it was not possible to actually estimate or identify any possible reduction in drug preparation time.

Future research work will focus on modelling further details of the pharmacy operations and resources to determine whether the drug preparation time (one of the major contributors to the ALOS) can be reduced or not and whether this reduction will lead to an overall improvement of the oncology clinic performance or not. Furthermore, alternative patients' schedules are to be modelled and analyzed to test their effectiveness in improving patients' ALOS and resources' utilization.

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