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A DETAILED SIMULATION MODEL OF AN INFUSION TREATMENT CENTER

Anali Huggins
David Claudio
Md Waliullah

Department of Mechanical and
Industrial Engineering
Montana State University
Bozeman, MT 59717, USA

ABSTRACT

Oncology clinics face several complexities in their processes. When patients arrive at the infusion chairs, nurses and pharmacy technicians must be available to get the patients ready for the infusion and mix their drug treatments. This requires having the right information at the right moment. This research develops a detailed discrete event simulation model which considers the interactions between resources, information, and patient flow. The model was used to evaluate different scheduling policies and determine which of them could be incorporated in the clinic with the objective of increasing daily throughput without affecting patient wait time or total time in the system.

1. INTRODUCTION

Improving efficiency in healthcare settings has been one of the most talked about topics in recent years. From a management standpoint efficiency frequently is measured through cost indicators. Patients, on the other hand, seek high service quality which could be measured through parameters such as patient wait time or schedule availability (De Angelis et al. 2003). Expenditure increases and the continuous pressure to improve quality have led healthcare administrators to adopt new policies. Healthcare researchers are increasingly examining cost effective tools that can improve patient flow, while reducing healthcare expenditures and increasing patients' and employees' satisfaction.

Discrete event systems simulation (DES) is a cost effective tool frequently adopted by healthcare researchers as it is used to analyze the simultaneous impact of changes in operations, scheduling policies, and resource allocation on wait time, overtime, and resource utilization (Santibáñez et al. 2009). Many healthcare systems are comprised of numerous processes interacting in complex ways (Carr and Roberts 2011). The central components of a healthcare system are generally human. The unpredictable nature of humans makes systems difficult to understand (Davies and Davies 1995). Oncology clinics are good examples of complex healthcare systems which require interactions between many components. They face several complexities in their processes; balancing schedules and synchronizing resources, to name a few. When patients arrive at the infusion chairs, nurses and pharmacy technicians must be available to get the patients ready for infusion and mix the treatments. This requires having the right information at the right moment.

This research develops a detailed DES model which considers the interactions between resources, information, and patient flow. The simulation model provides insight into the dynamics of the system. It considers several operational characteristics of a cancer outpatient clinic; most of which has been studied before in isolation. However, this research combines all of them in one model. The model was used to evaluate different scheduling policies and determine which of them could be incorporated in the clinic with the objective of increasing daily throughput without affecting patient wait time or total time in the system.

2. RELATED WORK

Several processes in healthcare delivery are related to high levels of uncertainty which makes resource planning a difficult task. Discrete event system simulation (DES) is one of the most popular and widely used techniques by healthcare researchers. DES is a type of modeling from the field of systems engineering designed to emulate the process of a system (Berg et al. 2010). Its popularity may be attributed to the numerous successful studies reported using simulation to address healthcare system problems (Jun et al 1999). DES has several advantages (Davies and Davies 1995) over other approaches: patients can be modeled as individuals and thus possess characteristics; models can include resource constraints; and models can be realistic and detailed (Kalton et al. 1997).

The use of simulation in healthcare settings has been established in previous research (England and Roberts 1978) in areas such as resource management, workload balance, and quality of services (Klein et al. 1993). Furthermore, simulation represents a powerful approach to evaluate different alternatives especially when hospital intervention studies are not feasible due to ethical, safety, economical, and logistic reasons (Vasilakis et al. 2007). For example, Kalton et al. (1997) presented a simulation model which attempted to model system complexity to evaluate the operating procedures of a clinic offering multi-disciplinary services. Through simulation, they are able to approach two main difficulties: resource contention and the need for coordination between providers (Kalton et al. 1997). Similarly, the model presented in this article coordinates different sources: services (nurses and pharmacy), chairs, and information availability.

Kachhal et al. (1981) conducted a simulation study in an ear, nose, and throat (ENT) clinic to improve patient scheduling policies. They tested three different alternatives for scheduling patients for ENT physicians and ended up selecting a policy that reduced the average patient wait time by 45% (Kachhal et al. 1981). Swisher et al. (1997) showed that under certain conditions staffing reductions could be made without sacrificing patient throughput or increasing staff overtime. They experimented with several models mixing different types of patients (Swisher et al. 1997). They also showed that scheduling more of a certain type of patient (patients that require extensive physician interaction; longer service time) in the morning reduces employee overtime significantly. Harper and Gamlin (2003) tested a number of different appointment schedules and showed how patient wait times can be significantly reduced through improved planning of the schedule and management engagement (Harper and Gamlin 2003). Rohleder and Klassen (2002) studied the use of rolling horizon appointment scheduling and considered two common management policies: Overload Rules (OLR) and Rule Delay (RD). The results showed that managers of appointment scheduling systems must carefully consider which measures are most important to them since the best choices of OLR and RD vary substantially by measure (Rohleder and Klaseen 2002).

Discrete-event simulation is a useful tool for defining optimal operating conditions for outpatient clinics, indicating the most adequate capacity configuration of equipment and human resources based on patient scheduling. Coelli et al. (2007) used DES to take into consideration the global assessment of patient flow, equipment utilization, available personnel (technicians and physicians), equipment maintenance scheduling schemes, and exam repeat rates. Cote (1999) developed a simulation model which was based on the physician's practice to study the impact of examining room capacity and patient flow. Akas et al. (2007) developed two models with different points of view: length of stay and a management-oriented decision support system which was used to represent the conditional dependencies as well as the uncertainties of variables affecting system efficiency. Vasilakis et al. (2007) developed a simulation model used to evaluate the likely impact of the scheduling method in clinic operations. Several studies have used simulation as a method to compare the scheduling system to improve the efficiency of outpatient clinics by reducing patient wait times or increasing resource utilization (Manansang and Heim 1996; Vasilakis and Kuramoto 2005; Swisher et al. 2001).

The preceding studies have proved the validity and benefits of using DES to test alternatives against the current state of the systems in order to improve one or more metrics of interest. However, most of these studies have developed a simulation model of the operations which primarily focuses on the patient and does not provide enough details on the dynamics and complexity of the true processes. Similar to previous studies, the present study uses DES to compare scheduling polices. However, it defers from previous studies in that it integrates information flow, patient flow, and the use of multiples resources at the same time. The simulation model presents a detailed depiction of the interaction between patients, information, and resources and studies the effect of their interaction over the total time that patients spend in the clinic.

3. METHODOLOGY

This research study was conducted in an outpatient cancer clinic in the state of Montana. The clinic provides a broad range of services with treatment options for all kinds of cancer.

3.1. Conceptual model

The infusion area at the clinic is a complex system which includes several processes working in parallel that are required to provide infusion services to patients. There are two main processes which take into account information flow and patient flow.

The information flow process is driven by the order and is used by the pharmacy to prepare drugs for patients. This is a critical process as some patients receive infusion in stages. Due to the fact that some drugs have a short shelf life, pharmacy needs to prepare the drugs for each stage only minutes prior to when the drug is needed. For example, a patient scheduled to receive infusion for 5 hours might undergo 5 different drugs (at an average of 1 per hour). The pharmacy cannot prepare the 5 drugs right away as the ones needed for the fourth and fifth stage might expire within 2 hours.

On the other hand, the patient flow process pertains to the patient moving through the different stages of their infusion treatment. Nurses are a critical resource in this process. To keep the patient flowing through the system it is essential for both the information process and the patient process to be synchronized in a way that would minimize waiting for patients, medication and nurses. Thus, at each stage of the treatment three things need to happen for the treatment to continue: 1) patient has to be ready for next drug; 2) next drug has to be ready; and 3) nurses have to be available to administer the new drug.

The following is a description of the conceptual model of patient and information flow as presented in figure 1. A staff nurse escorts the patient to his/her preferred seat in the infusion center and gives a copy of the treatment information to the pharmacy. For the purpose of our model, we assume that patient arrival at infusion center and the order placement for drugs to the pharmacy happen at the same time. Upon arrival of a patient, a nurse checks him/her into the system. The nurse collects different information about the patient (body temperature, blood pressure, patient general condition, etc.) and enters it into the electronic system as a part of the check-in process. The nurse also reviews the treatment plan, requirements for premed or hydro fluid, type of premed, number of infusion drugs, among other things.

If a patient needs oral premed, the nurse collects it from a medicine cabinet and administers it. If the patient needs an IV-premed, the nurse waits for the pharmacy to prepare it and then collects it when ready to administer it to the patient. The nurse may attend to another patient during this wait time. After the completion of administering premed, or if there is no premed required, a nurse prepares the patient for the infusion drug(s). When the pharmacy completes preparing the first infusion drug, a nurse brings it for administration. A second nurse joins the first nurse at this point to cross-check everything prior to administering the infusion drug. The infusion drug is then administered. The patient waits in the chair for the infusion treatment to be completed. The nurse may attend to other patients during this time. However, he/she comes back a few times to check on the patient while the treatment is going on. If the patient requires more infusion drug(s), the nurse brings it from the pharmacy after they are done preparing it. The same process of administering infusion drugs continues. When the patient is done with the entire infusion treatment, he/she leaves the chair and the infusion center releasing all the resources he/she seized during his/her stay.

The work flow of infusion center is very much dependent on the activities of the pharmacy. The pharmacy prepares the IV-premed and infusion drugs of all the patients. To make this preparation process more efficient, the pharmacists follow different priority rules to prepare different premed/drugs.

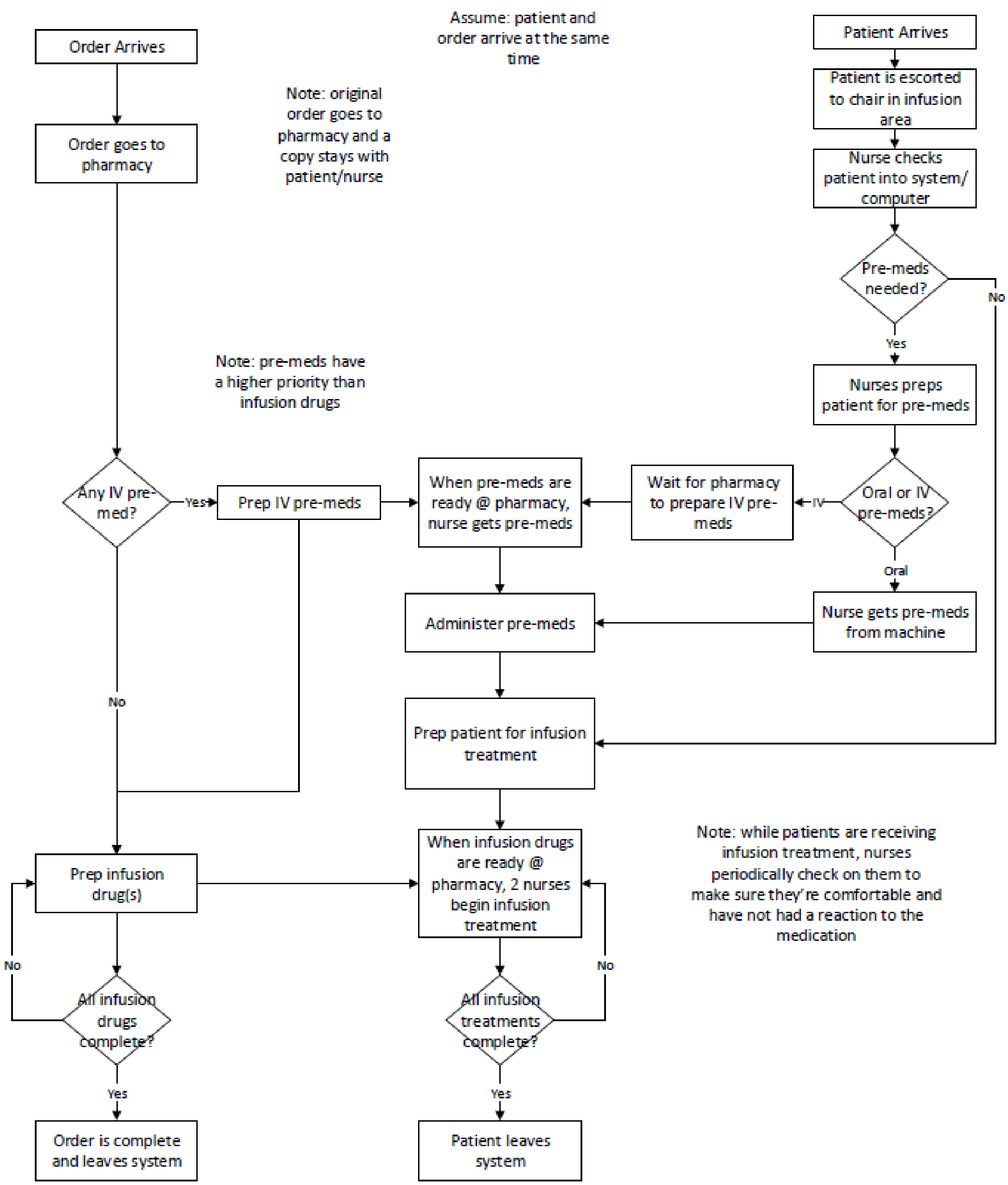

Figure 1: Conceptual model of patient and information flow

For example, when the order of medicines arrives at the pharmacy, they make a schedule for preparing the drugs/premeds. In general, IV-premeds get higher priority than the first infusion drugs. However, if a patient needs more than one infusion drug, the pharmacists prepare the first drug at first and schedule the additional infusion drugs for a later time with the highest priority. This time difference is selected based on the tentative time of administering the first (or current) infusion drug. By this way, the pharmacists can prepare the drugs for other patient quickly without keeping the current patients waiting. The conceptual model was validated by observing the process for several days. The simulation model was then built using Arena, version 14.0.

3.2. Development of Arena Simulation Model

Patient creation: Patient arrivals into the system were modeled using historical data of different patient types and approximate times for treatment. There are 12 different types of patients based on length of infusion treatment. Patients were scheduled in advance using historical schedules. Arena reads the scheduled time from a designated excel file. Patients were given appropriate attributes according to the 'patient type'. A cumulative probability matrix was used to assign the number of infusion drugs for each patient, as shown in Table 1. Another cumulative probability matrix was used to decide the type of premed (oral or IV), as shown in Table 2. These two matrices were derived using historical data.

Separating patient and information: Immediately after the arrival of each patient, a duplicate of the entity (as information) would go to the pharmacy creating an order for all necessary drugs. A unique patient ID is stored in an attribute to match the information and the patients through the system.

Deciding premed requirements: The decision if the premed was required or not was made using a probability matrix (Table 2). If a premed was required, another decision was made to decide the type of premed. A percentage distribution was used to make this decision. If IV-premed was selected, a duplicate of this information would go to the pharmacy to authorize them to prepare the IV-premed.

Processing of drugs at pharmacy: The IV-premeds were processed with priority 2 and the first infusion drugs were processed with priority 3 (priority 2 means higher priority than 3). Subsequent infusion drugs for the same patient (if any) were scheduled for processing 15 minutes before the first infusion treatment was scheduled to be completed. Preparation of any additional drugs followed the same principle. Preparation of second or any additional infusion drugs had priority 1 (highest priority) to minimize patient wait time between stages of a treatment.

Synchronizing patients and drugs: When both the patient and the drug were ready, a match occurred in order to initiate further processing towards the treatment. This matching was carried out using a specific identification attribute to ensure the prepared drug would go to its intended patient.

Table 1: Cumulative probability matrix for number of infusion drugs

		# of Infusion Drugs by Patient Type			
		1	2	3	4
Patient Type	Type 1	1	1	1	1
	Type 2	1	1	1	1
	Type 3	1	1	1	1
	Type 4	0.50	0.90	1	1
	Type 5	0.50	0.85	1	1
	Type 6	0.45	0.80	1	1
	Type 7	0.45	0.75	1	1
	Type 8	0.40	75.00	1	1
	Type 9	0.35	0.60	1	1
	Type 10	0.35	0.60	0.85	1
	Type 11	0.25	0.65	0.95	1
	Type 12	0.20	0.35	0.65	1

Table 2: Cumulative probability matrix for number deciding number of PreMed

		# of PreMed Requirements by Patient Type	
		1	2
Patient Type	Type 1	1	1
	Type 2	1	1
	Type 3	1	1
	Type 4	0.60	1
	Type 5	0.50	1
	Type 6	0.40	1
	Type 7	0.30	1
	Type 8	0.20	1
	Type 9	0.10	1
	Type 10	0.10	1
	Type 11	0.10	1
	Type 12	0.10	1

Administering Infusion Drug and Cross-checking: A preparation time was assigned to get the patient ready for the treatment prior to administering it. After a time study, a statistical function was used to assign the preparation time of the treatments. A single nurse was seized for this preparation job. After this process, a second nurse was seized with higher non-preemptive priority to cross-check the treatment plan. This cross-checking was a quick process but required the presence of two nurses.

Nurse Checks on the Patient during the Treatment: After administering the infusion drug, the nurse was then released. Infusion treatment continued as per its time. However, the nurse checked on the patient one time during each stage of a treatment. This checking typically occurred halfway through the treatment depending on nurse availability. A similar checking concept was applied while the IV-premed treatment was ongoing.

3.3. Model Assumptions

Assumptions made while developing the simulation model using Arena include:

1. No-shows or cancellations were not part of simulation process. Currently the clinic where the study was conducted has a low rate of no-shows and last-minute cancellations.
2. Patients arrived to the infusion area at their scheduled time.
3. Patients got the treatment they came for and no complication happened during treatment.
4. The infusion area had two pods of chairs, six chairs in each pod and one private bed. Though each pod has assigned nurses, it was observed that the nurses were switching pods if either side was significantly busier. To simplify the model, both pods were assumed as a single one and all nurses were assigned to serve patients from any pod.
5. Resources were fixed throughout the day (i.e. same number of nurses, chairs, and pharmacists).

4. MODEL VALIDATION

The simulation model was validated by comparing the average time a patient spent in the system from the simulation against the real system (from historical data). A week for the month of March of 2014 was used to validate the model. The historical schedules were also used to establish the inter-arrival time of patients to the system. It was determined that 10 replications were necessary in order to obtain a confidential interval half-width that was within 5% of the mean.

Table 3 presents the comparison between the simulation model and the real system. From the table it can be seen that the mean time in the system for the simulation is relatively close to the real system. In fact, it can be seen that the average time for the real system is within the 95% confidence intervals of the simulation output for each day.

Table 3: Comparisons among actual system outputs and simulation outputs

Day	Actual System Average time in system (min)	Simulation Model Average time in system (min)	95% Confidence Interval for simulation output
1	135.09	135.08	131.94-138.22
2	115.27	117.73	114.57-120.89
3	107.33	108.52	106.59-110.45
4	169.52	169.38	164.34-174.41
5	128.73	130.32	128.26-132.38

5. EXPERIMENTS

With the development and validation of a detailed model which allows the researchers to explore the interactions between patients, information and resources (chairs, nurses, pharmacists), three experiments were designed to test different scheduling policies. To compare the results from each experiment, one metric of interest was used: average patient time in the system.

The objective of the study was to establish a scheduling policy that would allow the clinic to increase its daily throughput while balancing its resources without affecting the quality of the services (measured by patient wait time). The current policy of the clinic is to schedule, on average, one patient every 20 minutes. However, they do not consider the length of duration of the infusion therapy when scheduling patients.

5.1. Experiment 1

This experiment studies the impact of increasing the number of patients arriving at the infusion area so that 2, 3, or 4 patients every 20 minutes. The proposed schedule reallocates the actual patients for each day according to the duration of the treatment from long to short duration. Consequently, the number of patients seen by the simulation model for each day is the same as in the actual system. Figure 2 presents an example of an actual schedule for the clinic whereas figure 3 presents the proposed schedule with 2 patients arriving every 20 min.

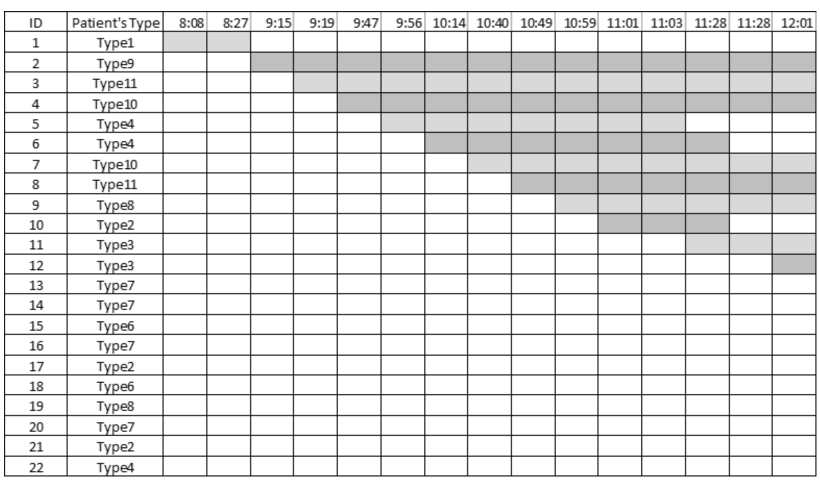

Figure 2: Actual schedule- day 1

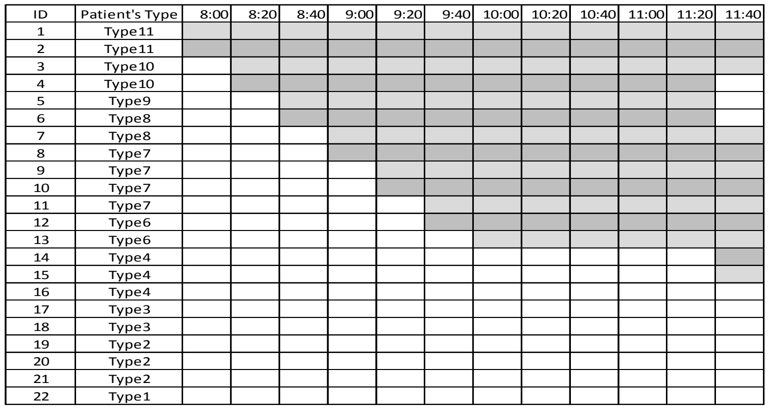

Figure 3: Proposed schedule with arrivals of 2 patients every 20 minutes- day 1

5.2. Experiment 2

Experiment 2 changes the arrival rate to 1 patient every 10 minutes. Once again, the proposed schedule reallocates the actual patients for each day according to the duration of the treatment from long to short duration. Figure 4 presents the proposed schedule with arrivals of 1 patient every 10 min.

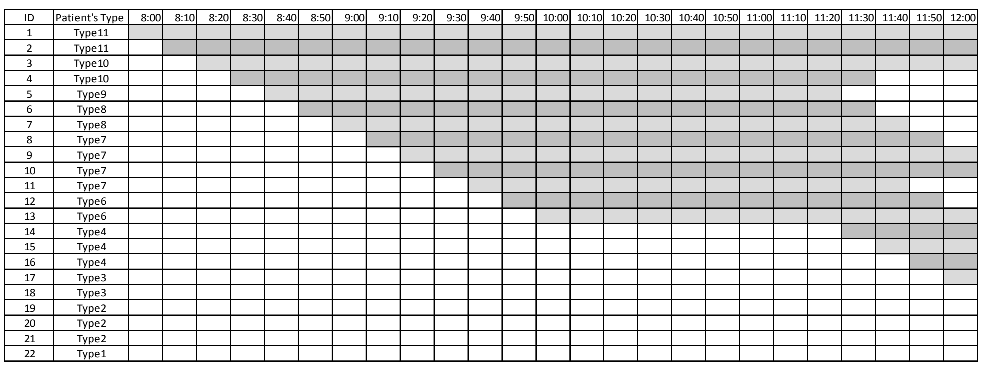

Figure 4: Proposed schedule with arrivals of 1 patient every 10 minutes- day 1

5.3. Experiment 3

This experiment is based on a heuristic derived with the purpose of balancing the workload for any 30 minute interval. The average of total cycle time is used as the baseline of the proposed schedule (see Table 3). The criteria to allocate appointments are:

- If the total time of patients in the system for a single appointment is greater or equal to 2 times the average total time of patients in the system for a given day it is allocated first, and the inter-arrival time between this appointment and the next one is 30 min.
- If the summation of the length of two appointments is equal to 2 times the average total time, in other words, the average of those two appointments is approximately equal to the average total time for a particular day, schedule these two appointments at a rate of 1 appointment every 15 min in the next available spot.

For example, day 1 had a patient average time in the system of 135 minutes. If a scheduled infusion treatment is expected to take 270 minutes or more, then it should be scheduled by itself and no other appointments are scheduled for 30 minutes. On the other hand, if one appointment is expected to last 60 minutes and another appointment is expected to last 210 minutes, then the average between those two appointments is 135 minutes. Both patients would be scheduled within 15 minutes of each other. Figure 5 presents the proposed schedule with the heuristic.

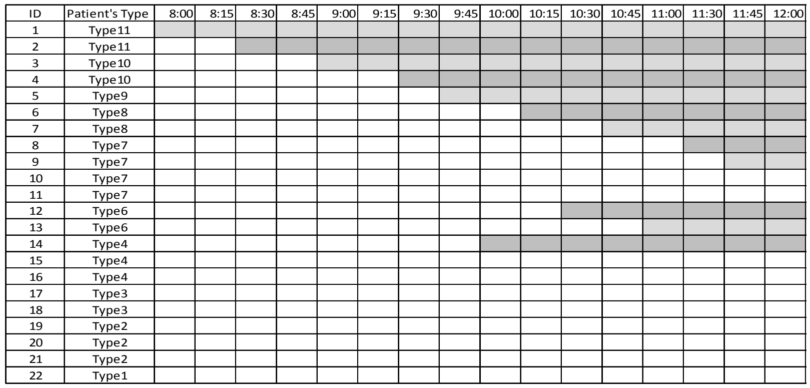

Figure 5: Proposed schedule heuristic methodology- day 1

6. RESULTS

The simulation of the actual system shows no patient wait time during the week. This implies that when patients arrived they found an available chair. However, the clinic currently has problems responding to an increase in their demand; as a result, the clinic management is working on alternatives to increase the daily throughput of the system. This study proposes different scheduling policies that may contribute to increasing the daily throughput. Statistical analysis was performed to compare the actual system versus the proposed system.

6.1. Experiment 1 Results

The results from experiment 1 showed an increase in the total patient time in all five days. Table 4 shows the results for the experiment. A statistical test shows, with a 95% confidence interval, a significant difference between the actual system and the proposed system with the actual system resulting in less time than the proposed system in four of the five days.

Table 4: Results for Experiment 1

		Day 1	Day 2	Day 3	Day 4	Day 5
Actual System						
	Total patient time	135.58	119.20	108.52	168.38	130.32
	Variance	19.23	19.52	7.27	49.52	13.17
2 patients every 20 min	Total patient time	140.91	121.09	117.06	168.29	134.73
	Variance	17.334	20.756	35.534	18.315	6.002
	Lower CI on diff	-9.36	-6.12	-13.05	-5.50	-7.36
	Upper CI on diff	-1.30	2.34	-4.03	5.68	-1.46
	Conclusion	Significant	Not Significant	Significant	Not Significant	Significant
3 patients every 20 min						
	Total patient time	143.72	127.74	120.56	170.28	137.33
	Variance	42.32	46.50	32.16	26.35	22.18
	Lower CI on diff	-13.43	-14.02	-16.37	-7.74	-11.00
	Upper CI on diff	-2.85	-3.06	-7.71	3.94	-3.02
	Conclusion	Significant	Significant	Significant	Not Significant	Significant
4 patients every 20 min	Total patient time	147.97	129.84	125.62	174.58	137.79
	variance	26.53	36.48	52.44	60.69	9.87
	Lower CI on diff	-16.90	-15.66	-22.48	-13.60	-10.67
	Upper CI on diff	-7.88	-5.62	-11.72	0.40	-4.27
	Conclusion	Significant	Significant	Significant	Not Significant	Significant

6.2. Experiment 2

The results from experiment 2 showed an increment in all the alternatives; however, the increment was not significant for the alternatives where one patient arrives every 15 min and for when one patient arrives every 10 minutes. Table 5 shows the result for experiment 2.

Table 5: Results for Experiment 2

		Day 1	Day 2	Day 3	Day 4	Day 5
Actual System	Total patient time	135.58	119.20	108.52	168.38	130.32
	Variance	19.23	19.52	7.27	49.52	13.17
1 patient every 15 min	Total patient time	136.05	120.34	110.16	164.61	131.21
	Variance	28.64	14.92	20.21	10.14	14.23
	Lower CI on diff	-5.09	-5.06	-5.20	-1.55	-4.38
	Upper CI on diff	4.15	2.78	1.92	9.09	2.60
	Conclusion	Not Significant	Not Significant	Not Significant	Not Significant	Not Significant
1 patient every 10 min	Total patient time	136.53	122.70	115.95	166.15	130.72
	Variance	15.92	29.37	46.47	18.53	16.66
	Lower CI on diff	-4.91	-8.1651	-12.53	-3.36	-4.04
	Upper CI on diff	3.01	1.1651	-2.33	7.82	3.24
	Conclusion	Not Significant	Not Significant	Significant	Not Significant	Not Significant
1 patient every 5 min	Total patient time	145.02	127.13	124.71	176.55	137.48
	variance	90.40	85.20	122.00	91.28	60.18
	Lower CI on diff	-16.65	-14.98	-24.20	-16.12	-13.06
	Upper CI on diff	-2.23	-0.88	-8.18	-0.22	-1.26
	Conclusion	Significant	Significant	Significant	Significant	Significant

6.3. Experiment 3

The results from experiment 3 showed no significant increment between the patient total time of actual system and proposed system. Table 6 shows the result of the experiment. The result shows that the better alternatives are: 1 patient arrives every 10 minutes and the heuristic methodology because they don't have significant differences between total cycle time of the current system and the proposed system. Nevertheless, the proposed systems could have a positive impact on the daily throughput of the system since they can allow for more patients to be scheduled each day.

Table 7 presents the number of patients that could be added in the proposed systems considering the fact that patients can not arrive after 4:00 pm. From the table it can be seen that by scheduling one patient every 10 minutes, the clinic has the potential to increase their daily throughput by an average of 12.2 additional patients per day; whereas, the heuristic has the potential to increase the daily throughput to an average of 4.4 additional patients per day. Even though the average daily throughput for the alternative of scheduling patients every 10 minutes results in a greater value than the heuristic, nurses and pharmacy could be negatively impacted by the possible workload increment in the system. The heuristic, on the other hand, potentially balanced workload throughout the day having two appointments for which average time doesn't exceed the average workload of the current day. In other words, the time requirements for the nurses throughout the day are balanced rather than having peaks and valleys.

Table 6: Result for Experiment 3 – Heuristic model

		Day 1	Day 2	Day 3	Day 4	Day 5
Actual System	Total patient time	135.58	119.20	108.52	168.38	130.32
	Variance	19.23	19.52	7.27	49.52	13.17
Heuristic	Total patient time	137.12	118.31	112.83	167.86	130.09
	Variance	46.64	9.41	11.43	28.15	10.85
	Lower CI on diff	-3.77	-2.72	-7.20	-5.39	-3.04
	Upper CI on diff	0.69	4.50	-1.42	6.43	3.50
	Conclusion	Not Significant	Not Significant	Not Significant	Not Significant	Not Significant

Table 7: Additional daily throughput

	Day 1		Day 2		Day 3		Day 4		Day 5		Average
	# addnl. patients	Type	# addnl. patients	Type	# addnl. patients	Type	# addnl. patients	Type	# addnl. patients	Type	
1 each 10 min	1	Type8	1	Type8	1	Type10	1	Type8	2	Type5	
	4	Type7	4	Type7	4	Type9	4	Type7	2	Type4	
	2	Type6	2	Type6	2	Type8	2	Type6	2	Type3	
	2	Type5	2	Type5	4	Type7	2	Type5	2	Type2	
	2	Type4	2	Type4	2	Type6	2	Type4	1	Type1	
	2	Type3	2	Type3			2	Type3			
Total # of addnl. Patients	13		13		13		13		9		12.2
Heuristic	3	Type3	1	Type5	1	Type5	2	Type6	No slots available		
	1	Type2	1	Type4	1	Type4	2	Type5			
			2	Type3	2	Type3	1	Type4			
			1	Type2	1	Type2	2	Type3			
							1	Type2			
Total of addnl. Patients	4		5		5		8		0		4.4

7. CONCLUSIONS

The objective of this study was to develop a detailed simulation model that embodies a closer representation of the operations of an outpatient cancer clinic and establishes different schedule policies that could be used to improve the system.

The simulation model provides a level of detail that accounts for the interaction between patients, nurses, pharmacy, and information flow. To the best of the authors' knowledge, such level of detail has not been previously reported in the literature. The model takes in consideration the synchronization of several resources to allow patients to flow through the system. A series of experiments were designed to test several scheduling policies. Three experiments were designed to increase the daily throughput of the system. The first experiment increased the patient arrivals and kept the time between arrivals constant. The next experiment decreased the time between arrivals, and the last one used a heuristic methodology to redistribute the patient appointments. From the results, it was concluded that the overlapping between patient appointments increases patient wait time and hence the total cycle time of the patients in the system. The better alternatives were: one patient arriving every 10 minutes and the heuristic method. The average total patient cycle time for both proposed systems is not statically different from the current system. However, the systems show increments on daily throughput by 12.2 and 4.4 patients respectively. Future research should consider the impact by new scheduling policies over resource workload.

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AUTHOR BIOGRAPHIES

ANALI HUGGINS is a PhD candidate in the Department of Mechanical and Industrial Engineering at Montana State University, Bozeman, Montana. Her research interests include Human Factors, Optimization Modeling, Simulation, Decision Making and Healthcare Engineering. Her email address is: anali.huggins@gmail.com.

DAVID CLAUDIO is an assistant professor of industrial engineering in the Department of Mechanical and Industrial Engineering at Montana State University, Bozeman, Montana.. His research interests include Human Factors, Service Systems, Healthcare Engineering, and Decision Making. His email address is david.claudio@ie.montana.edu.

MD WALIULLAH received his MS degree in Industrial and Management Engineering from Montana State University at Bozeman.. His email address is: wali_kishor@yahoo.com.