Improvement of chemotherapy patient flow and scheduling in an outpatient oncology clinic*

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Due to increasing demand, the oncology clinics have been experiencing higher workloads and increasing delays in laboratory, pharmacy, and chemotherapy administration areas. In this study, we worked with an oncology clinic where patients receive chemotherapy treatment. A discrete event simulation model is developed to evaluate the operational performance in the clinic and to identify initiatives for improvement in process flow, scheduling and staffing. A mathematical programming model is developed to generate balanced appointment schedules for oncologist visit and chemotherapy treatment. Our results show that patient waiting times and clinic total working times can be reduced and a more balanced resource utilization can be achieved by using better scheduling methods.

Key words: Discrete event simulation, appointment scheduling, patient flow, oncology, chemotherapy

1. Introduction

Cancer patients often receive multiple treatments including chemotherapy, radiotherapy, and surgery from different specialists for extended periods of time. Services such as blood work, physical exam, drug preparation, and chemotherapy administration, are required to be performed in different facilities such as laboratories, clinics, pharmacies, and treatment rooms. The services in each facility are performed by multiple resources such as phlebotomists, nurses, pharmacists, and medical oncologists. Clinic administrators face the difficult decision of improving efficiency in this complex multi-facility environment. The coordination of these services and resources is critical for timely and efficient treatment of patients. In this study, our aim is to show that delays due to inefficient care delivery can be eliminated by better coordination, planning, and scheduling.

This study is performed in the Department of Hematology and Oncology in Lahey Hospital and Medical Center, Burlington MA. We consider chemotherapy patients who come to the clinic according to their appointment times for oncologist visit and/or chemotherapy treatment, and

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go through multiple stages (oncologist visit, lab, pharmacy, chemotherapy administration). They require multiple resources (oncologists, nurses, chairs, pharmacists, phlebotomists) at each stage of the process. Uncertainties 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, occur during a typical clinic day. All these uncertainties affect patient flow and staff workflow. Patients experience long waiting times due to delays in laboratory, pharmacy, and chemotherapy administration areas, and providers and staff experience an unbalanced workload throughout the day. Reducing patient waiting times is among the highest priorities for quality improvement and patient satisfaction in outpatient cancer treatment facilities (Gesell and Gregory, 2004). Appointment scheduling that does not consider the availability of clinic resources and nursing care requirements is determined to be the main cause of delays and unbalanced workload (Gruber et al., 2003; Chabot and Fox, 2005). In this study, our aim is the incorporate the actual resource requirements into coordination and scheduling of appointments to minimize patient waiting times and balance clinic workload.

We use discrete event simulation to model the patient flow in the oncology clinic and test the impact of different operational decisions on patient waiting times, resource utilizations and overtime. The model considers multiple patient classes with varying routings and resource requirements, unpunctual arrivals, and stochastic service times and treatment durations. Earlier simulation studies, which proposed changing the arrival rates to have a smoother workload, did not develop a method to find a schedule that considers the dependencies between oncologist and chemotherapy appointments. In this study, we propose an optimization model to determine a coordinated appointment schedule for oncology and infusion clinics with the objective of balancing workload and resource utilization for both processes during the day. This study is one of the few studies that considers all the complexities and uncertainties that occur in multi-facility healthcare systems with multiple patient classes and varying patient routings.

The remainder of the paper is organized as follows. A brief review of the existing studies in the literature is provided in Section 2. The clinic environment including patient flow, patient mix, and clinic resources is explained in detail in Section 3. In Section 4, the appointment scheduling in current practice and proposed optimization model to find a balanced appointment schedule are explained. The details of the simulation model and the computational results are given in Sections 5 and 6. The last section provides concluding remarks.

2. Literature review

Simulation is one of the most commonly used approach to model clinic environments with several complexities. In oncology clinics, simulation is used to find the best scheduling method, test the impact of different scheduling methods on clinic performance, and determine the optimal resource levels. The studies by Ahmed, ElMekkawy, and Bates (2011), Yokouchi et al. (2012), Tanaka (2013), and Woodall et al. (2013) consider the patient flow for chemotherapy treatment only. Ahmed, ElMekkawy, and Bates (2011) and Yokouchi et al. (2012) use simulation to determine the best appointment scheduling rules by changing arrival rates, and nurse schedules by changing the number of nurses at each time interval. The objectives are minimizing patient waiting times and maximizing throughput. Tanaka (2013) uses simulation to test different scheduling rules based on bin-packing algorithms and determine the time allocated for pre-treatment process, preparation and nursing. Woodall et al. (2013) use simulation based optimization to determine the optimal nurse schedules with the objective of minimizing expected waiting times. Shashaani (2011) first determines the appointment schedule using a deterministic integer programming model, and then uses it as an input to the simulation model to evaluate the impact of variability in service times on key performance measures such as patient waiting times. Shashaani (2011) considers the impact of oncologist appointments while determining the optimal appointment times in the mathematical programming model, but do not consider the patient flow for oncologist visits in the simulation model.

It is difficult to optimize scheduling and patient flow in oncology clinics without considering the patient flow in upstream stages (i.e. oncologist appointment), because patient flow from upstream stage might incur start time limits, uncertainties (cancellations, add-ons), and delays in downstream stages (i.e. chemotherapy treatment). It is important to consider both stages (oncologist and infusion appointments) simultaneously for better coordination of appointment schedules, improved patient flow and more balanced resource utilization in oncology clinics. There are only a few simulation studies that consider patient flow for both oncologist and chemotherapy appointments. Sepulveda et al. (1999) use discrete event simulation to determine the impact of alternative floor layouts, number of patients scheduled per day and a new building plan. The simulation model helps decision maker to identify bottlenecks and analyze patient flow before building a new facility. Baesler and Sepulveda (2001) integrate simulation, goal programming and genetic algorithm to find the best combinations of control variables (i.e. resources) to meet the predetermined goals of patient waiting time, chair utilization, clinic total working time and nurse utilization. Matta and Patterson (2007) use simulation to evaluate the impact of different patient arrival rates, resource levels (i.e. additional nurses, doctors), queuing policies, and an express testing center for a group of patients. None of these simulation studies propose an optimization method to determine the appointment schedules for oncologist and chemotherapy appointments.

There are studies that use optimization methods to solve appointment scheduling problem, but most of them consider chemotherapy appointments only. Turkcan, Zeng, and Lawley (2012) propose an integer programming model to determine appointment times, nurse and chair assignments with the objective of minimizing the maximum completion of all treatments while satisfiying nurse and chair availability constraints. Shashaani (2011) extends the daily appointment scheduling model of Turkcan, Zeng, and Lawley (2012) by incorporating patient preferences, staggered nurse schedules, and start time constraints (i.e. start after the completion of oncologist appointment). Santibáñez et al. (2012) propose a multi-objective integer programming model to schedule all patients considering nurse capacity with the objectives of satisfying patients' time preferences, pharmacy capacity, balancing workload between nurses, balancing workload of each nurse throughout the day and assigning clinical trial patients to specialized nurses. These three studies assume all patients that should be scheduled are known in advance. Sevinc, Sanli, and Goker (2013) propose a multiple knapsack model for offline scheduling (where all patients are known) and two heuristics based on best-fit bin packing algorithm for online scheduling where patients are added to the schedule dynamically. Hahn-Goldberg et al. (2014) use constraint programming to develop a template schedule based on historical data and update the template dynamically when appointment requests that do not fit the template arrive. The proposed model determines the start times of drug preparation and treatment stages while not exceeding the pharmacy, nurse, and chair capacities at any time throughout the day.

To the best of our knowledge, Sadki, Xie, and Chauvin (2011) is the only study that determines both oncologist and chemotherapy appointments simultaneously using a mixed-integer programming (MIP) model. The proposed MIP model determines the oncologist start times, patient appointment times, and injection start times with the objective of minimizing a weighted combination of patient waiting time and makespan (clinic total working time). The proposed model assumes punctual arrivals, no idle time between patients of the same oncologist, and no cancellations. The patients see their oncologist as soon as they arrive. The chemotherapy treatment starts after the oncologist sees the patient, the pharmacy prepares the drug and a chemotherapy bed becomes available. The nurses and pharmacists are assumed to have enough capacity and their availability is not considered in the proposed model.

In this study, we use optimization and simulation approaches to improve chemotherapy patient flow and scheduling in an outpatient oncology clinic. We develop a mathematical programming model that evenly distributes patients into time slots to balance the workload throughout the day for oncologist and chemotherapy appointments. Instead of determining a scheduling template, we use the optimal schedule to determine a probability matrix that shows the probability of assigning different patients types (categorized according to their treatment durations) to different appointment times. With the probability matrix, the scheduler does not have to know the whole day demand and can schedule the patients as they arrive sequentially. We develop a discrete event simulation model that closely mimics the complex flow of chemotherapy patients in a real clinic environment. The simulation model incorporates several environmental complexities including unpunctual arrivals, stochastic oncologist and chemotherapy appointment durations (functions of scheduled appointment durations), add-ons, cancellations, and nurse workflow. It also considers multiple patient classes characterized by appointment types, laboratory test requirement, treatment durations, oncologist visit durations, and nursing times. The simulation model is used to evaluate the current performance and test alternative operational decisions to improve performance measures such as patient waiting times and clinic overtime.

3. Clinic Environment

We worked with The Hematology and Oncology Clinic at Lahey Hospital and Medical Center in Burlington, MA. The clinic provides care for patients with blood disorders and cancer. Patients come to the clinic for consultation or follow-up with the oncologist and for chemotherapy treatment. Patients arrive to the clinic according to their appointment times and go through several processes before being seen by the medical oncologist and/or receive chemotherapy treatment.

3.1. Patient flow

Figure 1 shows the patient flow in the hematology and oncology clinic. When patient arrives to the clinic, appointment scheduling coordinator (ASC) verifies patient information, prints medication list, and updates patient status in oncology information system. After check-in, a medical assistant (MA) prepares patient's chart. When the vital room becomes available, MA calls the patient from waiting room and takes vital signs. If the patient needs laboratory tests, then blood is drawn by the medical assistant in the lab room. However, if the patient has a PORT, the blood can be drawn only by a registered nurse (RN) in the infusion clinic. The patient waits in the waiting room until an RN becomes available for blood draw. The blood sample is sent to the central lab and the patient waits until the lab results are received. The patients who need lab tests are told to arrive one hour early to the clinic to have enough time for blood draw and laboratory tests. After the test results are received, MA takes the patient who has an oncologist appointment to an available exam room and notifies the oncologist. If the patient has both oncologist and infusion appointments, he/she receives chemotherapy after the oncologist appointment. If the patient has a chemotherapy appointment, RN assesses patient 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. When the drug is ready, RN picks up the drug and starts the treatment. While the patient is on the chair, RN continuously monitors patient status. When the treatment is completed, RN finishes the treatment and patient is discharged. The dotted lines in Figure 1 show the time stamps we get from the information system. We use these time stamps to determine patient mix, scheduled and actual oncologist visit and chemotherapy treatment durations, appointment schedules, arrival times, patient waiting times, and time in system for each patient type.

[Insert Figure 1 here]

3.2. Patient mix

The patients are first divided into three groups based on the appointments they have on a given day: i) patients with oncologist appointment only (Type O); ii) patients with chemotherapy appointment only (Type C); and iii) patients with both oncologist and chemotherapy appointments (Type OC). The oncologist appointment durations change according to provider practice, and whether patient is a new or an existing patient. The oncologists allocate 10 to 30 minutes for existing patients and 40 to 60 minutes for new patients. The chemotherapy treatment durations depend on chemotherapy protocols and show a high variability (range from 30 to 360 minutes). Based on current patient mix, approximately 45% of infusion appointments are scheduled for 30 minutes. The patients who are scheduled for their first chemotherapy treatment require additional nursing time for education. In order to allocate more nursing time to new patients, we determined whether the patient is a new patient or not. Patients who need lab tests require additional resources. Therefore, we further classified each patient group as i) patients who need lab tests; and ii) patients who need lab tests and have PORT access.

4. Appointment scheduling

4.1. Current practice

Patient access to the oncology clinic is guaranteed through appointments. The patients who have to see their oncologists and receive chemotherapy on the same day are scheduled based on oncologist availability and chemotherapy treatment duration. Long chemotherapy treatments are scheduled at earlier times to avoid overtime. When we look at the existing schedules, we observe that more patients of type OC are scheduled for oncologist appointments in the morning (Figure 2.a) to provide enough time for chemotherapy afterwards. Majority of oncologist appointments are scheduled between 8:30 AM and 4:00 PM. Figure 2.b shows the percentage of patients scheduled for chemotherapy treatment. Chemotherapy appointments are scattered throughout the day with no single peak time. However, more appointments are scheduled in the middle of the day compared to the rest of the day. The current schedules create unbalanced workload in the clinic and we believe a better scheduling method can provide a more balanced workload and lower patient waiting times.

[Insert Figure 2 here]

4.2. Proposed scheduling method

We propose a mathematical programming model to find a better schedule with a balanced workload. Table 1 shows the notation used in the proposed model. The following model assumes patient mix is given, where the number of appointments for each patient type and appointment duration are known.

[Insert Table 1 here]

$$min \quad \max_t c_t - \min_t c_t \tag{1.a}$$

$$min \quad \max_t o_t - \min_t o_t \tag{1.b}$$

$$st \quad \sum_{t=1}^{T-d+1} x_{idt} = NC_{id} \qquad i = OC, C \text{ and } \forall d \tag{2}$$

$$\sum_{t=1}^{T-d+1} y_{jdt} = NO_{jd} \qquad j = OC, O \text{ and } \forall d \tag{3}$$

$$\sum_d y_{OC,d,t} = \sum_d x_{OC,d,t+s} \qquad t = 1, \cdots, T-s \tag{4}$$

$$\sum_d \sum_{u=max\{t-d+1,1\}}^{t} (x_{OC,d,u} + x_{C,d,u}) = c_t \qquad t = 1, \cdots, T \tag{5}$$

$$\sum_{d} \sum_{u=max\{t-d+1,1\}}^{t} (y_{OC,d,u} + y_{O,d,u}) = o_t \qquad t = 1, \cdots, T \tag{6}$$

$$\frac{\sum_d (x_{OC,d,t} + x_{C,d,t})}{\sum_d (NC_{OC,d} + NC_{C,d})} \leq \frac{R_t}{\sum_{t=1}^{T} R_t} \qquad t = 1, \cdots, T \tag{7}$$

$$c_t \leq F \qquad t = 1, \cdots, T \tag{8}$$

$$o_t \leq P_t \qquad t = 1, \cdots, T \tag{9}$$

$$x_{idt}, c_t \geq 0 \text{ and } integer \qquad i = OC, C \text{ and } \forall d, t \tag{10.a}$$

$$y_{jdt}, o_t \geq 0 \text{ and } integer \qquad j = OC, O \text{ and } \forall d, t \tag{10.b}$$

The first objective (1.a) minimizes the difference between maximum and minimum number of chairs occupied to find a balanced chair utilization. The second objective (1.b) minimizes the difference between maximum and minimum number of exam rooms occupied at each time slot. Constraints (2) and (3) make sure all patients are scheduled for chemotherapy and oncologist appointments. When the patient has both oncologist and chemotherapy appointment, there should be enough slack time between the appointments, which is satisfied by constraint (4). Constraints (5) and (6) determine the number of chairs and exam rooms occupied at each time slot. Chemotherapy treatment can start only when a nurse is available and constraint (7) is used to limit the number of treatment starts based on the number of nurses. Constraints (8) and (9) are the capacity constraints for chairs and providers. Constraint (10.a) and (10.b) are the integrality constraints.

We solved the proposed model in two stages. In the first stage, we solved the model with the first objective (1.a) and constraints (2), (5), (7), (8), and (10.a) to determine the number of chemotherapy appointments that should be scheduled at each time slot. Once chemotherapy appointments are determined, the number of oncologist appointments for the patients who have both appointments are given as inputs to the second model with the second objective (1.b) and constraints (3), (4), (6), (9), and (10.b) to determine the number of oncologist appointments for other patients. Figures 2.c and 2.d show the proposed schedules for oncologist and chemotherapy appointments, respectively. According to the optimal oncologist appointment schedule, the last two appointment slots are allocated to type O patients, because those patients do not need chemotherapy treatment on the same day. For chemotherapy appointments, most type C patients are scheduled in early morning because their appointments do not need to be coordinated with the physician schedule.

Even though the proposed mathematical programming model is supposed to be solved as an integer programming model, we solve the problem as a linear programming model and use the results to determine a probability matrix. Table 2 shows the optimal probability matrix used to determine the appointment times for the proposed scheduling method. The appointment schedules are generated sequentially as the appointment requests are realized one at a time without knowing the future requests. In the simulation model, when a patient entity is generated, we first determine the patient type according to the current patient mix. If the patient is of type C or OC, the chemotherapy appointment duration is determined randomly according to the current patient mix. Based on the chemotherapy appointment duration, the appointment time is determined according to the probability matrix. For example, if the appointment duration is generated as 270 minutes, then the probability of assigning an appointment time of 7:30am is 0.5241, the probability of assigning an appointment time of 8:00am is 0.0313, and so on. If the patient is of type OC or O, then the appointment duration for the oncologist visit is determined. For patients of type O, the appointment time is determined based on an empirical probability distribution that depends on the number of oncologist appointments at each half-hour interval. For patients of type OC, the oncologist appointment time is one hour before the chemotherapy appointment. In both cases, the availability of the oncologist is checked. If the oncologist is not available, then another oncologist appointment time is determined randomly for Type O patients, and the chemotherapy appointment time is changed for the Type OC patients. Figure 3 shows the chair utilization for the current practice and proposed scheduling method. The proposed scheduling method gives a smoother workload during the day compared to current practice by balancing the number of patients treated at any time period. The difference between the optimal and generated schedule is due to random and sequential nature of patient mix and appointment schedule generation explained above.

[Insert Table 2 here]

[Insert Figure 3 here]

5. Simulation Model

We developed a simulation model of the clinic to identify the problems related to patient flow in current practice and evaluate the impact of a balanced appointment schedule on key operational measures including patient waiting times, clinic total working time, and resource utilizations.

5.1. Input data

We consider the patient mix in current practice, where 34% of patients have both oncologist and chemotherapy appointment (Type OC patient), 45% of patients have oncologist appointment only (Type O patient), and 21% of patients have chemotherapy appointment only (Type C patient).

The percentages of patients who need laboratory tests are 56%, 9% and 19% for Type OC, Type O and Type C patients, respectively. The percentages of patients who need laboratory test and have PORT access are 71%, 11%, and 83%, respectively.

We consider unpunctual arrivals and uncertain service times. Table 3 shows all the distributions used in the simulation model. In order to determine the arrival times, the difference between the appointment time and arrival time is calculated. However, since the patients who need lab tests are asked to arrive one hour early to their appointment to have enough time for lab tests, we fitted different arrival time distributions for each patient type. For example, the patients who have oncologist appointment only (type O patients) and need lab test arrive on the average 72.9 minutes early to their oncologist appointment.

[Insert Table 3 here]

The oncologist appointment and chemotherapy treatment durations might be longer or shorter than the scheduled durations due to several reasons. For example, difficulty in intravenous (IV) access or side effects of drugs might increase treatment durations. The side effects of chemotherapy drugs might lead to cancellations after the treatment starts. To consider the actual durations in the simulation model, we fitted distributions for the ratio between actual and scheduled durations. We use different distributions for short infusions (treatment duration ≤ 60 minutes) and long infusions (treatment duration > 60 minutes). For example, if a patient is scheduled for a 30-minute chemotherapy treatment, the actual treatment duration will be $30 \times 2.33 \times Beta(1.21, 2.7)$ minutes. That means, the actual treatment duration changes between zero and 70 minutes and the expected value is 21.6 minutes ($21.6 = 30 \times 2.33 \times 0.72$ where 0.72 is the expected value for $Beta(1.21, 2.7)$) for 30 minute appointments.

We included all other stages of the patient flow process including registration/check-in, taking vitals, blood draw, lab turnover time, pharmacy time for drug preparation, and nursing time to start and finish chemotherapy. In order to determine the service time distributions at these stages, we collected data from the oncology information system, performed additional time studies and received expert opinion. The clinic has 3 ASCs, 6 MAs, 12 oncologists, 2 pharmacists, 18 chairs and 9 full-time nurses. We assume the number of ASCs, MAs, oncologists, and pharmacists are fixed. The number of nurses and chairs is considered as an experimental factor in the computational study section.

5.2. Discrete event simulation model

We used Anylogic simulation software to model the patient flow in the oncology clinic. The patients are generated according to the current patient mix in the clinic as explained in Section 3.2. The appointment times are determined based on the scheduling method. For the patients who have two appointments, chemotherapy appointment time is determined first to reduce overtime. In current practice, the schedulers leave a 30-minute gap between oncologist and chemotherapy appointments (chemotherapy appointment time $\geq$ oncologist appointment time + oncologist appointment duration + 30 minutes).

For verification of the simulation model, we performed statistical analysis to compare the simulation outputs with the real data. We took 100 replications for five days and compared the results with the real data collected over five days. Table 4 shows the confidence intervals for the simulation model and the real system data. The results show that there is no significant difference between the results, which confirms the validity of the simulation model.

[Insert Table 4 here]

6. Computational study

We consider five experimental factors to show the impact of appointment scheduling on clinic performance in a clinic environment with several complexities including multiple processes and resources, unpunctual arrivals, delays, add-ons and cancellations. The factor levels can be seen in Table 5. The first factor is the patient volume. In current practice, patient volume varies significantly from day to day due to the treatment guidelines that should be followed strictly and lack of advanced planning methods to provide a more balanced workload among days. Since the average performance over all these varying patient volume scenarios would be misleading in determining the best operational policies, the patient volume is used as an experimental factor, where 80, 100, and 120 patients per day correspond to low, medium, and high volume days, respectively.

The second factor is the mean difference between appointment times and arrival times. In current practice, the patients who need laboratory tests are asked to arrive one hour early for their appointments. Based on our analysis, we also identified that other patients who do not need laboratory test arrive 30 minutes early for their appointment. During data collection and the validation phases of our study, we realized that the total time for initial check-in, vital signs, blood draw and lab turnover was less than one hour. We thought a shorter time difference between appointment time and arrival time would reduce the total patient waiting times. We consider three factor levels to determine the impact of the mean difference between appointment time and arrival times on patient waiting times. The first factor level of (60, 30) corresponds to current practice. The second factor level of (45, 15) and third factor level of (30, 5) assume patients who need laboratory test arrive on the average 45 and 30 minutes early to the clinic, respectively. The other patients arrive on the average 15 and 5 minutes early to the clinic, respectively. The main aim of choosing the time difference between appointment time and arrival time as an experimental factor is to find the best time difference so that the clinic managers can change their policy of asking the patient to arrive one hour early for their appointment.

The third factor is the percentage of patients who need laboratory tests. This factor is important, because the patients who need lab tests arrive to the clinic earlier and use additional resources (MA or nurse for blood draw, lab technician for blood test), different than the other patients. Although the chemotherapy protocols determine the need for laboratory tests, the patients might choose to have the test at another location and have the results sent to the clinic. The percentage of patients who need laboratory test might increase when patients prefer to have the test on the day of appointment in the clinic. As more patients who need lab tests arrive to the clinic, it will cause additional delays for other patients due to increased workload for MAs, nurses, and lab technicians. The current percentages of patients who need tests are 55%, 9% and 19% for type OC, type O and type C patients, respectively. We considered 20% and 40% increase with respect to current percentages as the other factor levels.

[Insert Table 5 here]

The fourth factor is the appointment scheduling method and nurse schedules. In this study, our aim is to show that better scheduling methods can improve patient flow by reducing patient waiting times and clinic overtime. In order to compare the proposed scheduling appointment scheduling method with current practice, we considered three factor levels. The first factor level corresponds to the current practice. In current practice, staggered nurse schedules are used where nurses start working at different times. According to the current appointment scheduling method used in the clinic, less number of patients are scheduled in early morning hours, which shows that staggered nurse schedules are taken into consideration. The second factor level, which uses the proposed scheduling method and staggered nurse schedule, is chosen to show the impact of the proposed appointment scheduling method alone. The proposed appointment scheduling method has the potential to provide a more balanced workload throughout the day. However, when a staggered nurse schedule is used, the number of available nurses should be considered in determining the optimal schedule. In order to match available number of nurses and chemotherapy appointments in each time slot, less patients are scheduled in the early morning hours. The third factor level with proposed scheduling method and non-staggered nurse schedule is chosen to show the impact of changing the appointment scheduling method and nurse schedules together. The non-staggered nurse schedule assumes same starting times for all nurses and the proposed appointment scheduling method reduces the clinic total working time by scheduling more patients in the early morning hours.

The fifth factor is the number of nurses and chairs for the chemotherapy treatment stage. The clinic currently has 9 nurses and 18 chairs for chemotherapy patients. In most of the oncology clinics, the number of nurses is adjusted based on patient volume. In order to show the importance of determining the right staffing level, we use the number of nurses as an experimental design factor. Even though the number of chairs does not change in a clinic, we assume it is not safe to have the same number of patients with less number of nurses. Therefore, we consider the number of staffed chairs instead of the actual number of chairs. The number of staffed chairs gives the maximum number of patients that can simultaneously be treated with the available nurses without compromising the safety of the patients. We consider 15 staffed chairs for 8 nurses and 18 staffed chairs for 9 nurses in order to measure the impact of change in staffing level on clinic performance.

In a literature review paper by Jun, Jacobson, and Swisher (1999), it is mentioned that "effective and efficient patient flow is indicated by high patient throughput, low patient waiting times, a short length of stay at the clinic, and low clinic overtime, while maintaining adequate staff utilization rates and low physician idle time". In this study, patient waiting times, total time in system and the total clinic working hours (which can be used to measure clinic overtime and the patient throughput) are used as the performance measures. The improvement in patient flow is measured by the amount of reduction in patient waiting time and total clinic working time. Patient waiting time to see the provider, and for chemotherapy treatment are calculated with respect to appointment time and arrival time. If a patient arrives early, the waiting time before the appointment time is not included in the calculations. However, chemotherapy patients who need lab tests are asked to arrive early for their appointments. They go through several processes and they wait between the processes due to limited resources. Instead of just looking at the waiting times from appointment time, we consider the total waiting time to show the importance of coordination between stages. Total working time shows the difference between the time last patient leaves the system and the clinic start time.

6.1. Results

The simulation model is run for a single day and replicated 100 times for each factor combination, resulting in 16200 ($3 \times 3 \times 3 \times 3 \times 2 \times 100$) simulation runs. We performed ANOVA to analyze the main and interaction effects of all factors on the performance measures. The main effects of five factors are found to be significant for all performance measures. Figure 4 shows the selected significant interaction effects on performance measures.

[Insert Figure 4 here]

Figures 4.a and 4.b show the interaction effect of scheduling method and patient volume on total waiting time and total working time, respectively. The proposed scheduling method gives lower patient waiting time compared to the current scheduling method. The effect of the proposed scheduling method is more significant when the patient volume is high. That means, using a more balanced schedule becomes more important especially when the workload is high. When the patient volume is low (80 patients/day), the waiting times are close to each other for all scheduling methods. The proposed scheduling method gives lower total working time compared to the current scheduling method. The proposed scheduling method with staggered nurse schedule gives 21 minutes lower total working time compared to the current method. The non-staggered nurse schedule gives 14 minutes lower total working time compared to the staggered nurse schedule since more patients are scheduled in the early morning hours.

Figure 4.c shows the interaction plot between the scheduling method and the arrival times. The proposed algorithm gives lower patient waiting time to see the provider compared to the current practice. The same figure shows that the waiting time to see the provider is 15 minutes for the patients who arrive (60, 30) minutes early to their appointment and it increases to 21 minutes if they arrive (45, 15) minutes early. However, we would like to note that the waiting times are calculated from the appointment time, and do not include the time from arrival to appointment time. If we include the waiting time due to early arrival, the patients who arrive much earlier than their appointment time would actually end up waiting more than other patients who arrive later. For example, when the patients arrive (45, 15) minutes early, even though the waiting time increases by 6 minutes (from 15 minutes to 21 minutes) compared to patients who arrive (60, 30) minutes early, they save 15 minutes of waiting time, which results in 9 minutes lower waiting time. The interaction plot between the arrival time and the laboratory test rate shows that the arrival time is critical especially when more patients need laboratory tests (see Figure 4.d).

Figures 4.e and 4.f show the effect of number of resources on total working time. When the number of resources increases, the decrease in clinic total working time is higher for high patient volume and high percentage of patients who need laboratory tests. Figures 4.g and 4.h show the interaction effect of scheduling method and number of resources on waiting time for chemotherapy treatment and total working time, respectively. When the clinic has less resources, the proposed algorithm gives a higher improvement in patient waiting time for Type C patients compared to current practice (7 minutes (22%) improvement for 15 chairs, 8 nurses, and 4 minutes (15%) improvement with 18 chairs, 9 nurses). The effect of using the proposed scheduling algorithm with staggered nurse schedule instead of current appointment schedule on total working hours is higher when number of resources is high. The effect of using a non-staggered schedule instead of a staggered schedule has a higher effect on total working time when number of resources is low.

The main objective of the proposed scheduling method is to provide a more balanced workload throughout the day. Figure 5 shows the average waiting time by appointment time. The results show that the proposed algorithm reduces the waiting times during the peak hours. The reduction in waiting time is achieved by moving the peak volume to early morning and late afternoon slots. The proposed algorithm also schedules the last patient at 3:30pm instead of 4:00pm, which reduces the clinic total working time by 20 to 30 minutes compared to the current scheduling method.

[Insert Figure 5 here]

6.2. Summary

As a summary, the proposed scheduling method gives better clinic performance, especially when patient volume is high. The proposed scheduling method, which provides a smoother workload, improves the patient flow by reducing the patient waiting times especially at peak hours. The non-staggered nurse schedule provides a lower clinic total working time due to higher number of patients scheduled in early morning hours. The arrival time of the patients is a critical factor that affects total waiting times. In current practice, patients who need laboratory tests are asked to arrive one hour early, which increases the patient waiting time unnecessarily. We showed that a shorter time between the arrival time and appointment time can reduce the waiting times for patients. The clinics should determine the time allocated for laboratory tests according to lab turnover times and the percentage of patients who need laboratory tests. The number of available resources (number of chairs and nurses) can become a critical factor that affects waiting times and clinic total working times especially when the patient volume is high.

7. Conclusion

A discrete event simulation model was developed to model the complex flow of chemotherapy patients in oncology clinics. The model considers multiple patient classes with varying routings and resource requirements, unpunctual arrivals, uncertainties in service and treatment durations, add-ons, and cancellations. The model is used to evaluate the performance of a real clinic and to test alternative operational decisions to improve system performance. Earlier simulation studies, which proposed changing the arrival rates to have a smoother workload, did not develop any scheduling method to find a schedule that considers the dependencies between oncologist and chemotherapy appointments. We developed an optimization model to determine a coordinated appointment schedule for oncology and infusion clinics. The proposed scheduling method determines the number of oncologist and chemotherapy appointments with the objective of minimizing the deviation between low and high utilization time slots. The impact of the proposed scheduling method is tested using the simulation model that incorporates several uncertainties of a real clinic environment.

The computational results showed that scheduling methods that aim to balance the workload provides lower patient waiting times and clinic total working times. Using a better scheduling method becomes more important especially when patient volume is high. The operational decisions that are not determined based on the actual data can cause unnecessary waiting times. For example, asking the patient to arrive one hour early can cause high waiting times, especially when the lab turnover time is much less. The decrease in patient waiting times during peak hours and the decrease in total clinic working time show the improvement in patient flow by using advanced scheduling methods and operational decisions based on actual data.

We presented our results to clinic managers and they decided to implement the scheduling method to reduce patient waiting times during peak hours. Currently, we are working on developing a scheduling template as a guideline for the schedulers. The clinic managers also decided to do an analysis of lab turnover times to understand the effect of patient volume throughout the day and determine the optimal time that should be allocated for the patients who need laboratory tests to minimize patient waiting times. The clinic also started scheduling the last patient half hour early so that overtime can be reduced.

The operational difficulties in oncology clinics are common to any other healthcare system where patients are seen in different departments/clinics on the same day and require a large number of resources (physicians, nurses, pharmacists, technicians, medical assistants). Multiple patient classes, varying patient routings, day-of-week and time of day differences in patient volume and resource availabilities complicate the process of improving the efficiency of these multi-facility systems. This study is one of the few studies that considers all the complexities and uncertainties that occur in multi-facility healthcare systems. As future research, the patient acuity levels and their impact on nurse workload can be incorporated into the simulation models. Patient acuity is a measure used to quantify the time and intensity of nursing care. For example, nurses allocate more time to the patients who have higher probability of having side effects from the drugs. When the patient shows allergic reactions to the drugs administered, the nurse might allocate all her time to that patient while other patients assigned to that nurse are being monitored by other nurses. The existing studies consider resources as "passive" objects and do not take into account the tasks that should be performed by the nurses other than direct patient care. Studies that aim to find the relationship between patient acuities and nurse workflow, and incorporating these into the simulation models would be valuable contributions to the literature in determining the optimal nurse-patient ratios. Another research area can focus on determining the best way of providing care by comparing different nursing care models including primary nurse models and team-based models.

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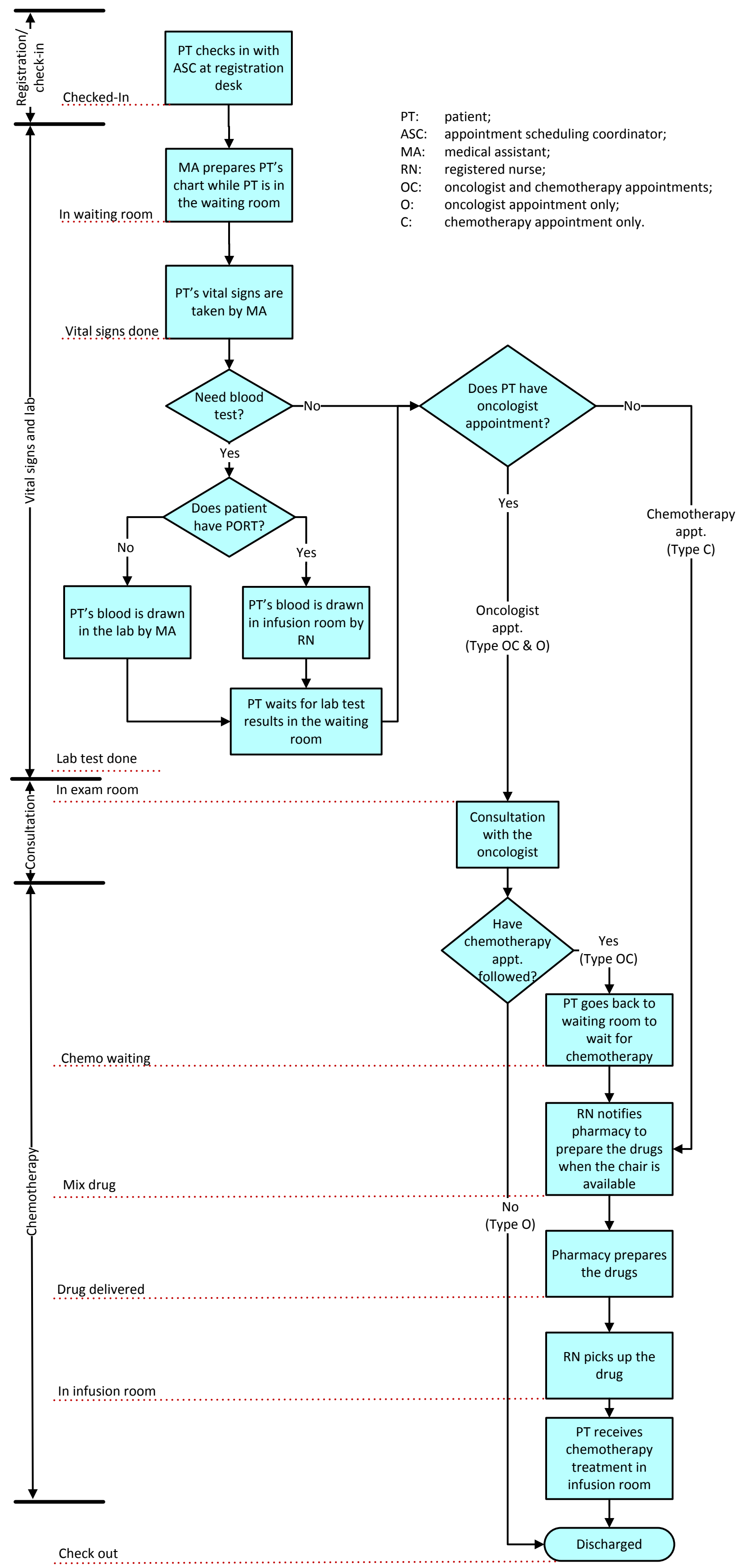

Figure 1 **Patient flow**

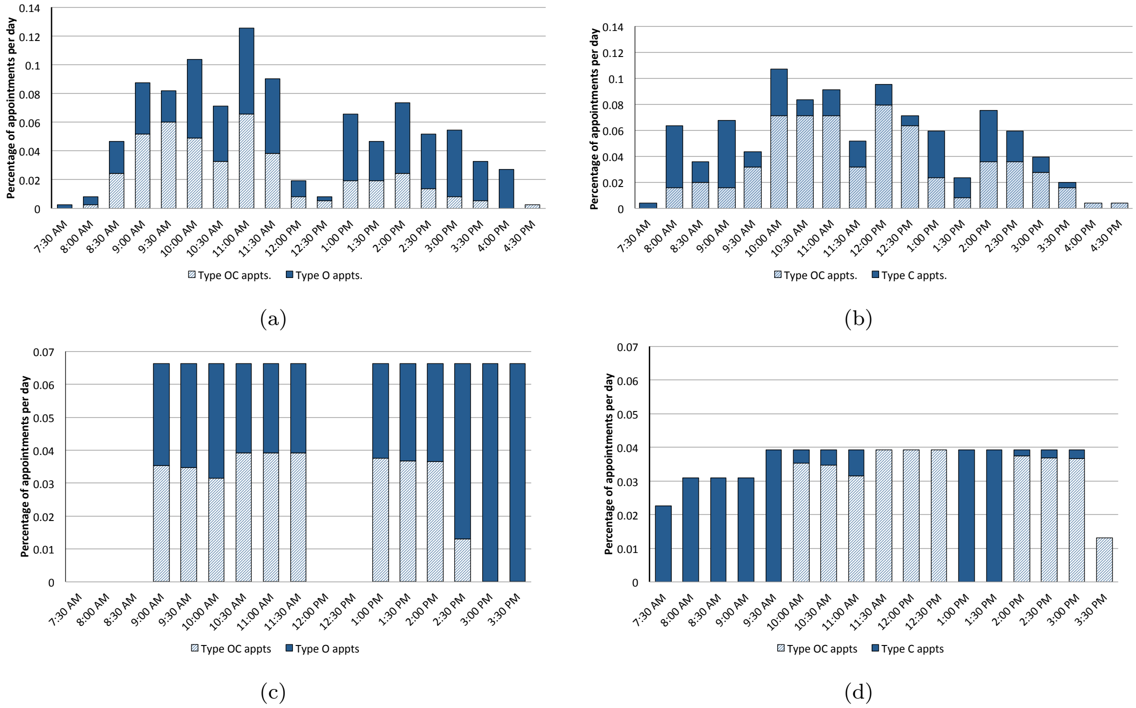

Figure 2 **Distribution of appointment times for each patient type; a) oncologist appointment times for current practice, b) chemotherapy appointment times for current practice, c) proposed oncologist appointment times, and d) proposed chemotherapy appointment times**

NC_{id}	Total number of patients of type i with chemotherapy appointment duration d ($i = OC, C$)
NO_{jd}	Total number of patients of type j with oncologist appointment duration d ($j = OC, O$)
T	Total number of slots in the planning horizon
R_t	Number of nurses available at time slot t
P_t	Number of physicians available at time t
F	Number of chairs
s	Slack time required between oncologist and chemotherapy appointments
x_{idt}	Number of patients of type i with appointment duration d scheduled to start chemotherapy at time t
y_{jdt}	Number of patients of type j with appointment duration d scheduled to start oncologist visit at time t
c_t	Number of chairs occupied at time slot t
o_t	Number of exam rooms occupied at time slot t

Table 1 **Notation**

Time	30	60	90	120	150	180	210	240	270	300	330	360	390
7:30 AM	0.0006	0.0023	0.0000	0.0000	0.1216	0.2046	0.0079	0.3137	0.5241	0.1686	0.0276	0.0266	0.0498
8:00 AM	0.0387	0.0024	0.0000	0.0017	0.0082	0.0111	0.0079	0.2049	0.0313	0.2088	0.0406	0.2650	0.9502
8:30 AM	0.0843	0.0024	0.0000	0.0017	0.0082	0.0104	0.0032	0.0523	0.0006	0.1766	0.1543	0.2488	
9:00 AM	0.0868	0.0024	0.0000	0.0003	0.0076	0.0042	0.0538	0.0529	0.0015	0.1185	0.2744	0.2492	
9:30 AM	0.0907	0.0024	0.0000	0.0203	0.0002	0.0033	0.0466	0.0295	0.0680	0.1153	0.2539	0.2105	
10:00 AM	0.0930	0.0024	0.0000	0.0207	0.0000	0.0038	0.0551	0.0522	0.0682	0.1038	0.2490		
10:30 AM	0.1039	0.0022	0.0000	0.0158	0.0017	0.0035	0.0398	0.0238	0.0748	0.1070	0.0001		
11:00 AM	0.0476	0.0095	0.0001	0.0583	0.0098	0.0916	0.1014	0.2084	0.2243	0.0015			
11:30 AM	0.0929	0.0211	0.0000	0.0422	0.0396	0.0368	0.0581	0.0617	0.0073				
12:00 PM	0.0611	0.0864	0.0000	0.0805	0.1505	0.1928	0.1754	0.0007					
12:30 PM	0.0491	0.0742	0.0000	0.0691	0.1413	0.1613	0.4423						
1:00 PM	0.0744	0.0526	0.0670	0.0579	0.1885	0.2614	0.0086						
1:30 PM	0.0749	0.1159	0.0733	0.0000	0.3137	0.0154							
2:00 PM	0.0051	0.0216	0.0000	0.6279	0.0092								
2:30 PM	0.0226	0.1801	0.8517	0.0038									
3:00 PM	0.0315	0.4197	0.0079										
3:30 PM	0.0429	0.0026											

Table 2 **Chemotherapy appointment time vs. duration**

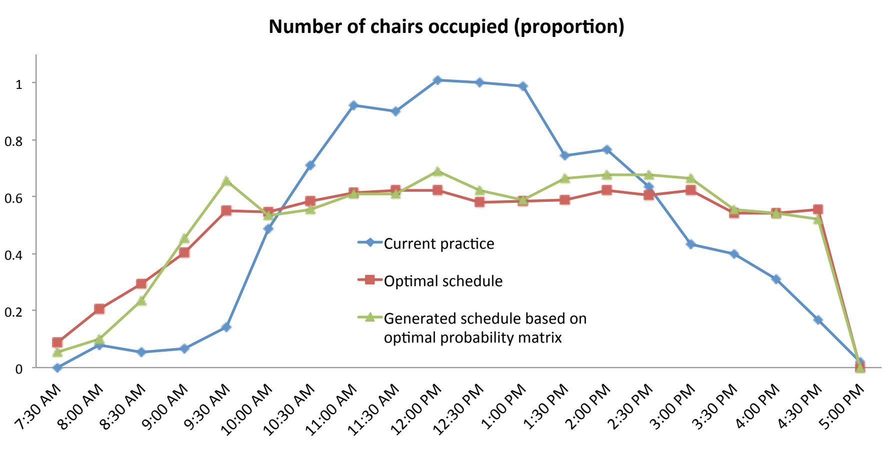

Figure 3 **Number of chairs occupied during the day (proportion over all chairs)**

Processes	Distribution	Fitted/Expert Opinion
Arrival time − appointment time		
Type OC patient with lab	−Normal(63, 44)	Fitted (p=0.0484)
Type OC patient without lab	−Normal(50, 54)	Fitted (p=0.133)
Type O patient with lab	−Normal(73, 42)	Fitted (p>0.15)
Type O patient without lab	−Normal(29, 41)	Fitted (p=0.015)
Type C patient with lab	−Normal(60, 31)	Estimated
Type C patient without lab	−Normal(19, 60)	Fitted (p=0.0139)
Actual / scheduled duration		
Oncologist appointment	Lognormal(0.068, 0.502)	p>0.15
Chemotherapy (scheduled ≤ 60 min)	2.33 * Beta(1.21, 2.7)	p>0.15
Chemotherapy (scheduled > 60 min)	1.57 * Beta(1.25, 1.6)	p>0.15
Other service times		
Check-in	Triangular (0.5, 1, 2)	Expert opinion
Time to get the chart ready	Lognormal (1.019, 0.716)−2.5	Fitted (adjusted) (p=0.267)
Taking vital signs	Triangular(3, 5, 10)	Expert opinion
Blood draw in lab	Erlang(3.98, 2)+0.5	Fitted (p=0.024)
Blood draw in infusion room	Triangular(2.5, 11.6, 36.5)	Fitted (p>0.75)
Lab turnover time	Triangular(5, 15, 30)	Expert opinion
RN assesses patient condition	Triangular(1, 2, 10)	Expert opinion
Pharmacy time	Weibull(10.5, 1.42)−1.5	Fitted (adjusted) (p>0.75)
RN starts chemo (new patient)	Triangular(25, 30, 45)	Expert opinion
RN starts chemo (established patient)	Triangular(5, 10, 15)	Expert opinion
RN finishes chemo	Triangular(2, 5, 10)	Expert opinion

Table 3 Distribution functions used in the simulation model

Performance measures	Actual		Simulated	
	Mean	95% CI	Mean	95% CI
Waiting time to see the provider (oncologist)	11.70	[10.06, 13.35]	11.71	[11.49, 11.93]
Waiting time for treatment (Type OC)	11.18	[7.59, 14.77]	8.49	[8.20, 8.79]
Waiting time for treatment (Type C)	19.07	[12.86, 25.28]	20.49	[19.94, 21.04]
Time in system	132.23	[121.47, 142.76]	123.46	[121.57, 125.36]

Table 4 Comparison of actual data with simulation output

Factors	**Level I**	**Level II**	**Level III**
Patient volume	80 patients/day	100 patients/day	120 patients/day
Mean difference between appointment time and arrival time (patients with lab, patients without lab)	(60, 30) minutes	(45, 15) minutes	(30, 5) minutes
Percentage of patients who need lab test	Current rate	20% increase	40% increase
Appointment scheduling method (AS)	Current AS	Proposed AS	Proposed AS
Nurse schedule (NS)	Staggered NS	Staggered NS	Non-staggered NS
Number of chairs and nurses	15 chairs, 8 nurses	18 chairs, 9 nurses	

Table 5 Experimental factors

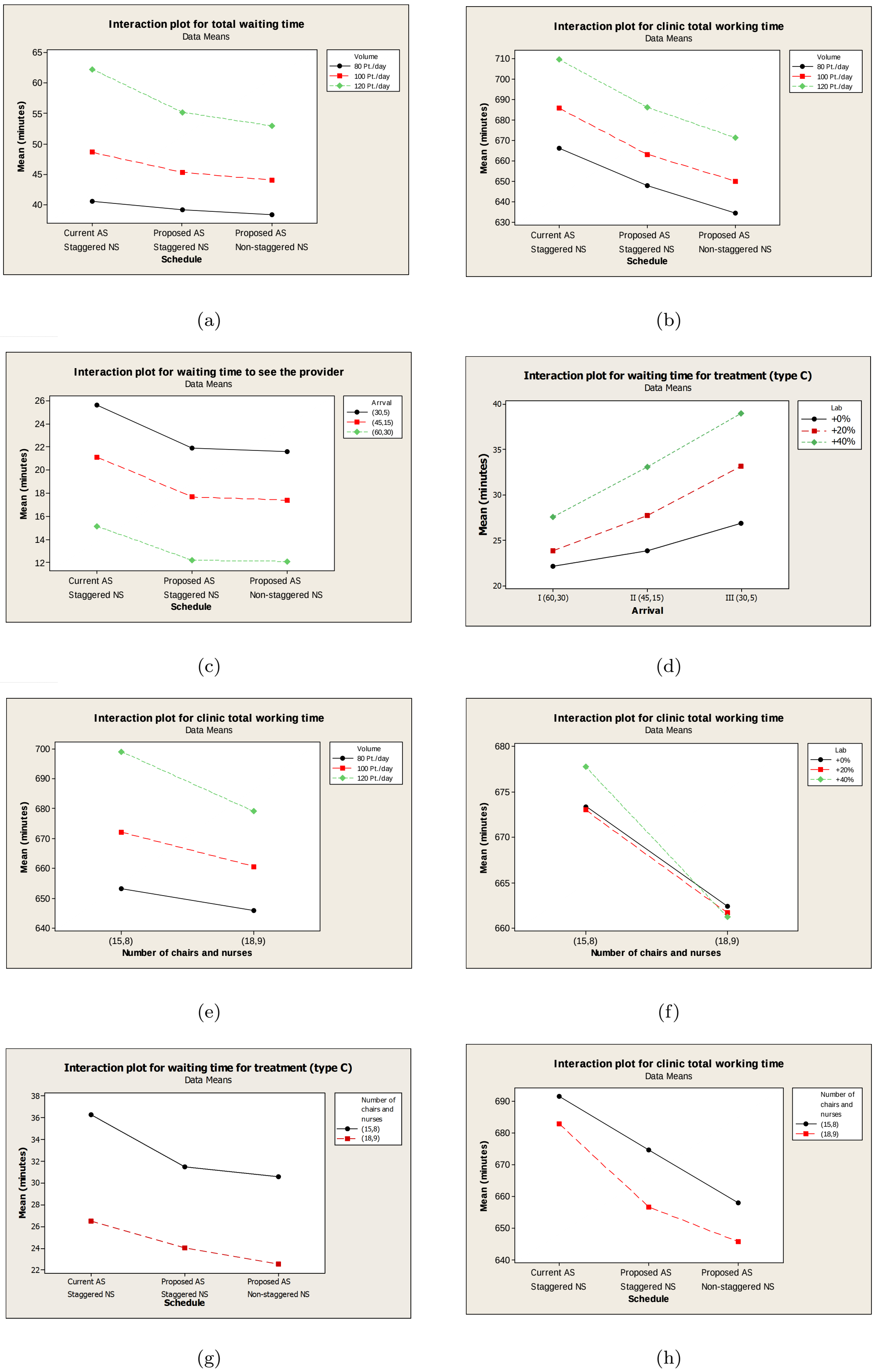

Figure 4 Two-way interaction effect of experimental factors on patient waiting time and total clinic working time

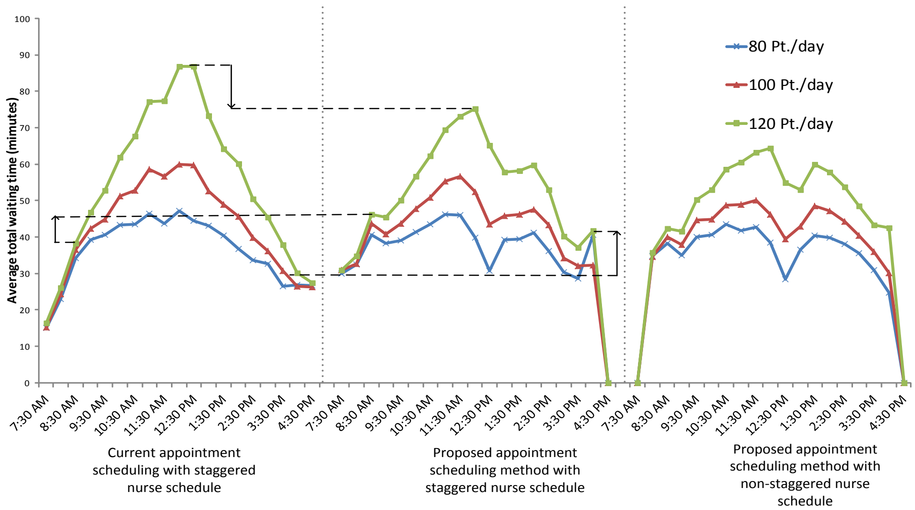

Figure 5 Average total waiting time by appointment time