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Improving Patient Access to Chemotherapy Treatment at Duke Cancer Institute

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This paper describes how we applied simulation and optimization in combination to improve patient flow within the Duke Cancer Institute, a large cancer center. We first developed a discrete-event simulation model to predict patient waiting time and resource utilization throughout various parts of the center, including the outpatient clinic, radiology, the pharmacy, laboratory services, and the oncology treatment facility. Simulation model studies showed that nurse unavailability during oncology treatment causes a serious bottleneck in patient flow. Next, we developed a mixed-integer programming model to relieve the bottleneck by optimizing weekly and monthly scheduling of different types of nurses. Finally, we developed a novel simulation-optimization model to further relieve the bottleneck by optimizing the starting times of nurse shifts. Our paper summarizes our main findings and the resulting recommendations that Duke Cancer Institute implemented.

Key words: simulation; optimization; integer programming; healthcare; nurse scheduling.

In many countries, cancer is a leading cause of death. As a result, patient demand for cancer services, which has been increasing steadily, is expected to continue to increase (Erikson et al. 2007). From the patient's perspective, these increases in demand can cause long waiting times, either at the cancer center or waiting for the day of a scheduled appointment. From the cancer center's perspective, they can result in higher-than-normal resource utilization, requiring overtime and causing congestion at the center. Furthermore, in a high-demand environment, variations in patient mix and patient-flow patterns can result in overutilization in some areas of the cancer center during some times of the day, and underutilization in others.

In this paper, we describe how we developed and implemented discrete-event simulation and mixed-integer programming (MIP) models to improve patient care at Duke Cancer Institute in Durham, North Carolina. Moreover, the insights we drew from our project are applicable to other cancer centers. We begin by describing a conceptual model of a cancer center. Next, we describe the various parts of the discrete-event simulation model and how we combined simulation and optimization methods to identify bottlenecks within the cancer center, optimize nurse staffing within the chemotherapy infusion center, and plan for future capacity expansion to meet patient needs. Finally, we summarize the benefits that Duke Cancer Institute gained from implementing our models and discuss opportunities for future research.

Cancer Center Background and Challenges

Patients visit cancer centers for many reasons, such as referrals from primary care physicians because of suspicion of cancer, second opinions, consultations about treatment, and follow-up consultations after completing treatment. A typical cancer center is organized into five departments (i.e., locations): clinic, radiology, central laboratory (lab), oncology treatment center (OTC), and pharmacy (see Figure 1).

Patients visit oncologists (cancer-specialist physicians) at the clinic, which is usually organized by type of cancer (e.g., breast, prostate, lung). Radiology performs imaging scans. The central lab performs lab tests, including blood tests—an important part of cancer diagnosis and treatment monitoring that must be reviewed before a patient receives chemotherapy. At the OTC, patients receive chemotherapy treatment as either an injection or an infusion, in which medicine is dripped intravenously into the patient (i.e., an IV). The pharmacy is the central location where the chemotherapy drugs are mixed prior to patient treatment. Because of the high cost of cancer drugs, the pharmacy typically does not mix them until the patient has checked into (i.e., registered at) the OTC and the patient's oncologist has reviewed the appropriate lab results. Thus, the services within a cancer center have many dependencies that can influence patient flow.

Most patients begin by registering at a clinic, have lab tests taken and processed, see an oncologist, and finish at the OTC. However, patient flow through a clinic varies. For example, some patients visit the cancer center for a clinic visit only. Of these patients, some require lab work and (or) radiology services; others do not. Some patients have previously visited the cancer center; others are there for the first time, and therefore tend to spend more time in the clinic. Some patients go from the clinic to the OTC on the same day; others return for treatment on another day. These variations can contribute to uncertainty (and therefore delays) in utilizing the downstream resources, such as the OTC, from day to day.

We developed detailed descriptions of the patient flow through each major area in the cancer center. However, because much of this paper focuses on changes within the OTC, we show the flow through this area in Figures 2 and 3.

Figure 2 illustrates the steps before treatment begins. First, the charge nurse—the nurse with overall responsibility for the OTC—reviews the patient's chart and medical information and determines if the drug order is complete. If the order is incomplete, the charge nurse contacts the patient's oncologist to

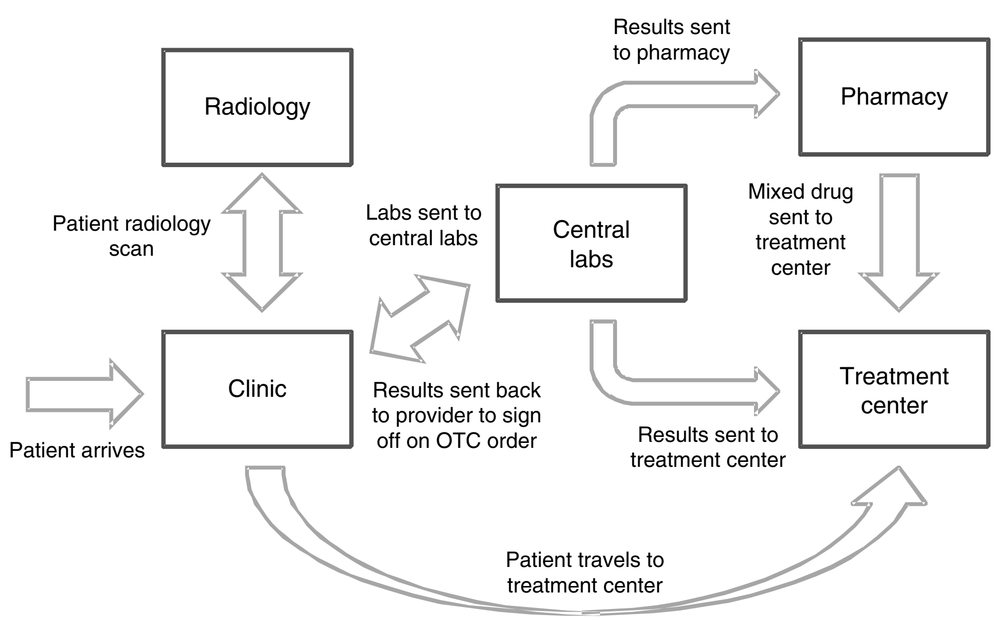

Figure 1: This figure depicts the patient and information flow among locations in a cancer center.

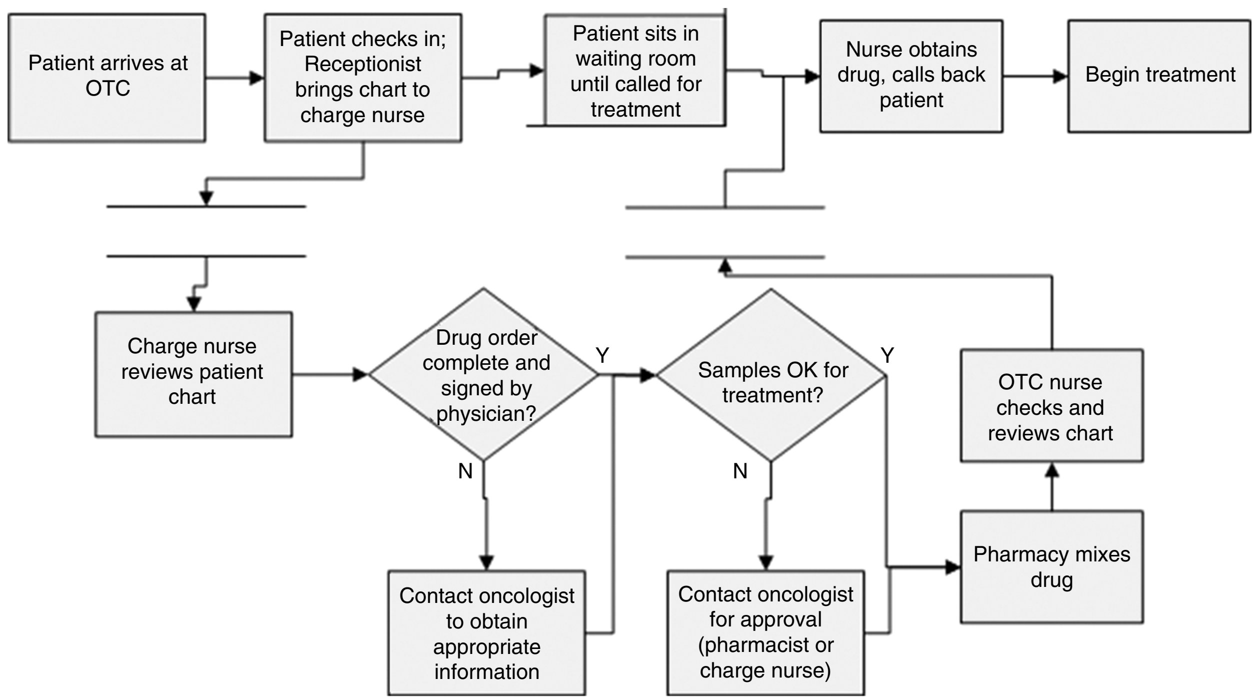

Figure 2: This flowchart of the OTC illustrates the patient, charge nurse (i.e., nurse with overall OTC responsibility), OTC nurse (i.e., nurse directly taking care of patient), and pharmacy activities prior to administering chemotherapy treatment in the OTC.

obtain the appropriate information. The charge nurse also reviews the lab results to ensure that treating the patient is appropriate, and contacts the oncologist if the lab results are abnormal. Once the pharmacy verifies the drug order and labs, it mixes the drug. Finally, before the patient is called back for treatment, the OTC nurse also reviews the chart and lab results.

Figure 3 illustrates the steps of treatment. Once the aforementioned process described in Figure 2 is complete, the OTC nurse caring for the patient brings the patient back to a treatment chair (i.e., a chair in which the patient will sit for the duration of the chemotherapy treatment). Of the two treatment types—injections and infusions—injections take

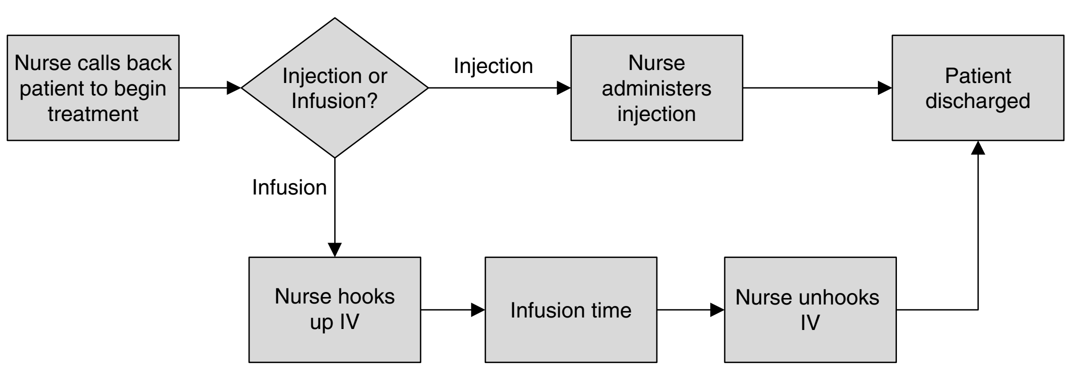

Figure 3: This flowchart shows the OTC flow when the patient requires either an injection or an infusion.

much less time. Prior to injection, the nurse reviews and discusses the appropriate medical history with the patient and gives the patient relevant information about the injection and managing symptoms. Once the injection is complete, the patient can be discharged.

For a chemotherapy infusion, a nurse reviews the patient's medical history, discusses necessary medical information with the patient, connects the IV, takes the patient's vital signs, and begins the infusion. The nurse can then prepare other patients, up to a maximum of four, concurrently. When the infusion has completed, the nurse disconnects the IV and discharges the patient.

Although patients are generally punctual in arriving at the cancer center, most visits involve a clinic appointment, lab tests, and other activities (e.g., radiology) that can delay their arrival time at the OTC. After the patient arrives at the OTC, additional delays may occur before treatment can begin. For example, delays may arise in receiving an order from the pharmacy, obtaining lab results, or gaining physician approval of orders.

Prior Work on Cancer Center Planning and Scheduling

Santibáñez et al. (2009) examine a cancer center at the BC Cancer Agency in Canada. They focus on the interaction of cancer clinics and study resource allocation decisions. The authors present scenarios that include changes to operational factors (e.g., clinic start time and faculty, such as residents and fellows), appointment scheduling (e.g., sequence of appointment types during the day, scheduling of urgent patients that arises on short notice), and resource allocation (e.g., pooled clinic resources or designated resources). They find that to obtain significant improvements, multiple changes to the existing systems are required.

Sepúlveda et al. (1999) present a model for the MD Anderson Cancer Center in Orlando, Florida, including the oncology clinic, OTC, and pharmacy. Their simulation model examines several scenarios involving changes to the layout and scheduling policies within this facility. The authors test policy changes in which they increase the number of short-term patients during slow times of the day and decrease this number during busier times.

Turkcan et al. (2010) examine patient-scheduling decisions in the setting of a cancer center. The authors combine two MIP models to plan patient chemotherapy treatment over a specified length of time, such that the same patient returns for multiple treatments over a sequence of days. The first MIP determines the resources required for the patient; the second MIP determines the best time to schedule the patient for treatment, subject to the constraint that the nurse does not exceed a specified acuity level for the day, where the acuity level is a measure of effort required for patient care. These authors also examine staffing levels to establish the optimal allocation of resources.

Project Contributions

We developed and implemented the project described in this paper from 2010 to 2011. It resulted in a number of findings that are transferrable to other cancer centers and other areas of the healthcare delivery system; however, it differs from the works cited previously in several ways. First, in contrast to Santibáñez et al. (2009) and Sepúlveda et al. (1999), our focus was on the OTC and in optimally designing nurse schedules to match daily provider (i.e., cancer center) supply and patient demand. Because of a national shortage of skilled nurses, efficiently allocating nurse resources is a high priority at most cancer centers. Second, in contrast to the aforementioned studies, we sought the best ways to staff nurses in light of nonstationary patient arrival behavior, including the simulation and optimization of nurse shift start times during the day. Third, in contrast to Turkcan et al. (2010), we combined simulation and optimization methods to understand ways to mitigate the impact of uncertainty from various sources, including patient service times, nurse availability, and pharmacy procedures. Finally, to the best of our knowledge, we have developed the most comprehensive model of a cancer center described in the published literature, and we believe that other cancer centers could adapt it to their environments. Woodall (2011) provides complete details of the model formulation, data collection, validation, and implementation.

Model Formulation and Validation

Following a detailed assessment of the patient flow through the cancer center, the project involved three modeling phases: (1) development of a discrete-event simulation model of the cancer center; (2) development of a MIP to optimize weekly and monthly nurse staffing decisions in the OTC; and (3) development of a simulation-optimization model to determine the optimal nurse shift start times from the weekly and monthly nurse staffing decisions. In this section, we describe the three models, model parameter estimates, and the model validation activities that led to our recommendations.

Discrete-Event Simulation Model

We built our simulation model using Rockwell's simulation software, Arena version 11. As part of our preliminary work, we collected sample observation times for services in all parts of the cancer center. Our data sources included computer information systems, time studies, and interviews with oncologist, administrator, and nurse experts. Collaborative work with this diverse group of experts allowed us to make assumptions about times when data did not exist or were not available immediately.

When we finished collecting data, we developed a prototype version of the simulation model. The initial model included the major areas within the cancer center (e.g., clinics, labs, radiology, pharmacy, and OTC). We estimated patient arrivals by looking at the mean number of arrivals during the day using historical data. We chose to use a nonhomogeneous Poisson arrival process because such a stochastic process is commonly used in similar applications, and because this assumption was reasonable based on our model validation. The Poisson arrival process is nonstationary because patient arrival rates vary significantly over the course of a day. From the historical data, we were able to estimate the average expected arrival rate by each half hour of the day and define the Poisson arrival process. Scheduled resources for each clinic include check-in (i.e., patient registration) and check-out (i.e., patient discharge) receptionists, and phlebotomists (i.e., technicians who draw blood samples), nurses, and oncologists; for the OTC, it includes the receptionist at the OTC check-in desk, charge nurse, nurses by disease-based groups (DBGs), treatment chairs, and beds. These resources are available according to predefined schedules that we entered into the model to define availability over the course of the day.

OTC nurses engage in both direct and indirect patient care, and work on some activities in parallel; to represent this, we assumed that each nurse has six capacity units available. For a patient infusion to begin, at least three units of nurse time must be available. Once the nurse finishes the start-up activities and begins monitoring the patient, two units of the nurse are freed. As a result of these assumptions, the number of patients a nurse can serve at one time is limited to four, which is an upper limit on the number of patients for which a nurse can be responsible simultaneously.

We fit probability distributions to historical data using the Arena 11 input analyzer. Criteria for selecting distributions were visual inspection and the results of chi-square and Kolmogorov-Smirnov tests. We also considered the squared error of the fit. If the data were lacking or unreliable, we fit probability distributions in two ways: time studies and expert opinions. We performed three time studies: one for the pharmacy (pharmacist time and drug mixing time), one for the check-out timings at the clinics, and one for the length of time the OTC charge nurse took to review patient charts. Table 1 shows the list of probability distributions. In the absence of historical data and time studies, we solicited expert opinions for the minimum, most-frequent (mode), maximum, and average processing times, with which we defined Beta distributions.

Validating the simulation model required that we take multiple approaches, including requesting expert opinions and statistically validating model outputs. We consulted the following experts: the clinical operations director, the assistant vice president and associate chief nursing officer of oncology, a management engineer in oncology, the administrative manager, and healthcare administration staff. Any results identified as potentially invalid were examined further. Accordingly, we made a number of changes to the initial model to refine our assumptions. Following the expert validation, we compared our observations to the model-generated patient arrival distributions, patient throughput, and the flow times (time from

Process type	Location	Probability distribution	Source
Charge nurse chart check	OTC	$0.5 + 37.5 \times \text{BETA}(1.30, 23.05)$	Time study
Pharmacist processing	Pharmacy	$-0.5 + \text{LOGNORM}(5.46, 6.74)$	Time study
Pharmacy drug mixing	Pharmacy	$1.5 + \text{ERLANG}(2.94, 2)$	Time study
OTC nurse chart check	OTC	$2 + 15.5 \times \text{BETA}(1.84, 4.52)$	Expert opinion
Injection treatment length	OTC	$\text{TRIANGULAR}(1, 2.1, 30)$	Expert opinion
OTC nurse IV setup	OTC	$5 + 25 \times \text{BETA}(3.31, 4.46)$	Expert opinion
Acuity level 1 treatment time	OTC	$15 + 75 \times \text{BETA}(4.46, 3.31)$	Expert opinion
Acuity level 3 treatment time	OTC	$90 + 120 \times \text{BETA}(4.6, 2.2)$	Expert opinion
Acuity level 5 treatment time	OTC	$210 + 210 \times \text{BETA}(4.36, 3.52)$	Expert opinion
Blood drawn to be processed at labs	Labs	$9.5 + \text{GAMMA}(12, 1.33)$	Historical data
Processing of blood samples	Labs	$19.5 + \text{LOGNORMAL}(19.5, 35.7)$	Historical data
Radiology processing	Radiology	$30 + \text{GAMMA}(62.2, 1.18)$	Historical data

Table 1: This table provides a list of probability distributions that we included in the simulation model for the OTC and pharmacy (all times are in minutes).

Cancer center area	Simulation model (50 replications) Mean	LCL	UCL	Historical data Mean	LCL	UCL	Sample size
Monday arrivals and throughput validation							
Surgical oncology	146.32	143.23	149.41	147.40	130.71	164.09	2,211
Oncology	167.04	163.12	170.96	167.87	159.47	176.26	2,518
Brain tumor	46.18	44.03	48.33	46.53	44.06	49.01	698
Prostate	36.08	34.27	37.89	36.40	33.19	39.61	546
Surgery	169.56	166.44	172.68	170.87	161.43	180.30	2,563
OTC direct arrivals	26.76	25.59	27.93	27.40	26.01	28.79	411
OTC throughput	100.34	97.53	103.15	103.20	98.22	108.18	1,548

Table 2: This table compares simulation model-estimated arrivals and observed arrivals to the OTC. OTC direct arrivals are patient arrivals that do not originate from a clinic. The 95 percent confidence interval is defined by the lower confidence limit (LCL) and the upper confidence limit (UCL).

check in to discharge) to statistically validate our findings. Table 2 illustrates results for arrivals and OTC patient throughput for a Monday. To aid with validation and verification, we created animations, which we generally built to troubleshoot behavior that the experts identified as unusual, for one clinic and for the OTC.

Mixed-Integer Programming Model for Nurse Staffing

As the last step in documenting the patient flow, OTCs are subject to time variability because of upstream services (i.e., clinics, labs, radiology), and are also typically resource constrained. In our simulation model, patient waiting times showed the OTC as a significant bottleneck within the cancer center. Further analysis identified OTC nurse availability as the most significant resource constraint. High variations in the types of patients, lengths of time required for the infusions, and numbers of patients arriving at the OTC throughout the day, contributed to this problem. As a result, the project team focused on exploring methods to improve nurse shift schedules, and thus better match nurse supply with patient demand.

Our approach to planning nurse schedules is twofold and hierarchical in nature. Figure 4 illustrates daily, weekly, and monthly scheduling. Total daily demandvarying from Monday through Friday, drives the weekly and monthly schedules. We used a MIP to solve the monthly and weekly planning problem to allocate a predetermined number of nurses across the weeks within the month to match aggregate nurse supply to historical demand estimates (the appendix has the complete mathematical formulation). Although a number of potential choices for the objective function are available, we chose to minimize the total shortage of nurse hours relative to patient demand because (1) project team members from the cancer center identified it as the most important consideration, and (2) it can be easily interpreted. The MIP contained many constraints, including a minimum allocation level across DBGs, fair allocation of long weekends (i.e., a Monday or Friday as a day off) among nurses, and others. After looking

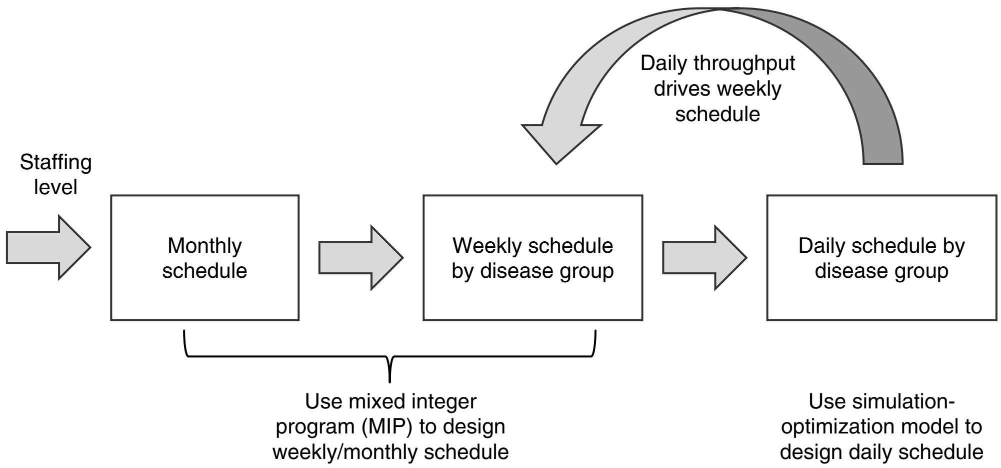

Figure 4: This diagram illustrates the relationships between major decisions involved in OTC nurse scheduling. The arrows define the information flow.

at the results of the MIP, we developed a simulation-optimization model to optimize daily shift start times to minimize average patient waiting time. Feedback (i.e., communication) between the monthly, weekly, and daily schedules iteratively improved the nurse schedules.

In our MIP model for weekly and monthly planning, we considered three types of nurses: 10-hour nurses who work four days a week (i.e., 40 hours), 8-hour nurses who work five days a week (i.e., 40 hours), and part-time nurses who work a variable number of days per week, hours per day, and hours per week. Constraints in our MIP define feasible schedules for the OTC. First, OTC daily hours of operation are fixed (e.g., 7:00 AM–8:30 PM). At least two nurses must be in the OTC at all times; thus, two openers (i.e., nurses who begin their shift at 7:00 AM) and two closers (i.e., nurses who end their shift at 8:30 PM) must be on duty. In addition, a minimum coverage level is required in each DBG during peak hours (i.e., 10:00 AM–6:30 PM). Furthermore, the OTC we studied requires each DBG to have a minimum of three nurses scheduled each day, 14 nurses Monday–Thursday, and 13 nurses on Friday (reflecting the lower number of patients the OTC sees on Fridays). Constraints also reflect the allocation of days off to 10-hour-shift nurses. Each 10-hour-shift nurse works four of the five weekdays and receives one day off. Each nurse must receive at least one long weekend per month (i.e., four-day weekend)—the nurse has Friday off one week and Monday off the following week. For part-time nurses with days off, the location of the day off is not constrained; thus, part-time nurses tend to be scheduled on the busiest days.

In the monthly and weekly scheduling MIP tests, we sought to determine the best way to allocate nurses across the week to meet variable day-to-day demand, with a particular focus on constraining the model to allot one four-day weekend for each 10-hour-shift nurse. The objective was to minimize total shortage hours in the OTC nurse schedule, with shortage hours determined by the daily scheduling requirements. Each day, a specific number of nursing hours is required to meet patient demand (assuming the discrete nature of nurse shifts is relaxed). However, because of the discrete nature of nurse shifts and constraints on the number of nurses available, these requirements may not be met each day. We refer to the nurse shortage as a deficit.

Simulation-Optimization Model for Daily Nurse Scheduling

In our daily schedule-optimization tests, we sought to determine the best daily shift start times to minimize the average time a patient must wait in the OTC. The appendix gives the complete formulation for our model. In this model, each nurse has a series of associated shifts to which he or she could be allocated; these shifts correspond to start and end times in half-hour increments during the day. Binary decision variables define nurse arrival times at these discrete time points (1 represents arrive; 0 represents not arrive). Sets of opening and closing shifts define the nurses working at the beginning and ending of the day, respectively, and off shift defines the sets of nurses who are working (i.e., on) or not working (i.e., off) on this day. A constraint determines the shifts for which a nurse may be scheduled (i.e., a binary indicator for each nurse and day combination). Nurse experience working in the various DBGs, as defined by the OTC clinical operations director, is the source of this indicator. A second constraint enforces the limitation that nurses do not work on their days off. Additional constraints require that at least two nurses are available for opening and closing the OTC.

In general, models such as the one we describe previously are computationally challenging because of the intractable nature of the expectation in the objective function. Closed-form expressions for expected waiting time in complex service systems, such as the cancer center we explore, are generally not available. Thus, resorting to heuristics is necessary. As a result, we solved this model using simulation and optimization by sampling expected patient waiting times via our discrete-event simulation model, described previously. The *Results* section provides details of our implementation.

Results

We conducted our testing on a Dell Optiplex 980 PC, Intel® Core™, 2.93 GHz computer with 8 GB RAM. The preliminary results from the complete simulation model for the cancer center and expert opinions aided us in identifying system bottlenecks. We applied our deterministic MIP model to analyze the monthly and weekly nurse-scheduling problem to determine the optimal allocation of nurses and nurse shift-length policies, subject to scheduling constraints on variable daily demand. Finally, our simulation-optimization model helped us to analyze the daily scheduling problem to find optimal work schedules under various shift-length policies, with optimal defined as the least amount of patient waiting time. The remainder of this section illustrates some of the analyses we conducted to obtain the recommendations that Duke Cancer Institute implemented.

Min. no. of FT nurses	No. of FT 10 hours	No. of FT 8 hours	No. of PT nurses	Shortage (hours)
Staffing level: 21 nurses				
0	6	1	18	18
9	7	5	10	17
10	6	5	12	11
11	7	4	12	26
12	7	5	10	17
13	9	4	9	18
14	12	2	7	88
15	9	6	4	90
16	12	4	4	65
17	11	6	2	57
18	9	9	0	85

Table 3: This table depicts results from the MIP for the optimal allotment of full-time (FT) and part-time (PT) nurses for a scenario in which 21 nurses are available.

Monthly and Weekly Schedule Optimization

We chose Premium Solver, the solver add-on, to solve instances of the MIP for monthly and weekly planning using branch and bound, with a tolerance of 0.1 percent, because this solver was easy to implement on a standard PC in the clinic environment. Additionally, we set the computation time to a maximum of one hour.

Table 3 shows results for a sample instance of the MIP for a 21-nurse scenario. We solved a series of model instances in which we varied the minimum number of full-time nurses between 9 and 18 to control the number of part-time nurses. We also include the case in which we set this minimum number to zero full-time nurses as a reference point. Table 3 shows the number of full-time nurses for both 10-hour and 8-hour shifts, and the number of part-time nurses in the best solution obtained after one hour of computing time. The last column provides the shortage hours (objective function). The results suggest two primary conclusions. First, using part-time nurses could significantly reduce total shortage hours. This is intuitive because shorter nurse shift schedules permit better matching of supply and demand during the day. Second, as the number of part-time nurses increases, the reduction in shortage hours either diminishes or shows no improvement. These results can help decision makers in trading off the pros and cons of employing part-time nurses to help match supply and demand; however, they may also require a greater number of handoffs of patients among nurses when shifts end.

Daily Schedule Optimization: Simulation-Optimization Results

We solved our simulation-optimization model using OptQuest version 6.4, which applies a combination of tabu search and other heuristics to attempt to find a near-optimal solution (Kelton et al. 2007). We set the stop-time criterion to end the simulation-optimization run after 1,000 iterations. We selected this number as a conservative upper bound when, following our simulation-optimization runs, we noted that significant objective function improvements did not typically occur after several hundred simulation runs. We set the indifference parameter (a user-defined parameter that defines a threshold at which schedules are considered indistinguishable) to be 0.1 minutes of patient waiting time. We allowed the optimizer to vary simulation model replications from 10 to 100, under the constraint that confidence interval widths were within 10 percent of the mean. For each instance of the model, simulation run times were approximately two to four hours.

The daily schedule simulation-optimization model used candidate schedules that we developed in a series of meetings with decision makers; our MIP model, combined with expert opinions, gave us the starting point for the daily schedule. We examined three nurse staffing levels with three promising shift-policy combinations; all 10-hour shifts, all 8-hour shifts, and a mix of 10-hour and 8-hour shifts (with the ratio of 10-hour to 8-hour shifts as approximately 2:1).

Table 4 illustrates each combination of nurse staff level and shift policy we considered. Because of variations in patient arrivals by day of week, we defined the simulation-optimization model for each day of the week in each scheduling scenario.

Table 5 shows the results of the simulation-optimization runs for scenarios 1–3 (the 21-nurse scenarios). The "Original" column shows the average waiting time for the candidate schedules developed manually; the "Optimal" column shows the average waiting time that OptQuest found as the best solution after 1,000 iterations. Table 5 also provides the half width of the confidence interval.

Scenario	Nurse staff level	Shift policy	Breakdown
1	21	All 10s	(21) 10-hour
2	21	Mix of 10s and 8s	(13) 10-hour, (8) 8-hour
3	21	All 8s	(21) 8-hour
4	18	All 10s	(18) 10-hour
5	18	Mix of 10s and 8s	(12) 10-hour, (6) 8-hour
6	18	All 8s	(18) 8-hour
7	16	All 10s	(16) 10-hour
8	16	Mix of 10s and 8s	(10) 10-hour, (6) 8-hour
9	16	All 8s	(16) 8-hour

Table 4: This table depicts results for the nurse staff-level and shift-length combinations for daily schedule optimization for various nurse staffing levels from 16 to 21 nurses.

	Original		Optimal	
	Mean	HW	Mean	HW
	Mean OTC waiting time			
Monday				
All 10s	32.28	2.78	29.02	2.32
(13) 10s	29.63	2.18	27.36	1.31
All 8s	29.33	2.29	27.69	1.84
Tuesday				
All 10s	34.44	3.41	29.43	1.88
(13) 10s	32.11	3.18	29.66	2.74
All 8s	38.48	3.24	27.73	1.45
Wednesday				
All 10s	38.06	3.96	35.79	3.52
(13) 10s	34.66	3.33	33.31	3.30
All 8s	36.06	4.02	33.47	3.33
Thursday				
All 10s	38.18	3.93	32.73	3.16
(13) 10s	36.55	3.75	30.32	2.16
All 8s	35.17	3.65	28.86	2.78
Friday				
All 10s	32.81	3.16	26.95	1.63
(13) 10s	30.75	2.97	25.88	1.58
All 8s	32.07	3.20	25.75	1.27

Table 5: This table depicts results of the 21-nurse simulation-optimization by comparing the original and optimal schedules for "All 10s" (i.e., all 10-hour nurse shifts), "All 8s" (i.e., all 8-hour nurse shifts), and a mix of shift lengths in which 13 nurses work 10-hour shifts (HW denotes half width).

These results suggest some general conclusions. First, given the complex nature of scheduling, ad-hoc scheduling (i.e., scheduling based on expert opinion) worked surprisingly well for generating good solutions, because many schedules were statistically indistinguishable from the simulation-optimization model-generated schedules. However, in some cases, ad-hoc scheduling did not provide the best solution; in such cases, the simulation-optimization model was helpful in improving the schedule. These differences depend on the day of week, suggesting that the ad-hoc approach does not consider variations in patient flow from day to day. Second, the addition of shift starts on the half hour helped, because the optimizer chose an 8:30 AM–7:00 PM shift for 10-hour-shift nurses in most cases. The 8:00 AM–6:30 PM and 9:00 AM–7:30 PM shifts were not removed completely; the optimizer adjusted many of them to 8:30 AM–7:00 PM.

Another general conclusion we drew is that as nurses become a bottleneck, the optimizer becomes more advantageous. As we reduced the nurse staff level across scenarios, the number of days and shift policies in which the optimizer has a statistically significant improvement on the candidate schedules increases. Additionally, as nurses become a scarcer resource, the benefits of shorter shift lengths increase because the nurses can be scheduled during periods of higher demand. However, the impact of changing the mix of shift types is still significantly less than the impact of adjusting work schedule times.

Finally, it is important to point out that although the improvement in average waiting time was moderate, the benefits were allocated disproportionately to patients who were seen during peak hours. The results for the maximum waiting times typically averaged about 90 minutes, and improvements in waiting time at peak times during the day improved by as much as 25 minutes in some cases. Thus, small changes in the daily shift schedule can significantly impact the waiting time for the patients who are most affected by it at the OTC.

Conclusions

In this section, we describe our general conclusions that could apply to other cancer centers.

Our model revealed bottlenecks for phlebotomy and oncologist consultation in the clinics. Patient waiting times for phlebotomists in the clinics varied by clinic and day of the week, but ranged from 10 to 30 minutes on average. Patient wait times for an oncologist in the oncology examination room also varied by clinic and day of the week, also ranging from 10 to 30 minutes on average. The model indicated a large variability in waiting times by clinic and day, which is consistent with what we expected and expert opinions confirmed.

We also identified bottlenecks in the OTC. Patient wait times in the OTC are greatest for chairs, with an average wait time of 2–10 minutes; however, more significantly, the maximum average wait time ranges from 25 to 40 minutes at peak times during the day. Additionally, patient wait times for OTC nurses range from one to two minutes on average; however, specific DBGs have maximum average wait times as high as 30 minutes at peak times of the day. In particular, most of the longer waiting times for nurses are centralized in the hematologic malignancy and off-service DBG, ranging from five to 30 minutes for the maximum average waiting time across all replications.

Our MIP model analyses show that full-time nurses are helpful for covering supply needs during the day, whereas part-time nurses help to meet the variable day-to-day peak demand. Part-time nurses provide the capability to target increased nurse availability at peak times during the day. Thus, they can help in reducing shortage hours in a nurse schedule. Furthermore, we found that adding part-time nurses had diminishing returns in reducing shortage hours; thus, we concluded that a small number of part-time nurses can have a significant impact in reducing shortage hours. As a result, we recommended replacing one or two full-time nurses with equivalent levels of part-time nurses.

The simulation-optimization model indicated that changing arrival and departure times in nurse schedules has the greatest impact on patient waiting time. In particular, the addition of shift starts on the half hour helped, because the optimizer frequently selected an 8:30 AM–7:00 PM shift for 10-hour-shift nurses. Thus, we recommended changing some of the 8:00 AM–6:30 PM and 9:00 AM–7:30 PM shifts to 8:30 AM–7:00 PM. A combination of 10-hour and 8-hour shifts, rather than 10-hour-only or 8-hour-only shifts, can also significantly impact average patient waiting time; however, in our testing, we saw mixed results on whether this improved patient waiting times. Our results indicated that the lower nurse staff levels are, the more of a bottleneck they become, and the larger the improvement optimization methods make in improving candidate schedules.

Implementation

Next, we summarize some of our recommendations that the Duke Cancer Institute—Cancer Center in Durham, North Carolina—adopted.

After evaluating the results and conclusions described previously, Duke Cancer Institute implemented the following strategies to optimize its OTC staffing: First, it hired four part-time nurses to assist in meeting the variable day-to-day peak demand. Second, it adjusted the start times for both these new hires and some existing nurses to the half-hour mark. Third, it followed our recommendation to hire additional nurses by hiring 1.75 additional full-time equivalent (FTE) nurses. The simulation optimizer also found that a combination of 10-hour and 8-hour shifts can impact average patient waiting time; therefore, the cancer center stopped the practice of allowing nurses to work longer shifts.

The changes described previously are some of the most important tangible benefits achieved by applying the operations research methods described in this paper. We also used our model to explore resource capacity planning for a new cancer center that opened in spring 2012. Our model forecast bottlenecks and OTC performance in several scenarios to inform the planning process for administrators. The results of the model showed that an expansion of chair capacity from current levels removed most of the waiting time for chairs in the OTC. Thus, the proposed increase in chair levels in the new cancer center was projected to sufficiently meet the demand needs. Additionally, we identified nurses as the primary bottleneck in this cancer center under demand increases of 6–12 percent. These results helped administrators make staffing decisions for this cancer center.

Appendix

Next, we describe the mathematical formulation of the MIP model for the monthly and weekly nurse planning problem:

Indices

t = day in the four-week schedule ($t = 1, 2, \ldots, 20$).
k = disease-based group (DBG) ($k = 1, 2, \ldots, 6$).
j = index for long weekends during the month ($j = 1, \ldots, 4$).
i = index for nurses ($i = 1, 2, \ldots, 3N$);
- ($i = 1, 2, \ldots, N$ corresponds to a part-time nurse);
- ($i = N+1, N+2, \ldots, 2N$ corresponds to a full-time, 8-hour-shift nurse);
- ($i = 2N+1, 2N+2, \ldots, 3N$ corresponds to a full-time, 10-hour-shift nurse).

Decision Variables

x_{it} = nurse i scheduled on day t (binary variable).
y_{ij} = nurse i scheduled on long weekend j (binary variable).
z_i = nurse i selected on the schedule (binary variable).
s_t = shortage of nurse hours on day t (continuous variable).
o_t = overage of nurse hours on day t (continuous variable).

Parameters:

f_i = FTE (full-time equivalent) value for each nurse i.
d_t = number of nursing hours required for day t.
a_{ik} = binary indicator defining if a nurse i is associated with DBG k ($a_{ik} = 1$) or not ($a_{ik} = 0$).
N = maximum number of nurses for a particular DBG shift type.
n = minimum nurses in each DBG for the day.
r_t = minimum number of nurse in OTC on day t.
M = maximum number of FTE for OTC nurses.
F = minimum number of full-time nurses.
w_i = number of days worked per week by nurse i;
- $w_i = 2, 3, 4$, or 5 for $i = 1, 2, \ldots, N$ (part-time nurses under varying policies);
- $w_i = 5$ for $i = N+1, N+2, \ldots, 2N$ (full-time, 8-hour-shift nurses);
- $w_i = 4$ for $i = 2N+1, 2N+2, \ldots, 3N$ (full-time, 10-hour-shift nurses).

k_i = number of hours available per day for nurse i;
- $k_i = 4$, 8, or 10 for $i = 1, 2, \ldots, N$ (part-time nurses);
- $k_i = 8$ for $i = N+1, N+2, \ldots, 2N$ (full-time, 8-hour shift);
- $k_i = 10$ for $i = 2N+1, 2N+2, \ldots, 3N$ (full-time, 10-hour shift).

MIP Formulation

$$\text{Minimize} \quad \sum_{t=1}^{20} s_t$$

s.t.

$$\sum_{i=1}^{3N} z_i f_i \le M \quad \text{Total FTE Constraint,} \tag{1}$$

$$\sum_{i=N+1}^{3N} z_i \ge F \quad \text{Minimum number of full-time nurses used,} \tag{2}$$

$$\sum_{i=1}^{3N} x_{it} \ge r_t \quad \forall t \quad \text{Minimum nurse requirement for entire OTC,} \tag{3}$$

$$\sum_{i=1}^{3N} a_{ik} x_{it} \ge n \quad \forall t, k \quad \text{Minimum nurse requirement for each DBG,} \tag{4}$$

$$x_{it} \le z_i \quad \forall i, t \quad \text{Nurse } i \text{ selected constraint}, \tag{5}$$

$$\sum_{i=1}^{3N} x_{it} k_i + s_t - o_t = d_t \quad \forall t \quad \text{Nursing hours per day constraint}, \tag{6}$$

$$\sum_{t=1}^{5} x_{it} = w_i z_i \quad \forall i \quad \text{Days worked per week 1 constraint}, \tag{7}$$

$$\sum_{t=6}^{10} x_{it} = w_i z_i \quad \forall i \quad \text{Days worked per week 2 constraint}, \tag{8}$$

$$\sum_{t=11}^{15} x_{it} = w_i z_i \quad \forall i \quad \text{Days worked per week 3 constraint}, \tag{9}$$

$$\sum_{t=16}^{20} x_{it} = w_i z_i \quad \forall i \quad \text{Days worked per week 4 constraint}, \tag{10}$$

$$x_{i5} + x_{i10} + x_{i15} + x_{i20} = 3z_i \quad i = 2N+1, \ldots, 3N \quad \text{FT 10-hour nurse no. Fridays worked constraint}, \tag{11}$$

$$x_{i1} + x_{i6} + x_{i11} + x_{i16} = 3z_i \quad i = 2N+1, \ldots, 3N \quad \text{FT 10-hour nurse no. Mondays worked constraint}, \tag{12}$$

$$\sum_{j=1}^{4} y_{ij} = z_i \quad i = 2N+1, \ldots, 3N \quad \text{Four-day weekend constraint for full-time 10-hour shift nurses}, \tag{13}$$

$$x_{i5} + x_{i6} \le 2(1 - y_{i1}) \quad \forall i \quad \text{Long-weekend constraint, weekend 1}, \tag{14}$$

$$x_{i10} + x_{i11} \le 2(1 - y_{i2}) \quad \forall i \quad \text{Long-weekend constraint, weekend 2}, \tag{15}$$

$$x_{i15} + x_{i16} \le 2(1 - y_{i3}) \quad \forall i \quad \text{Long-weekend constraint, weekend 3}, \tag{16}$$

$$x_{i20} + x_{i1} \le 2(1 - y_{i4}) \quad \forall i \quad \text{Long-weekend constraint, weekend 4}, \tag{17}$$

$$x_{it}, z_i, y_{ij} \text{ binary} \quad \forall i, j, t \quad \text{Binary variables constraint}, \tag{18}$$

$$s_t, o_t \ge 0 \quad \forall t \quad \text{Nonnegativity constraints}. \tag{19}$$

Simulation Optimization Model Formulation

Next, we describe the mathematical formulation of the simulation-optimization model for the daily nurse scheduling problem. The decision variables x_{ij} are binary decision variables that represent whether nurse i, of m nurses is working shift j ($x_{ij} = 1$), or not ($x_{ij} = 0$). Each nurse i has a series of n associated shifts to which he or she could be allocated that correspond to start and end times in half-hour increments during the day. The simulation-optimization model can be expressed as follows:

$$\begin{aligned} \text{Minimize} \quad & E[\textit{Patient Waiting Time}] \\ \text{s.t.} \quad & x_{ij} \le a_{ij}, \quad \forall i, j, \\ & \sum_{j=1}^{n} x_{ij} = 0, \quad \forall i \in \textit{OFFSHIFT}, \\ & \sum_{i=1}^{m} x_{ik} \ge 2, \\ & \sum_{j=1}^{m} x_{il} \ge 2, \\ & x_{ij} \in \{0, 1\}, \quad \forall i, j, \end{aligned}$$

where $j = k$ and $j = l$ denote the opening and closing shifts, respectively, and *OFFSHIFT* denotes the sets of nurses who are working (on) or not working (off) for the day. The first constraint determines the shift on which a nurse may be scheduled; indicator a_{ij} is 1 if the assignment of nurse i to j is allowed, and 0 otherwise. Nurse experience working in the various DBGs, as defined by the OTC clinical operations director, determines this indicator. The second constraint enforces the limitation that nurses do not work on their days off. The third and fourth constraints require that two nurses are available for opening and closing the OTC.

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