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MODELING AND ANALYSIS OF THE TRADE-OFFS IN SURGICAL SUITE PERFORMANCE MEASURES

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ABSTRACT

Uncertainty in the duration of surgical services may result in excessive patient waiting times and surgical suite overtimes. In this paper, we follow a two-phase approach by first constructing a discrete-event simulation model of an Outpatient Procedure Center using a commercially available simulation package (Arena) to evaluate the actual system configuration with respect to two competing criteria of waiting time and overtime. Using the model, we perform a preliminary analysis to set the direction for a detailed analysis to find the Pareto optimal set in the solution space. Subsequently, we construct a replica of the same simulation model using a programming language to facilitate the interactions on the interface of the simulation model and the analysis tool, a bi-criteria Genetic Algorithm. We perform the analysis based on real data from a large health care provider.

1 INTRODUCTION

Surgical services are performed through three different stages: Patient intake and surgical preparation, surgery, and patient recovery. Surgery schedule construction turns out to be highly complicated for surgical suite directors because of the effort to coordinate these activities. In addition, uncertainty in the duration of these activities makes scheduling tasks even more complicated for suite managers. Outpatient Procedure Centers (OPC) are special kinds of surgical service systems and serve higher amount of patients per day compared to inpatient surgery centers. Therefore, all the factors listed above such as the task coordination, uncertainty in procedure duration, and high volume of surgeries create highly challenging scheduling problems for OPC directors.

Three major steps are followed throughout the surgical procedures. Intake begins when the patient check-in process starts on the day of surgery and ends at the time the patient is taken to an operating room (OR) for the surgery. The intra-operative care period begins immediately in the OR and ends when the patient leaves there for the recovery. The recovery is the last stage being handled in the recovery room and it ends when the patient is discharged from the recovery bed.

The performance measures we consider in this study are expected procedure waiting time and surgical suite overtime. We select these measures because they are conflicting: a schedule with a relatively small estimated duration allocated to surgeries tends to lower overtime but increase patient waiting times. Due to the conflict between the performance measures, we do not look for a single solution dominating all the other solutions. Instead, we perform a bi-criteria analysis to evaluate the (near) Pareto optimal set of schedules. In bi-criteria solution space, Pareto optimality for a schedule is established when no other schedule dominates it with respect to both criteria. To identify optimal trade-offs, we selected evolutionary multi-objective optimization approaches as the analysis methodology since their working structure is more appropriate for exploring the solution space efficiently compared to the other stochastic optimization techniques such as simulated annealing or tabu search (Abraham and Jain 2005).

An OPC at Mayo Clinic, in Rochester, Minnesota, forms the test bed for our study. We first constructed a discrete event simulation model in Arena and used it to evaluate the performance of the OPC with respect to expected patient waiting time and expected surgical suite overtime. Next, we tested easy-to-implement scheduling heuristics and evaluated the resulting schedules on the model. Then, we rebuilt the simulation model using a programming language instead of a simulation package in order to embed this within a bi-criteria Genetic Algorithm (GA) for further analysis to construct the (near) Pareto optimal set of schedules. In this paper, we compare the results of the heuristics and our GA-based method, and provide general insights on the overall performance of the OPC based on real data.

2 OUTPATIENT PROCEDURE CENTER CHARACTERISTICS

OPCs are complex systems with a number of surgical groups sharing resources to perform outpatient procedures within a fixed time interval. There are two main sections in the OPC. The first is the pre/post room area having twenty small rooms, and the second is the operating room area with eight ORs. The ORs in the OPC are dedicated to certain surgical areas and the allocation scheme is as follows: One OR for Pain Medicine, two for Urology and Ophthalmology each, and three for Oral Maxillofacial.

In conventional OPC designs, patient flow is provided through intake, surgery, and a recovery area, which are physically separated. However, recent designs combine intake and recovery resources into a single area by allowing the usage of rooms for both intake and recovery processes. In this configuration, patients move first from the patient waiting area into a pre/post room, from pre/post into a specific OR, back into pre/post for recovery, and finally exit the surgical suite.

3 LITERATURE REVIEW

Simulation modeling is a widely used approach in the Operating Room (OR) scheduling literature. An overview of general OR scheduling methods can be found in Magerlein and Martin (1978), Blake and Carter (1997), Gupta (2007), and Gupta and Denton (2008). Following is a sample of papers that use simulation to analyze specific surgical delivery systems.

Dexter and Marcon (2006) test several sequencing heuristics such as the Longest Cases First, Shortest Cases First, and Johnson's rule to explore the impact on workload of a post anesthesia care unit (PACU). Marcon et al. (2003) perform analysis of a PACU as well and simulate a surgical suite to estimate the number of beds required for PACU.

Testi et al. (2007) use sequencing heuristics (surgery waiting longest first, longest processing time first and shortest processing time first) and test the resulting schedules via a simulation model. Denton et al. (2006) use simulation for modeling an endoscopy suite and evaluate different surgeon-to-OR allocation scenarios through the model. Lowery and Davis (1999) study a more strategic problem in which they used a simulation model to examine the consequences of the potential decrease in the amount of operating rooms at a surgical suite.

The contributions of our work in relation to the collection of papers described above are the following: first, we perform analysis by considering the trade-offs between the performance measures influencing both the patient and the provider. Second, we propose a bi-criteria GA based solution technique to identify the optimal trade-offs between the measures. Third, we examine the relative impact of patient appointment time setting heuristics in the scheduling procedure. Fourth, we consider the upstream and downstream stages of the surgical procedures, including intake and recovery, throughout the analysis and examine a modern design with reentrant patient flow.

4 SIMULATION MODELING AND ANALYSIS

We built a discrete event simulation model of the OPC first using Arena 10.0 to evaluate the actual schedule and observe the resulting performance measure values (Huschka et al. 2007). Using data from the Mayo Clinic for the year 2006, probability density functions were fit for intake, surgery and recovery, and transfer times between the stages and for procedure room turnover times. Distributions were independently fit for each specialty since each of them exhibits different characteristics in terms of the length of the processes. Erlang, Gamma, Beta, Log-normal, Weibull, and Exponential distributions were those distribution types found.

The model is a terminating simulation, in the sense that a daily surgical schedule is simulated independently for each day. The overall performance measure values are calculated by taking the average of these independent daily amounts. Patient arrival times are deterministic and we assume that they arrive in the surgical suite on time. In addition, all patients show up for their procedures. The procedure times are generated during the simulation run using the distributions we fit. We validated the model by reviewing the model output with the schedulers and directors of the OPC.

After evaluating the actual schedule, we tested a number of combinations of simple sequencing and time-setting heuristics to investigate the improvement potential for the schedule used in practice. We again used the Arena simulation model to observe the resulting impact. We sequenced surgeries according to increasing mean (SPT), decreasing mean (LPT), increasing variance (VAR), and increasing coefficient of variation (COV) of surgery time. Then, we

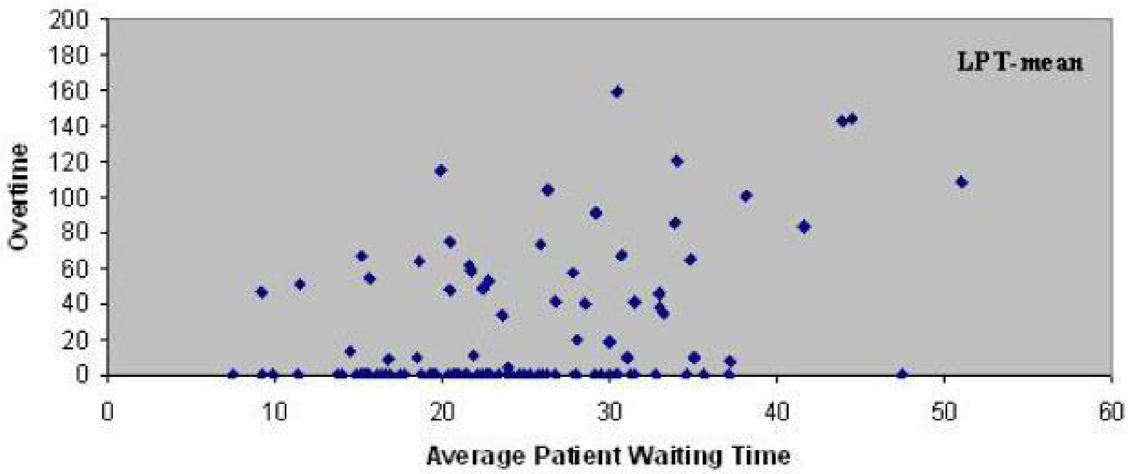

Figure 1: The relative performance measure values for 100 daily schedules created using LPT as the sequencing and mean duration as the patient appointment time setting heuristic.

set patient appointment times. Patients' appointment times were calculated by estimating the immediately preceding patient's surgery duration and adding the amount to the same patient's appointment time. Assuming the times to follow a normal distribution, we estimated the surgery durations using the equation $h_i = \mu_i + k\sigma_i$ where k is a multiplier determining the *hedging level*. The procedure allocated mean duration to the surgeries in the case of $k = 0$, while it provided an extra buffer when $k > 0$, which is known as job hedging in the literature (Yellig and Mackulak 1997). We determine the value of k according to the percentile of the surgery duration distribution that we decided to allocate to surgeries. As a preliminary analysis, we first tested the combinations of the above listed sequencing heuristics with the 50th, 65th and 75th percentiles of the surgery durations. Figure 1 shows the individual mean waiting time and overtime values for the 100 daily schedules created using the combination of the heuristics, LPT and the mean duration. The figure indicates that there is significant variation in performance measure values from day to day since the surgical mix is different for each day. Therefore, we examined the potential impact of changing the mix in a day on the performance measures.

We developed a bi-criteria Genetic Algorithm (GA) based approach which treats the day of surgery as a decision variable. The specifics of the methodology can be found in Gul et al. (2008) and Denton et al. (2009). In this approach, we let surgeries be moved back and forth only within a one week time window. This assumption is relevant to the current scheduling practices at some of the surgery centers where the week of the surgery is defined first before setting the exact date (Gupta 2007). Chromosomes represent the surgery schedules of n weeks, while each gene (except the last one) represents a surgery. The last gene is for keeping the percentile value that we use during the appointment time setting procedure right after determining the surgery sequence.

We use the NSGA-II algorithm (Deb et al. 2000) as the basis of our bi-criteria GA approach. Utilizing the operators defined and implementing the steps in NSGA-II, we sequence the surgeries of each week and then combine the resulting weekly schedules into one string. However, the schedule is not complete without the appointment times set for the patients. Therefore, we make use of the percentile values being kept in the last gene to allocate durations to surgeries in order to determine the appointment times. After having the complete schedule, we simulate the schedule to get the resulting performance measure values which help us in the comparison of the chromosomes to select the fittest ones to be carried forward into the following iterations.

For the simulation of the schedules to be evaluated throughout the steps of the algorithm, we reconstructed the simulation model using Visual C++. After building the model, we embedded it into our scheduling approach. Our Arena model could also have been called by the algorithm for the schedule evaluations but that would cause excessive number of interactions between the modules and thus an enormous increase in computation time. Moreover, the actual running of the simulation in Arena takes considerably more time than running in Visual C++ model. The reduction of computation time allows us to increase the number of simulation replications for a fixed computing budget. For these reasons, we rebuilt the simulation model for further analysis of the system to find the (near) Pareto optimal solutions. Then, we validated our Visual C++ model by

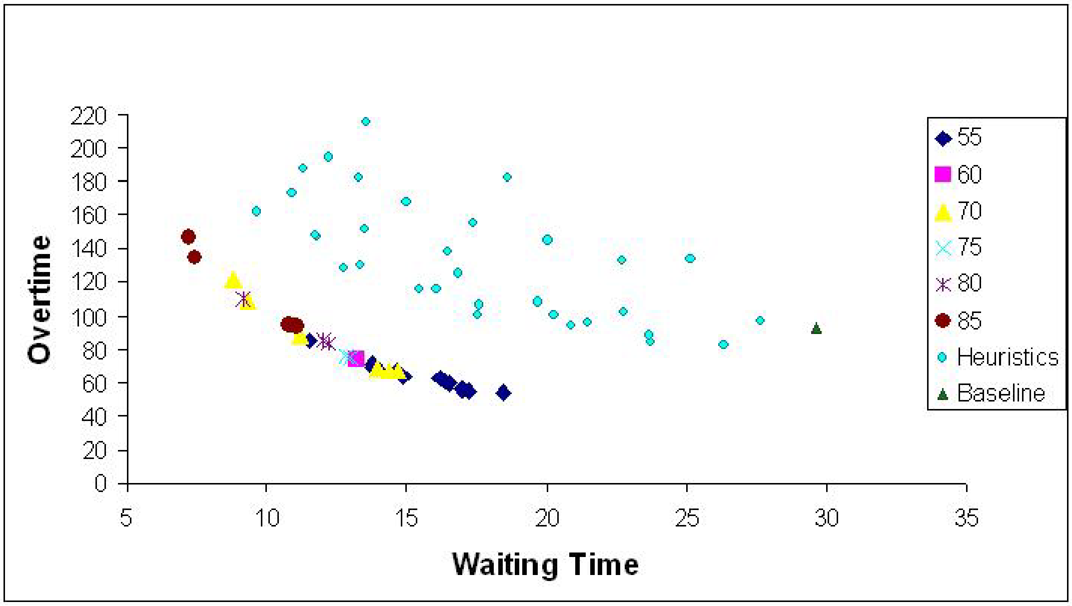

Figure 2: Comparison of the (near) Pareto optimal set of schedules (indicating the hedging levels used for each schedule) with the heuristics solutions used as the initial chromosomes and the baseline schedule.

comparing the results we extracted from the model with the simpler results from Arena model.

Figure 2 shows the relative performance measure values for the evaluation of the schedules generated using the bi-criteria GA and simple heuristics (initial population of schedules created using the combination of sequencing and appointment time setting heuristics) as well as of the baseline schedule (the one used in practice). All of the non-dominated schedules on the plot are found using the bi-criteria GA and each symbol on the figure represents a different hedging level used while setting the patient appointment times. Eight different hedging levels (50th, 55th, 60th, 65th, 70th, 75th, 80th and 85th percentiles) were considered for the time setting procedure during the experimentation. Comparison of the GA and heuristics results indicates that recreating the test-bed for utilizing it in a more sophisticated approach for further investigation of the criteria space to detect the efficient schedules paid off.

The first insight we can get from the figure is that the job hedging improves the waiting time amounts without considerably increasing the overtime values. Another important point is that no schedule using mean duration (corresponding to the 50th percentile since we assume normal distribution while calculating the duration amounts to allocate) survived after the GA iterations. Furthermore, slightly increasing the hedging level to the 55th percentile would help the schedules to be located on the Pareto optimal set. One more observation worth noting is that the schedules are generally grouped together in different clusters on the criteria space based on the hedging level used to construct them. This evidence indicates that the appointment time setting procedure dominates the sequencing procedure in the sense of influencing the performance measure values.

5 CONCLUSIONS

The coordination of the activities in the intake, surgery and recovery stages of an OPC is a challenging task which complicates the preparation of efficient surgical schedules. In this article, we first developed a simulation model of an OPC and observed how the system behaves by testing the actual schedule as well as easy-to-implement heuristics using the model. Observing the analysis directions having potential for improvements, we replicated the model using Visual C++ to develop a more sophisticated, a bi-criteria GA based, approach to better explore the criteria space. With the additional flexibility that the latter simulation model provided, we performed a detailed analysis and revealed the near Pareto optimal set highly dominating the solutions found in the preliminary analysis.

For future research, we plan to compare the performance of an alternative patient flow (the linear flow - separate pre and post rooms), through the OPC using our Arena model that we created for modeling purposes. In addition, allocation of the other resources having potential for becoming a bottleneck of the process in an OPC environment such as specialized equipment, nurses, and nurse anesthetists will be investigated using the same model.

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