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CONSTRAINED OPTIMIZATON FOR HOSPITAL BED ALLOCATION VIA DISCRETE EVENT SIMULATION WITH NESTED PARTITIONS

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ABSTRACT

This paper aims to further motivate the use of simulation of complex systems in optimizing healthcare operations under uncertainty. One argument to use optimization only such as mathematical programming instead of simulation optimization in making decisions is the ability of the former to account for constraints and to consider a large number of alternatives. However, current state-of-the art of simulation optimization has opened the possibilities of using both simulation and optimization in the case of multiple performance measures. We consider the case of hospital bed allocation and give an example on how a stochastically constrained optimization via simulation can be applied. Nested Partitions are used for the search algorithm and combined with OCBA-CO, an efficient simulation budget allocation, as simulation is time-consuming.

1 INTRODUCTION

Stochastic simulation and optimization are two powerful tools in decision making. Simulation enables decision makers to understand complex systems and evaluate their performances under uncertainty. Optimization is useful as it considers wider range of solutions in selecting the best instead of pre-generated alternatives in a simulation study. Simulation optimization or optimization via simulation are able to capture both benefits of stochastic simulation and optimization (Fu 2002). At the same time, there are still some challenges in integrating simulation optimization into practice as described in Fu et al. (2014).

Out of many real-world problems, the application of simulation to healthcare is ubiquitous (Jun, Jacobson, and Swisher 1999). There have been some applications of simulation optimization to healthcare but their numbers are relatively fewer than simulation case studies. Brailsford et al. (2007) combine discrete-event simulation with a metaheuristic called Ant Colony Optimization (ACO) to determine the optimal screening policies in addressing diabetic retinopathy. Tanfani, Testi, and Alvarez (2010) use simulation optimization to determine the optimal plan for the Operating Room.

In this paper, we consider the bed allocation problem which is not new but remains challenging. Poor bed allocation could cause overcrowding in Emergency Department leading to increase in mortality (Sprivulis et al. 2006). Despite the wide range of literatures on the bed allocation problem, only few works use simulation optimization techniques. Wang et al. (2015) applied multi-objective optimization via simulation on the bed allocation problem. Zhang et al. (2012) to address the issue of long-term care planning. Holm, Lurås, and Dahl (2013) and Keshtkar, Salimifard, and Faghih (2015) consider both simulation and optimization. Most of other literatures either use only optimization or only simulation. Those which use only optimization aim to find the best way of allocating beds by considering a huge number of possibilities (Ridge et al. 1998, Teow and Tan 2008). It is possible to consider uncertainties in optimization using stochastic programming. At the same time, some decision makers may need to use simulation to evaluate performance measures which do not have closed-form expressions such as the number of bed overflow. In addition, simulation is able to evaluate policy to model the hospital complexities or preferences (Goldman, Knappenberger, and Eller 1968). Simulation studies have given useful insights on bed allocation (El-Darzi et al. 1998, Harper and Shahani 2002, Akkerman and Knip 2004, Cochran and Bharti 2006). However, the use of only simulation is limited as it only considers a pre-determined set of alternatives which may not be the real best solution.

One of the challenges of simulating complex service systems such as healthcare is the amount of times required as multiples replications are needed to get better estimates of the performance measures of interest. Lapierre et al. (1999) mentioned that once a valid simulation model for the bed allocation problem is obtained, we could compare among the alternatives using ranking and selection procedure (R&S) that efficiently determines the number of replications. R&S have been shown to be much more efficient than if the simulation budget is equally distributed among the alternatives. Another challenge is to consider constraints in the performance measures separately instead of lumping it into a single objective. These two challenges can be tackled by integrating R&S with optimization methods. For example, Ahmed and Alkhamis (2009) integrates the constrained R&S procedure by Andradóttir, Goldsman, and Kim (2005) with the search algorithm (Alkhamis and Ahmed 2004) to find the optimal number of staffs in the emergency department.

In this paper, we apply the proposed allocation procedure (OCBA-CO) and Nested Partitions method in finding the best feasible bed configuration which consists the number of beds for each specialty. This provides an alternative for decision makers who wish to model the problem as a constrained optimization instead of a single objective problem or a multi-objective problem. For the case where all performance measures are equally important, Wang et al. (2015) provides an excellent example on how to efficiently obtain the set of non-dominated solutions.

2 PROBLEM STATEMENT

2.1 Sample of System Description and Modeling

We consider a hypothetical setting as described in Pujowidianto et al. (2012). The bed management unit is open 24 hours daily and we consider two sources to the bed management unit, namely the emergency patients and the elective patients. For the emergency patients arrivals, we treat their service time in the emergency department as a one lump sum. We assume that the service time distribution is uniform across different levels of patient acuity. Some patients from the emergency department will then be admitted to the bed management unit based on the historical probability of admission for different types of patient attributes. We assume that there is no physical limit for the number of patients in the emergency department. For both the emergency and the elective patients, we consider 5 different specialties.

We use non-stationary Poisson process to model both the emergency patients and the elective arrivals. The length of stay is exponentially distributed. The more critical patients receive a higher priority in practice. However, for simplicity, we do not consider different patient acuity levels and so first-in first-out (FIFO) is used as the queue discipline. In addition, we assume that the travelling time to the ward and the cleaning time are incorporated inside the length of stay. Figure 1 shows the process flow in modeling the bed allocation problem. It is possible to allow for an overflow when the bed with the correct specialty for a particular patient is not available. This is governed by the overflow protocol in Table 1. For each specialty, there are at most three other specialties where the overflow can be allowed.

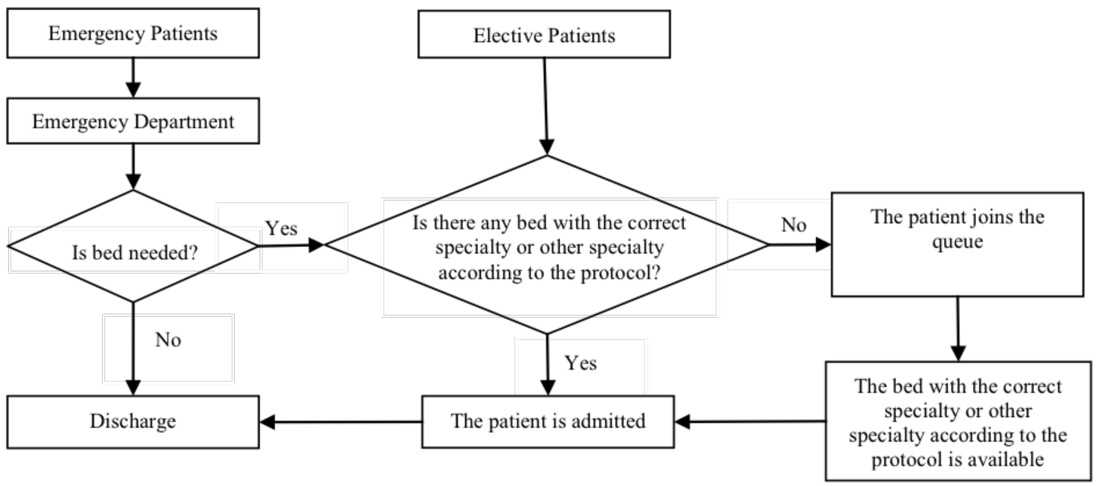

Figure 1: Process Flow.

Table 1: Overflow protocol.

Specialty	1st Overflow	2nd Overflow	3rd Overflow
Medicine	Oncology	Cardiac	Not Applicable
Cardiac	Medicine	Surgery	Orthopedic
Oncology	Medicine	Surgery	Orthopedic
Surgery	Medicine	Oncology	Cardiac
Orthopedic	Surgery	Medicine	Not Applicable

2.2 Problem Description

Let c be the total number of specialties considered while x_m and u_m are the number of available bed and the number of occupied bed respectively at a given fixed time of the day for the specialty $m = 1,\ldots,c$. We consider three daily performance measures, namely the bed occupancy rate (BOR), the 99$^{\text{th}}$ percentile of the turn-around-time (TAT_{99}), and the number of overflow (O). BOR is defined as the total number of occupied beds at a particular time of the day divided by the total number of bed, i.e. $BOR = \frac{\sum_{m=1}^{c} u_m}{\sum_{m=1}^{c} x_m}$. In this study, the parameters x_m and u_m are measured at 6 a.m. Let r_p, a_p, and t_p be the time of bed request, the time of the admission to the bed management unit, and the turn-around-time for patient $p \in W$ where W is the set of all possible patients. The turn-around-time for patient p is measured from the time of bed request to the time the patient is admitted, i.e. $t_p = a_p - r_p$. TAT_{99} can then be obtained by taking the 99$^{\text{th}}$ percentile of t_p of all patients $p \in W$ in a day. The daily number of overflow represents the number of mismatched between the specialty of the patients and that of the bed. It is measured in terms of percentage of the number of overflow with respect to the total number of admitted patients in a given day.

Our goal is to determine the best feasible bed configuration, that is to find the configuration $\mathbf{x_i} = [x_1 \ldots x_c]$ among k designs, i.e. $i = 1,\ldots,k$, which returns the largest BOR while ensuring the 99$^{\text{th}}$ percentile of the turn-around-time and the number of overflow are less than the maximum limits γ_1 and γ_2 as described in the following

$$max_{x_i} BOR \text{ subject to } TAT_{99} \leq \gamma_1, O \leq \gamma_2. \tag{1}$$

Due to the uncertainties in the patients arrival time and the length-of-stay, the values of *BOR* and TAT_{99} need to be estimated via simulation. Let H_{ijd} be the *BOR* in the j-th simulation replication and in the d-th day for the bed configuration i, $h_i = E_j[E_d[H_{ijd}]]$. Similarly, the simulation sample for TAT_{99} is G_{i1jd}, $g_{i1} = E_j[E_d[G_{i1jd}]]$ and that for the percentage of overflow is G_{i2jd}, $g_{i2} = E_j[E_d[G_{i2jd}]]$. The comparison of the bed configurations are based on sample means, i.e. $\hat{H}_i = \frac{1}{N_i}\sum_{j=1}^{N_i}(\frac{1}{D}\sum_{d=1}^{D} H_{ijd})$, $\hat{G}_{i1} = \frac{1}{N_i}\sum_{j=1}^{N_i}(\frac{1}{D}\sum_{d=1}^{D} G_{i1jd})$, and $\hat{G}_{i2} = \frac{1}{N_i}\sum_{j=1}^{N_i}(\frac{1}{D}\sum_{d=1}^{D} G_{i2jd})$ where N_i is the number of simulation samples for bed configurations i and D is the number of simulated days. We assume that simulating the system for D days excluding the warm-up period is sufficient to represent the original system. The key for an efficient comparison is then on the determination of N_i.

We note that the problem in (1) can be modified depending on the goal of the decision maker. For example, we can consider an additional constraint if the *BOR* should not exceed 85%. Gorunescu, McClean, and Millard (2002) show that hospitals need to keep $10-15\%$ emptiness to maintain the service efficiency using queuing model. This is in line with the finding in Bagust, Place, and Posnett (1999) that regular shortages can occur if the average bed occupancy unit is 90% or more.

3 PROPOSED METHOD

Our goal is to propose a procedure that allows hospital decision makers to select the best feasible bed allocation design, i.e. the design which optimizes the main objective while satisfies all constraints. Both the main objective and the multiple constraint measures need to be estimated via simulation. This is done by integrating a constrained ranking and selection procedure for efficiently allocating the simulation budget in comparing the designs and a search algorithm for generating the next sets of designs to be compared as shown in Figure 2.

We use the Optimal Computing Budget Allocation for Constrained Optimization (OCBA-CO) which efficiently allocates the simulation budget to the critical designs based on the means and variances in selecting the best feasible alternative. When the number of alternatives is small enough for all designs to be simulated, we can use this procedure directly. The sequential algorithm for implementing OCBA-CO can be found in Lee et al. (2012).

For the searching algorithm, we use Nested Partitions method by Shi and Ólafsson (2000). In Nested Partitions, the search space is partitioned into several regions. In each region, design points are randomly sampled. Based on these samples, the most promising region is determined based on the promising index. Once a region is declared as the most promising region, it will be further partitioned in the next iteration. The other region will be aggregated as one partition called as the surrounding region. The most promising region can be defined as the area where the best feasible alternative is located. This matches the characteristics of OCBA-CO which emphasizes on selecting the best among a fixed number of alternatives instead of accurately estimating the performance of each alternative. To avoid being trapped in a local optimal, Nested Partitions allows backtracking if the best alternative at the current iteration is not located to any partitions of the previous iterations most promising region.

4 NUMERICAL EXAMPLES

For the simulation, we use 4 warm-up days and afterwards 90 working days are simulated. The parameters for the emergency patients arrivals are taken from Ahmed and Alkhamis (2009) as they are easier to generate. Table 2 shows the arrival rates for each time period. The service time in the emergency department is exponentially distributed with mean of 180 minutes. Aside from the arrival rates and the service time, we adapt the data from the work in a Singapore hospital by Calugcug et al. (2009). For the emergency patients, 64% of them are admitted. Table 3 shows the length of days for each specialty together with the breakdown of the admitted emergency patients and elective patients for each specialty.

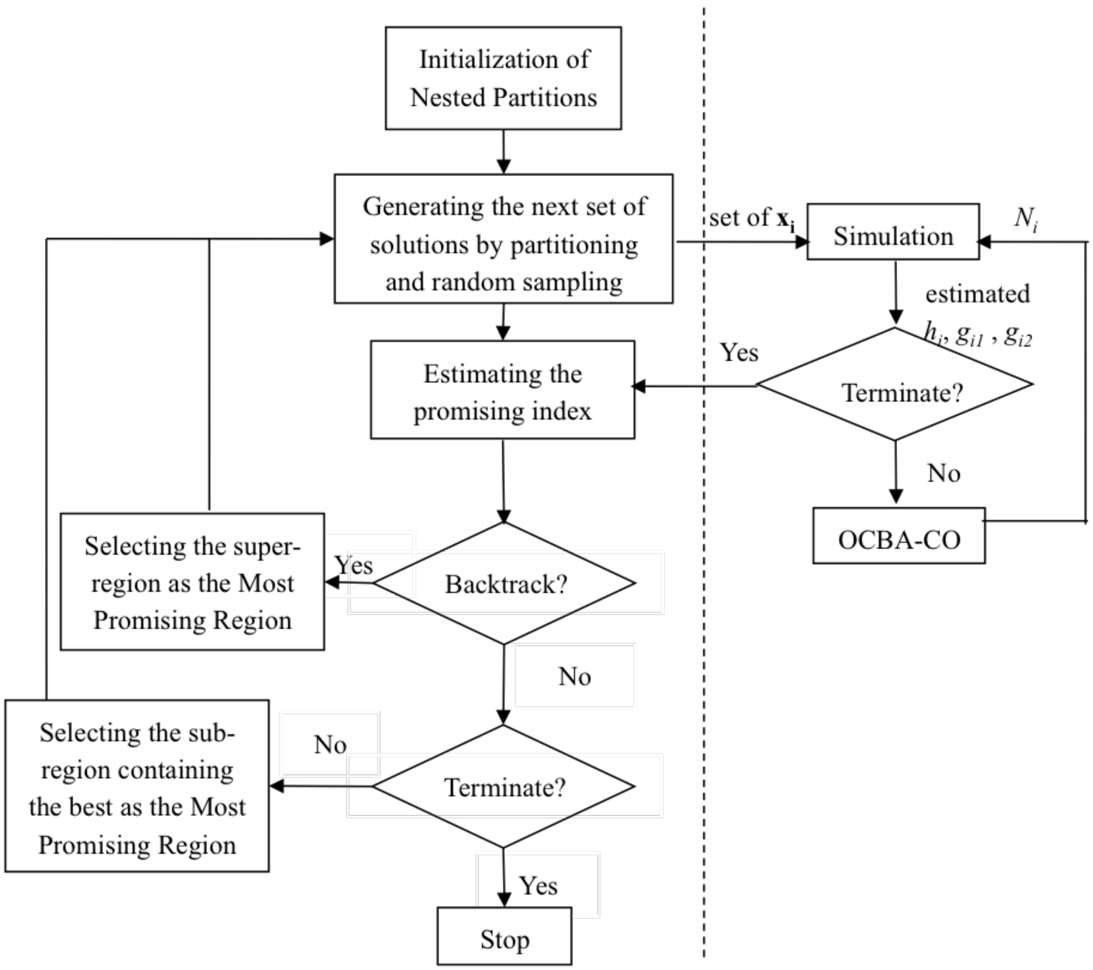

Figure 2: The framework for integrating Nested Partitions and OCBA-CO.

In this example, 5 specialties are considered and the average bed occupancy rate (BOR), the average 99^{th} percentile of the turn-around-time (TAT_{99}), and the number of overflow are measured. The maximum limit for the TAT_{99} is $\gamma_1 = 480$ (in minutes). For the number of overflow, several values of the maximum limit are used to see the effect of the selection of the overflow limit. For the setting where only one value is used, the limit of overflow is defined as 30%.

4.1 Selection from a small number of alternatives

Pujowidianto et al. (2012) considered a simple case where there are only 5 alternatives. All designs are simulated and there is no search needed. The constrained ranking and selection approach we use, namely OCBA-CO and the commonly used Equal Allocation (EA) are being compared. The measurement of effectiveness is the probability correct selection (*PCS*) which is estimated by the fraction of obtaining

Table 2: The arrival rates for each time period.

Time	0	2	4	6	8	10	12	14	16	18	20	22
Emergency Patients	5.3	3.8	3	4.8	7	8.3	9	7.8	7.8	8	6.5	3.3
Elective Patients	0	0	0	0	0.2	0.4	0.7	4.7	5.3	3.2	0.8	0.3

Table 3: The simulation parameters for each specialty.

	Medicine	Cardiac	Oncology	Surgery	Orthopedic
Length of Stays (days)	6.3	3.8	9.1	4.8	11.2
Proportion of Admitted Emergency Patients	50%	14%	5%	18%	13%
Proportion of Elective Patients	14%	22%	20%	28%	16%

correct selection out of a pre-determined number of independent experiments. The results show that OCBA-CO performs better than EA.

4.2 Selection from a large number of alternatives

In this paper, we consider the case where the number of alternatives is huge. For each specialty, the minimum number of bed is 5 while the maximum number of bed is 500. In other word, the search space is $\Theta = [5,500]^5$ as there are 5 specialties. This translates to 3.002×10^{13} alternatives. Thus, a searching algorithm is needed as it is virtually impossible to simulate all alternatives.

For the settings of Nested Partitions, we divide each axis of the most promising region into two. In other word, there are 2^5 subregions as with 5 considered specialties. The first experiment shows the result where 1 sample is taken from each region. The total computing budget for the first iteration is 215. Subsequently, we increase the total computing budget by 50 in each of the iteration of Nested Partitions. For the OCBA-CO, we run 5 initial replications for each design considered. Afterwards, there is an increment of 50 replications to be allocated to the designs until the total computing budget in each of the NP iteration is exhausted. Figure 3 shows that NP+OCBA-CO is able to converge in terms of the main objective value as the search algorithm progresses.

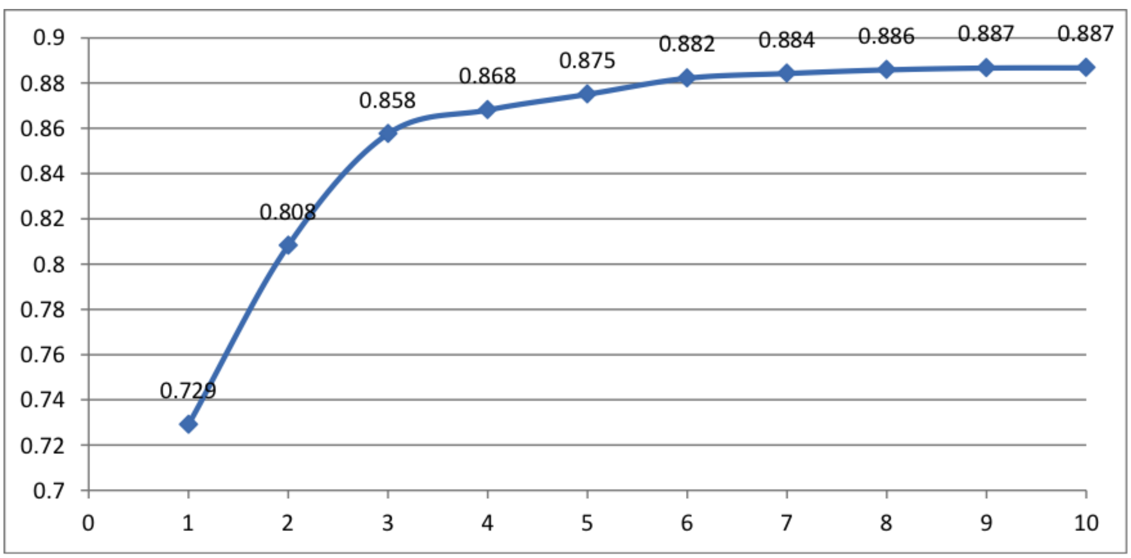

Figure 3: Convergence of NP+OCBA-CO in terms of the main objective *BOR*.

In addition, we run different values of the limits to observe the effect of these limits to the total number of bed changes. Table 4 shows the effect of the limit on TAT_{99} while the effect of overflow limit can be seen in Table 5. As expected, a stricter requirement results in a solution with higher total number of beds. The solution to the case with a lower turn-around-time (TAT_{99}) limit has a higher total number of beds so as to reduce the waiting time. Similarly, reducing the allowed percentage of overflow follows in a higher total number of beds due to the reduction in flexibility which decreases the pooling effect.

Table 4: Effect of TAT_{99} limit when the overflow limit is 50%.

Turn-around-time (TAT_{99}) limit	Total number of bed
480	705
360	824

Table 5: Effect of overflow limit when the TAT_{99} limit is 480 minutes.

Percentage of overflow limit	Total number of bed
50%	705
30%	802
10%	920

5 CONCLUSION

In this paper, we formulate the bed allocation problem as a stochastically constrained optimization via simulation. This allows the consideration of uncertainties embedded in patients arrival and service time and the constraints on some of the performance measures. As simulation is computationally intensive, we apply the OCBA procedure for constrained optimization. We provide an alternative for addressing the stochastically constrained optimization via a black-box simulation by integrating OCBA-CO with Nested Partitions method for selecting the best design given a huge discrete search space. The integrated procedure is the methodological contribution and it is able to provide a guideline on how to select the best feasible bed configuration.

The desire of the paper is to provide more motivations for hospital decision makers to use simulation optimization as it is able to incorporate constraints in the performance measures. For those who prefer to incorporate the constraints into a single objective, the constrained ranking and selection (R&S)procedure by Hu and Andradóttir (2014) can be used. In terms of how to implement the integration of simulation, R&S, and optimization algorithm, one can refer to SimOpt by Pasupathy and Henderson (2011) which provides abundant examples on how to code them. One can also use the framework by Li et al. (2015) which proposes an object-oriented discrete event simulation modeling for ease of development. Their modeling paradigm facilitates the integration of simulation, efficient simulation budget allocation methods, and search algorithms.

In practice, the parameters can be updated to model arrival and service time characteristics in a more realistic manner. The potential configurations can be obtained by both the users preference and by searching algorithms for randomly sampling the configurations out of the possible combinations. In addition, the schedule of the elective patients in this paper is assumed to be given. When necessary, the model can be extended to capture the interaction between the elective patients and the patients entering the bed management unit from the emergency department. It is possible to do other what-if scenarios such as changing the order of the overflow protocol. In the case where a single optimal solution is not preferred, the OCBA method for selecting optimal subset can be explored. These show the flexibilities of simulation optimization in addressing bed allocation problem.

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