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Applying Scenario Reduction Heuristics in Stochastic Programming for Phlebotomist Scheduling

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ABSTRACT

Laboratory services in healthcare play a vital role in inpatient care. Studies have indicated laboratory data affect approximately 65% of the most critical decisions on admission, discharge, and medication. This research focuses on improving phlebotomist performance in laboratory facilities of large hospital systems. A two-stage stochastic integer linear programming (SILP) model is formulated to determine better weekly phlebotomist schedules and blood collection assignments. The objective of the two-stage SILP model is to balance the workload of the phlebotomists within and between shifts, as reducing workload imbalance will result in improved patient care. Due to the size of the two-stage SILP model, a scenario reduction model has been proposed as a solution approach. The scenario reduction heuristic is formulated as a linear programming model and the results indicate the scenarios with the largest likelihood of occurrence. These selected scenarios will be tested in the two-stage SILP model to determine weekly scheduling policies and blood draw assignments that will balance phlebotomist workload and improve overall performance.

Key words: Healthcare; Scheduling; Laboratory

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INTRODUCTION

Laboratory medicine, which can also be described as clinical pathology, is an area in which pathologists provide testing of patient samples (generally blood or urine). For example, the presence of bacteria can be detected from a patient sample, which provides information for the necessary treatment. A clinical test can be conducted on a sample to determine the level of enzymes in the blood to see if a patient has a risk of a heart attack or if the level of glucose in the blood of a patient is related to diabetes. Hospital laboratories are facilities within healthcare delivery systems where laboratory medicine is conducted. Phlebotomists are the staff members that work in hospital laboratories and collect samples from patients.

This research has addressed achieving phlebotomist workload balance, resource utilization, service quality, and patient satisfaction through optimizing the preanalytical stage, which is the most critical stage in the laboratory process of a local hospital facility. According to the literature, optimizing scheduling in laboratory medicine has not been regarded as a necessity for laboratory management. In actuality, without optimal scheduling policies in place for laboratory medicine, there is a great risk for patients to be negatively affected due to work overload. When work overload is present, patient neglect has the potential to be introduced due to patients not receiving the time and attention required. Also, with work overload there is a risk for the optimal performance of the phlebotomist to decrease. Phlebotomist performance is critical in laboratory medicine because in the event of an error this could result in serious and even fatal consequences for the patient. Through balancing workload, phlebotomists can provide the necessary time and attention required for each patient. Balancing phlebotomist workload, improving resource utilization and patient satisfaction, providing high service quality, and accurate laboratory performance are vital necessities for healthcare delivery systems as laboratory medicine is a pivotal part of the intricate decision making process, influencing close to 70% of medical diagnosis(Da Rin, 2009).

A two-stage stochastic integer linear programming (SILP) model for phlebotomist scheduling and blood draw assignments is developed. This model has been formulated to determine the number of phlebotomists to schedule during each shift and the number of blood draw collections that should be assigned to each phlebotomist, in order to balance workload within and between shifts. Due to the size of the two-stage SILP problem, a scenario reduction heuristic model is proposed to solve the problem. This paper is organized into the following sections. First, a background on laboratory medicine environments is provided. In the next section, a linear programming (LP) scenario reduction model to determine the scenarios with the largest likelihood of occurrence which are to be tested in the two-stage SILP model is provided. After which, the case studies and the LP scenario reduction model results are discussed in detail. Finally, future directions are summarized in the conclusions of this paper.

1. MODELING

The major problems faced in the preanalytical stage of hospital laboratories are how to schedule the phlebotomists for each shift while accounting for the uncertainty associated with the number of blood draws ordered, and how to assign blood draws collections to each phlebotomist to balance workload. In order to alleviate the problems faced in the preanalytical stage of the laboratory process, the phlebotomist shift scheduling and blood draw assignment problem is studied to determine the optimal number of phlebotomists to schedule and the optimal number of blood collections to assign during each shift. Poor scheduling policies can result in work overload for the phlebotomists, which can lead to patient neglect. Therefore, the objective is to balance workload amongst phlebotomists between and within shifts.

The two-stage SILP model will be solved using a LP scenario reduction model. The scenarios in the two-stage SILP model represent the different combinations of the number of blood draw that could be requested in each time block. For example, if there are a total of N time blocks, one scenario would represent the number of blood collections ordered in each block, for blocks one through N. For this study, there are 15 time blocks, where each time block includes one to five hours. The number of blood draw collections in each time block is treated as a random demand. An assumption of this study is the blood collection demands in the time blocks are independent of one another.

There are several algorithms available to solve stochastic programming problems(Ahmed et al., 2004; Norkin et al., 1998; Carøe & Schultz, 1999; Dupačová, 2003; Heitsch & Römisch, 2003). In two-stage stochastic programming problems, a solution approach widely used involves discretizing the uncertain parameters to develop a deterministic equivalent of the stochastic problem, which will then present a multi-scenario optimization problem[7]. For this study, due to thousands of possible scenarios for the two-stage SILP model, a LP scenario reduction model has been formulated and solved to reduce the number of scenarios to be considered. The LP scenario reduction model is a heuristic often utilized to reduce the number of scenarios in two-stage SILP models[8]. The idea behind the LP scenario reduction model is to select only the scenarios with the highest likelihood of occurrence. Researchers have tested multiple cases and determined by implementing this heuristic, a high quality solution would be achieved within 10% of the best solution.

The scenario reduction problem has been formulated as a LP model and is discussed in detail in the following section. In Table 1 the indices, sets, parameters, and decision variables are defined for the LP scenario reduction model. The software used to solve this heuristic model is the optimization package, General Algebraic Modeling System (GAMS). GAMS is a high level modeling software for mathematical programming and optimization problems. GAMS is tailored for complex, large scale modeling applications and allows the user to build large maintainable models that can be adapted quickly to new situations. The scenarios selected by the LP scenario reduction model will be considered in the two-stage SILP model.

1.1 Notation

Table 1
Indices, Sets, Parameters, and Decision Variables

Indices	
i	Time block index; $i \in \{1, \dots, \lvert I \rvert\}$
m_i	Value index; $m_i \in \{1, \dots, \lvert V_i \rvert\}$
Sets	
I	Set of time blocks
V_i	Set of possible values for the number of blood draws requested in time block i
Parameters	
v^{mi}_i	Value of the m_i^{th} element in V_i
p^{mi}_i	Probability that the number of blood draws requested in time block i equals v^{mi}_i over all scenarios
Decision variables	
$p'_{m1,m2,\cdots,m\lvert I \rvert}$	Probability of a scenario with the numbers of blood draws in time blocks 1, ..., $\lvert I \rvert$ equal to $v^{m1}_1, \dots, v^{m}_{\lvert I \rvert}{}_{\lvert I \rvert}$, respectively, in the reduced scenario set

1.2 Linear Programming (LP) Scenario Reduction Model

The scenario reduction LP model is formulated as follows:

$$\min \sum_{m_1=1}^{|V_1|}\sum_{m_2=1}^{|V_2|}\cdots\sum_{m_{|I|}=1}^{|V_{|I|}|}(1-p_1^{m_1}p_2^{m_2}\cdots p_{|I|}^{m_{|I|}})\,p'_{m_1,m_2,\cdots,m_{|I|}}\ , \quad (1)$$

$$\text{s.t.} \quad \sum_{m_2=1}^{|V_2|}\sum_{m_3=1}^{|V_3|}\cdots\sum_{m_{|I|}=1}^{|V_{|I|}|}p'_{m_1,m_2,\cdots,m_{|I|}} = p_1^{m_1} \qquad \forall m_1\in\{1,\ldots,|V_1|\}, \quad (2\text{-}1)$$

$$\sum_{m_1=1}^{|V_1|}\sum_{m_3=1}^{|V_3|}\cdots\sum_{m_{|I|}=1}^{|V_{|I|}|}p'_{m_1,m_2,\cdots,m_{|I|}} = p_2^{m_2} \qquad \forall m_2\in\{1,\ldots,|V_2|\}, \quad (2\text{-}2)$$

$$\vdots$$

$$\sum_{m_1=1}^{|V_1|}\sum_{m_2=1}^{|V_2|}\cdots\sum_{m_{|I|-1}=1}^{|V_{|I|-1}|}p'_{m_1,m_2,\cdots,m_{|I|}} = p_{|I|}^{m_{|I|}} \qquad \forall m_{|I|}\in\{1,\ldots,|V_{|I|}|\}, \quad (2\text{-}|I|)$$

$$\sum_{m_1=1}^{|V_1|}\sum_{m_2=1}^{|V_2|}\cdots\sum_{m_{|I|}=1}^{|V_{|I|}|}p'_{m_1,m_2,\cdots,m_{|I|}} = 1\ , \quad (3)$$

$$p'_{m_1,m_2,\cdots,m_{|I|}} \le 1 \qquad \forall m_1\in\{1,\ldots,|V_1|\},\ \ldots,\ \forall m_{|I|}\in\{1,\ldots,|V_{|I|}|\}, \quad (4)$$

$$p'_{m_1,m_2,\cdots,m_{|I|}} \ge 0 \qquad \forall m_1\in\{1,\ldots,|V_1|\},\ \ldots,\ \forall m_{|I|}\in\{1,\ldots,|V_{|I|}|\}. \quad (5)$$

The objective function (1) includes the known probabilities of the existing set of scenarios and these are here to force the optimization to reduce the number of scenarios, while selecting the scenarios that have the reasonably larger probabilities. Constraints (2-1) – (2-|I|) enforce the sum of the probabilities of the scenarios selected in which $v^m{}_i$ appear to be equal to $p^{mi}{}_i$. Constraints (3) force the sum of the probabilities of the scenarios selected to be equal to one. Constraints (4) guarantee the probabilities of all scenarios selected to be less than or equal to one. Constraints (5) guarantee the probabilities of all scenarios selected to be larger than or equal to zero.

The questions in this study to be answered include:

- Which scenarios have the highest likelihood of occurrence?
- What is the likelihood probability associated with each of the selected scenarios?

2. CASE STUDY

Table 2
Time Blocks for Hospital Laboratory

Time block index	Hours
T1	10pm-11pm
T2	11pm-4am
T3	4am-5am
T4	5am-6am
T5	6am-7am
T6	7am-8am
T7	8am-11am
T8	11am-12pm
T9	12pm-1pm
T10	1pm-2pm
T11	2pm-3pm
T12	3pm-4pm
T13	4pm-7pm
T14	7pm-8pm
T15	8pm-10pm

Table 3
Shifts for Hospital Laboratory

Group	Shifts	Hours
Morning shifts	1	4am-12pm
	2	5am-1pm
	3	6am-2pm
	4	7am-3pm
	5	8am-4pm
Afternoon shifts	6	11am-7pm
	7	12pm-8pm
	8	2pm-10pm
Evening shifts	9	10pm-6am
	10	11pm-7am

2.1 Current System for the Hospital Laboratory

The base case represents the current state of the hospital laboratory for a local hospital system. For the base case, there are 34 phlebotomists available to schedule. The shift availability is 400 minutes for each phlebotomist, which represents the amount of time available to perform blood collections. There are 15 time blocks, which do not overlap and cover all 24 hours. The time blocks are presented in Table 2. There are ten shifts in which phlebotomists could be scheduled. Table 3 presents the working hours for all ten shifts, which are grouped into morning, afternoon, and evening shifts.

Table 4
Blood Collection Demand for Selected Scenarios

Scenario	Blood collection demand in each time block S(T1,T2,T3,T4,T5,T6,T7,T8,T9,T10,T11,T12, T13,T14,T15)	Probability
1	S(4,98,4,3,5,7,52,13,10,12,9,9,22,5,8)	.001
2	S(4,98,4,3,5,7,52,13,10,8,9,9,22,5,8)	.518
3	S(4,98,4,5,5,7,52,13,10,12,9,9,22,5,8)	.020
4	S(4,113,4,5,5,7,52,13,10,12,9,9,22,5,8)	.049
5	S(4,113,4,5,5,7,64,13,10,12,9,9,22,5,8)	.006
6	S(4,113,4,5,5,7,64,13,10,12,9,9,30,5,8)	.034
7	S(4,113,4,5,5,7,64,13,15,12,9,9,30,5,13)	.009
8	S(4,113,4,5,5,7,64,13,15,12,9,9,30,5,8)	.012
9	S(4,113,4,5,5,7,64,19,15,12,9,9,30,5,13)	.015
10	S(4,113,4,5,5,7,64,19,15,12,14,9,30,5,13)	.061
11	S(4,113,4,5,5,7,64,19,15,12,14,14,30,5,13)	.054
12	S(4,113,4,5,5,12,64,19,15,12,14,14,30,5,13)	.036
13	S(7,113,4,5,5,12,64,19,15,12,14,14,30,5,13)	.007
14	S(7,113,7,5,5,12,64,19,15,12,14,14,30,5,13)	.094
15	S(7,113,7,5,10,12,64,19,15,12,14,14,30,5,13)	.051
16	S(7,113,7,5,10,12,64,19,15,12,14,14,30,10,13)	.033

2.2 Results and Discussion

The LP scenario reduction model was solved using the optimization software package GAMS. Of the thousands of possible scenarios, the results indicated sixteen scenarios with the largest likelihood of occurrence. The blood collection demand in each time block and the likelihood probability for each selected scenario is presented in Table 4. For each selected scenario, the numbers in parenthesis indicate the number of blood draws requested in each time block. Table 4 indicates scenario 2 has the largest likelihood of occurrence of all selected scenarios with a probability of 0.518. Scenario 1 has the smallest likelihood of occurrence with a probability of 0.001. All sixteen scenarios will be used in the two-stage SILP model, as they represent the highly probable blood collection demands for the hospital laboratory. The results from the LP scenario reduction model will decrease the size of the two-stage SILP model, which allows a near optimal solution to be determined in a reasonable amount of time. The solution to the two-stage SILP model will indicate the number of phlebotomists to schedule for each shift and the number of blood draws to be assigned to each phlebotomist to minimize work overload and improve phlebotomist performance.

CONCLUSION

It is imperative for laboratory management to understand the blood collection demand and how this impacts phlebotomist scheduling policie. A two-stage SILP model will address the development of optimal phlebotomist schedules to balance workload and reduce patient neglect caused by work overload. The LP scenario reduction model presented in this study demonstrated that it was a viable heuristic to reduce the number of scenarios tested in the two-stage SILP model. The application of the scenario reduction technique on many numerical examples has indicated that close to optimal solutions can be achieved using the approximate model with the smaller number of scenarios (Karuppiah, Martín, & Grossmann, 2010).

Future research directions include solving the two-stage SILP model with the selected scenarios from the LP scenario reduction model to determine optimal phlebotomist scheduling policies. This study focuses on scheduling in the most critical stage of the hospital laboratory process, the pre-analytical stage. Future work will consist of developing optimal scheduling policies for the remaining two stages of the hospital laboratory process, the analytical and post-analytical stages. Lastly, through the investigation of scheduling in the total testing process of hospital laboratories, optimal scheduling policies can be determined which will significantly increase service quality and overall patient satisfaction.

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