A two-stage stochastic programming model for phlebotomist scheduling in hospital laboratories

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ABSTRACT

This paper introduces a two-stage stochastic integer linear programming model to improve phlebotomist scheduling in laboratory facilities of healthcare delivery systems. The model developed enables laboratory management to determine optimal scheduling policies that minimize work overload. The stochastic programming model considers the uncertainty associated with the blood collection demand in laboratory environments when optimizing phlebotomist scheduling. The paper presents an application of the model to a hospital laboratory in urban North Carolina as a case study discussing the implications for hospital laboratory management.

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1. Introduction

Laboratory services in healthcare delivery systems play a vital role in patient care. Studies have shown that laboratory data affect approximately 65% of the critical medical decisions such as diagnosis, medication, hospital admission, and discharge (Da Rin, 2009; Plebani, 1999). The total testing process in hospital laboratories includes a series of activities, starting with the clinical question in the clinician's mind, leading to test selection, sample collection, transport to the laboratory, analysis, reporting back to the clinician, and final interpretation and decision making by the clinician (Hawkins, 2012). These activities have traditionally been separated into three phases: pre-analytical, analytical, and post-analytical. In our previous study, the pre-analytical stage has been identified as the most critical stage in the total testing process of the hospital laboratory studied (Leaven, 2014). This study addresses optimizing the pre-analytical stage by reducing phlebotomist work overload and hence improving resource utilization and service quality.

In the pre-analytical stage, the phlebotomist is responsible for collecting a blood sample from a patient for testing purposes. This is the primary responsibility of the phlebotomist. Once the sample is collected, it is then delivered to the medical technicians for analysis in the analytical stage of the testing process. The role of a phlebotomist is different from that of a nurse, as once the blood sample has been collected, the phlebotomist/patient interaction is complete. Nurses are typically

assigned to a certain number of patients for the duration of their shift, whereas phlebotomists are assigned to blood collections based on the anticipated demand and a patient could interact with multiple phlebotomists during any particular shift. Of the three stages, the pre-analytical stage is the only stage where there is direct contact with patients. As a result, reducing phlebotomists' work overload can ensure that phlebotomists can provide the necessary time and attention required for each patient, and reduce the amount of errors occurring in the laboratory process (Risser et al., 1999), which could result in serious and even fatal consequences for a patient.

In the context of improving phlebotomist scheduling in hospital laboratories, this paper proposes a decision-making tool, which is an optimization model to minimize phlebotomist work overload. The proposed model allows the decision maker, i.e., the laboratory manager, to create a weekly schedule that optimizes phlebotomist workload. Designed as a two-stage stochastic integer linear program (SILP), the model explicitly considers the uncertainty associated with the blood collection demand, which is an important aspect in phlebotomist scheduling. To solve the developed model, a scenario reduction strategy is adopted (Leaven & Xiuli, 2014) and a heuristic algorithm is proposed in this study.

In the following section, a brief overview of related studies is provided along with the academic contribution of this study in the context of quantitative approaches to improve staff scheduling in hospital settings. In Section

2, the two-stage stochastic integer linear programming (SILP) model for phlebotomist scheduling is presented followed by the solution approaches in Section 3. Section 4 provides a real-world application of the model as a case study based on a large urban hospital system located in North Carolina. Lastly, Section 5 includes the conclusions of this research study, the limitations of the model proposed, and prospective future research directions.

2. Related work and contribution

In this research study, we have applied stochastic programming in phlebotomist scheduling by developing and solving a two-stage SILP model to determine a weekly shift schedule in a hospital laboratory that balances phlebotomist workload between and within shifts. Based on our best knowledge, it is the first study applying stochastic programming in phlebotomist scheduling. Stochastic programming has been used in nurse scheduling studies (Bagheri, Devin, & Izanloo, 2016; Burke, De Causmaecker, Berghe, & Van Landeghem, 2004; Campbell, 2011; Kim & Mehrotra, 2015; Punnaikittikashem, Rosenberger, & Behan, 2008). In the study of (Burke et al., 2004), researchers have proven that stochastic programming is a viable approach for solving nurse scheduling and rostering problems. In their study, the specific skills and the demand uncertainty are considered in the stochastic programming model. Their results indicate this method is beneficial in staff planning and scheduling for many hospital systems. (Punnaikittikashem et al., 2008) have developed a stochastic integer programming model for a nurse assignment problem with an objective of minimizing the excess nurse workload. A Benders' decomposition approach is utilized to solve the problem along with a greedy algorithm to solve the recourse sub-problem. In this study, the scheduling templates that minimize the excess nurse workload were identified for several different cases. In another study, a two-stage stochastic programming model has been developed to schedule and allocate cross trained workers in multi-department service environments with random demands (Campbell, 2011). The model has been applied in hospital nurse scheduling to determine the off-duty days for each nurse and the number of nurses to be scheduled on each day in order to meet the realized demand. In two recent nursing scheduling studies (Bagheri et al., 2016; Kim & Mehrotra, 2015), two-stage SILP models have been developed to generate optimal nurse schedules that minimize the total cost including regular staffing cost and expected overtime cost. To solve their SILP models, Kim and Mehrotra (2015) have developed a modified multicut approach in an integer L-shaped algorithm, and (Bagheri et al., 2016) have used the sample average approximation (SAA) method.

Although the phlebotomist scheduling problem is similar to the nurse scheduling problem, they differ in several ways. Firstly, due to the primary responsibility of phlebotomists, demand in phlebotomist scheduling is different from that in nursing scheduling. As mentioned previously, a nurse is typically assigned to a certain number of patients/beds for the duration of her shift, whereas a patient could interact with multiple phlebotomists during any particular shift. Thus, hourly demands of blood collections instead of demand per shift are used to schedule phlebotomists. As a consequence, the second difference is that overlapped shifts are considered in phlebotomist scheduling in order to handle peak demand and reduce response time. Typically, in nurse scheduling problems in the literature, nurses are scheduled to one of the two or three shifts that do not overlap and cover each day. Thirdly, demand coverage requirements in phlebotomist scheduling is different from that in nursing scheduling because blood collections for non-urgent test orders can be carried over to the next hour. In the two-stage stochastic integer linear programming (SILP) model developed in this study, the blood draw delay function is captured, which indicates that certain blood draws can be carried over to the next shift if it will positively affect the workload balance for the phlebotomists scheduled. To our best knowledge, the delay function has not been studied in nurse scheduling problems in the literature. In addition, a specific consideration in our SILP model addresses varying skill levels of the phlebotomists in the phlebotomist scheduling problem. The skill level of a phlebotomist affects the number of tasks/blood collections assigned to him or her during a shift.

According to the literature, determining optimal scheduling policies in laboratory medicine has not been studied extensively. In practices, 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 (Reader & Gillespie, 2013). Meanwhile, we have proposed a new efficient heuristic algorithm to find a near-optimal solution to the two-stage SILP model. The heuristic algorithm was developed after other solving techniques, such as the deterministic equivalent (DE) and DECIS stochastic solvers in the GAMS software, proved to be unsuccessful in obtaining an optimal solution. For the cases in the hospital laboratory motivating this research, the heuristic algorithm proposed could find near-optimal solutions (with a relative gap less than 3.5%) within 20 min. The two-stage SILP model and the heuristic algorithm will assist laboratory management in balancing phlebotomist workload in hospital laboratories, which could reduce the risk of poor phlebotomist performance and work overload.

3. Two-stage stochastic programming model for phlebotomist shift scheduling

3.1. Problem statement

The major problems faced in the pre-analytical stage of hospital laboratories are how to schedule the phlebotomists for each shift while accounting for the uncertainty associated with the number of tests that will be ordered, and how to assign blood draw collections to each phlebotomist in order to balance workload. In order to alleviate the problems faced in hospital laboratories, the phlebotomist shift scheduling problem is studied to determine the optimal number of phlebotomists to schedule during each shift. Poor scheduling policies can result in work overload for the phlebotomists. Therefore, the objective is to balance workload among phlebotomists between and within shifts. Due to the uncertainty of the amount of blood tests ordered in a time block, the phlebotomist shift scheduling problem has been formulated as a two-stage stochastic integer linear program (SILP). The indices, sets, parameters, random variables, and decision variables for the two-stage SILP model are provided below. The decision variables x_{jkn} are the first-stage decision variables, while $y_{ik}(\omega)$ are the second-stage decision variables.

3.2. Assumptions

In the phlebotomist shift scheduling problem studied, the following assumptions have been made:

- Only one resource (phlebotomists) is scheduled in J days.
- There are only K phlebotomists available.
- There are a total of N overlapped shifts per day in which phlebotomists could be scheduled.
- Each shift is 8 h in length.
- N shifts are separated into three groups: morning, afternoon, and night shifts.
- Each phlebotomist works one shift per day and 5 days per week.
- A phlebotomist could not be scheduled in two consecutive shifts.
- The service time for a phlebotomist to perform a regular blood draw and a STAT (term given for blood collections that have to be performed immediately without delay) blood draw is the same. However, service times for phlebotomists of different skill levels to perform a blood draw are different.
- A regular blood draw can be delayed up to three hours and a STAT blood draw has to be collected in the hour ordered without delay.
- The phlebotomists are divided into three levels: beginner, average, and experienced.
- The service time for the phlebotomists corresponds to the level they are associated with.

All of these assumptions are based on the real-world case utilized for this study, a hospital laboratory in a local healthcare system. The laboratory management staff provided all information listed in the assumptions section; however, each assumption has been given a generic form with the purpose of the model in this study being applicable to other hospital laboratories interested in achieving phlebotomist workload balance.

4. Notation and decision variables

Indices

i	Time block index; $i \in I$
j	Days worked; $j \in \{1, \dots, J\}$
k	Phlebotomist index; $k \in \{1, \dots, K\}$
n	Hospital shift; $n \in N$
ω	Realization (scenario) index; $\omega \in \Omega$

Sets

I_1	Set for time blocks with no task delay
I_2	Set for time blocks with an up to one time block task delay
I_3	Set for time blocks with an up to two time block task delay
I_4	Set for time blocks with an up to three time block task delay
I	$I_1 \cup I_2 \cup I_3 \cup I_4$
N_1	Set of morning shifts
N_2	Set of afternoon shifts
N_3	Set of night shifts
$N =$	$N_1 \cup N_2 \cup N_3$
Ω	Set of all realizations (scenarios)

Parameters

a_{ijn}	$= \begin{cases} 1, & \text{if time block } i \text{ is included in shift } n \text{ on day } j \\ 0, & \text{otherwise} \end{cases}$
b_i	Max number of STAT tests ordered in time block i
D	Total number of days required to work
F	Max time blocks for which a regular blood draw could be delayed in subset I_3
F'	Max time blocks for which a regular blood draw could be delayed in subset I_4
J	Total number of days available
K	Total number of phlebotomists available
s_k	Average service time for phlebotomist k to perform a task
T_i	Total hours for time block i

Random variables

X_i	Number of tasks occurring in time block i under
(ω)	realization ω

Decision variables

x_{jkn}	$= \begin{cases} 1, & \text{if phlebotomist } k \text{ works on day } j \text{ during shift } n \\ 0, & \text{otherwise} \end{cases}$
$y_{ik}(\omega)$	Number of tasks assigned to phlebotomist k in time block i under realization ω
$z_i(\omega)$	Number of tasks left over at the end of time block i under realization ω
$t_{\max}(\omega)$	Maximum phlebotomist workload in each shift under realization ω

5. Model Formulation

The phlebotomist shift scheduling problem is formulated as follows:

$$\min E[t_{\max}(\omega)] \quad (1)$$

$$s.t. \sum_{n \in N} \sum_{k=1}^K x_{jkn} \leq K, \quad \forall j \in \{1, \dots, J\} \quad (2)$$

$$\sum_{n \in N} x_{jkn} \leq 1, \quad \forall j \in \{1, \dots, J\} \quad \forall k \in \{1, \dots, K\} \quad (3)$$

$$x_{jkn} + x_{j-1,k,n'} \leq 1, \quad \forall j \in \{1, \dots, J\}, \quad \forall k \in \{1, \dots, K\}, \quad \forall n \in N_1, \forall n' \in N_3 \quad (4)$$

$$\sum_{n=1}^N \sum_{j=1}^J x_{jkn} = D, \quad \forall k \in \{1, \dots, K\} \quad (5)$$

$$s_k y_{ik}(\omega) \leq T_i \sum_{j=1}^J \sum_{n=1}^N a_{ijn} x_{jkn}, \quad \forall i \in I, \quad \forall k \in \{1, \dots, K\}, \quad \forall \omega \in \Omega \quad (6)$$

$$z_i(\omega) = z_{i-1}(\omega) + X_i(\omega) - \sum_{k=1}^K y_{ik}(\omega), \quad \forall i \in I, \forall \omega \in \Omega \quad (7)$$

$$\sum_{k=1}^K y_{ik}(\omega) \geq b_i, \quad \forall i \in I, \quad \forall \omega \in \Omega \quad (8)$$

$$z_i(\omega) = 0, \quad \forall i \in I_1, \quad \forall \omega \in \Omega \quad (9)$$

$$z_i(\omega) \leq \sum_{k=1}^K y_{i+1,k}(\omega) \quad \forall i \in I_2, \quad \forall \omega \in \Omega \quad (10)$$

$$z_i(\omega) \leq \sum_{i'=i+1}^{i+F} \sum_{k=1}^K y_{i'k}(\omega) \quad \forall i \in I_3, \quad \forall \omega \in \Omega \quad (11)$$

$$z_i(\omega) \leq \sum_{i'=i+1}^{i+F'} \sum_{k=1}^K y_{i'k}(\omega) \quad \forall i \in I_4, \quad \forall \omega \in \Omega \quad (12)$$

$$t_{\max}(\omega) \geq \sum_{i \in I} s_k y_{ik}(\omega) a_{ijn}, \quad \forall j \in \{1, \dots, J\}, \quad \forall k \in \{1, \dots, K\}, n \in N, \forall \omega \in \Omega \quad (13)$$

$$x_{jkn} = 0, 1, \quad \forall j \in \{1, \dots, J\}, \quad \forall k \in \{1, \dots, K\}, \quad n \in N \quad (14)$$

$$y_{ik}(\omega) \geq 0, \text{int}, \quad \forall i \in I, \quad \forall k \in \{1, \dots, K\}, \quad \forall \omega \in \Omega \quad (15)$$

$$z_i(\omega) \geq 0, \text{int}, \quad \forall i \in I, \quad \forall \omega \in \Omega \quad (16)$$

$$t_{\max}(\omega) \geq 0, \quad \forall \omega \in \Omega \quad (17)$$

The objective function (1) aims to balance workload among phlebotomists between and within shifts through minimizing the expected maximum workload of the phlebotomists in each shift. Constraints (2) enforce the total number of phlebotomists scheduled for all shifts to be less than or equal to the total number of phlebotomists available. Constraints (3) and (4) guarantee that each phlebotomist works at most one shift per day. Constraints (5) enforce each phlebotomist to work 5 days a week. Constraints (6) are stage linkage constraints and guarantee that all blood draws assigned can be completed based on the phlebotomist time availability. Constraints (7) determine the number of blood draw collections left over at the end of each time block. Constraints (8) force all STAT blood collections to be completed in the time block requested. Constraints (9–12) place restrictions on the number of tests that can be left over at the end of each time block. Constraints (13) determine the maximum workload among the phlebotomists and shifts. Constraints (14–17) ensure binary, integer, and non-negativity variables. In this model, the decision variables $y_{ik}(\omega)$ are non-negative integer variables and x_{jkn} are binary variables. Meanwhile, the number of patients requiring a blood draw during time block i (X_i) is a random variable. Therefore, the model formulated is a two-stage SILP model.

6. Solution approaches

The two-stage SILP model is solved using a scenario reduction model and heuristic algorithm. The scenarios in the two-stage SILP model represent the different combinations of the number of blood draws 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 . The number of blood draw collections in each time block is treated as a random demand. An assumption for this study is the blood collection demands in the time blocks are independent of one another. The scenario reduction model determines the scenarios considered in the two-stage SILP model.

7. Scenario reduction model

The scenario reduction model is a heuristic approach often utilized to reduce the number of scenarios in two-stage stochastic programming models (Karuppiyah, Martí, & Grossmann, 2010). The idea behind the scenario reduction model is to select only the scenarios with the highest probability of occurrence. The scenario reduction problem has been formulated as a linear programming (LP) model and solved using General Algebraic Modeling System (GAMS) (Leaven & Xiuli, 2014). GAMS is a high-level modeling software for mathematical programming and optimization problems (www.gams.com). The scenarios selected by the scenario reduction model are considered in the two-stage SILP model.

8. Heuristic algorithm

The two-stage SILP model, considering the scenarios selected by the scenario reduction model, was first solved using a stochastic programming solver in GAMS. It took this solver several days to find a few feasible solutions to the two-stage SILP model. Their objective function values were far from the estimated lower bound. To verify the estimated lower bound, the two-stage SILP model was reduced by only considering a single scenario. After the reduced two-stage SILP model was solved under each selected scenario, the results revealed that for each selected scenario, the objective function value of the best feasible solution found is close to the estimated lower

bound. Based on this discovery, an efficient heuristic algorithm is developed. The procedure of the heuristic algorithm is provided in Figure 1.

The key idea of this heuristic algorithm is to achieve a schedule that works for all selected scenarios, such that the relative gap between the lower bound for each scenario and the best objective function value for each scenario is less than the desired relative gap, denoted by β . The lower bound for each scenario represents the best possible case with phlebotomist workload completely balanced. This lower bound is calculated using the following equation: Lower Bound for Balanced Phlebotomist Workload

$$= \frac{D \times J \times S}{K \times N},$$

where D is the blood draw demand, J is the total number of days, S is the average phlebotomist service time, K is the total number of phlebotomists available, and N is the total number of shifts required to work for each phlebotomist. Thus, the lower bound to the optimal objective function of the two-stage SILP model is calculated using the sum of the probabilities of each scenario multiplied by the lower bound for each scenario.

9. Case study

Three questions are addressed in this case study. (1) How does the workload differ from hour to hour, i.e., are there typically hours with higher workloads? (2) How does

Figure 1. Procedure of the proposed heuristic algorithm.

the change in phlebotomist capacity affect the number of phlebotomists scheduled in each shift? (3) How does the change in phlebotomist capacity affect the number of phlebotomists scheduled on each day? The results of the first question provide insights into how workload varies from hour to hour and the hours that typically have the highest workload. This will aid laboratory managers in making appropriate shift assignments when developing the weekly schedule. The second question addresses how the change in phlebotomist capacity affects the number of phlebotomists to schedule in each shift. This will assist the hospital laboratory in determining proper shift scheduling rules if they desire to increase phlebotomist utilization. The last question addresses how the change in phlebotomist capacity affects the number of phlebotomists scheduled on each day. This will allow laboratory management to determine if there is significant variance in the number of phlebotomists to schedule for each day, i.e., if there are certain days that require more phlebotomists than others. The results of this case study will serve as support in drawing conclusions for the phlebotomist shift scheduling problem.

The hospital laboratory used in this case study was selected for several reasons. First, the hospital laboratory management had a variety of projects in place to improve the laboratory process using six sigma and other improvement strategies. The management had identified issues within the current scheduling process of the laboratory facility, but did not have extensive knowledge on how to use quantitative decision-making models to address this problem. Therefore, developing a two-stage SILP model, scenario reduction model, and heuristic algorithm to address phlebotomist scheduling in hospital laboratories would not only benefit this hospital system, but could be applied to other hospital systems faced with a similar scheduling challenge.

10. Base case and extended cases

To address the three questions, the base case is extended by varying the number of phlebotomists available and the available service time per hour for each phlebotomist. In the base case of the hospital laboratory, there are 34 phlebotomists available to schedule. During an 8-h shift, 400 min are available for an on-duty phlebotomist to perform blood collections, i.e., 50 min per hour. Each day is divided into 15 time blocks, which do not overlap and cover all 24 h. The time blocks are presented in Table 1. There are ten shifts on each day, in which phlebotomists could be scheduled. Table 2 presents the working hours of the ten shifts, which are grouped into morning, afternoon, and evening shifts. Based on the distribution of the blood collection demand in each time block, which is estimated from the historical data in the hospital, 16 scenarios are selected using the scenario reduction model discussed previously. The 16 scenarios

Table 1. Time blocks for hospital laboratory.

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

Table 2. Shifts for hospital laboratory.

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

Table 3. Blood collection demand for selected scenarios.

Scenario	Blood collection demand in each time block	Probability
	$S(D1, D2, D3, D4, D5, D6, D7, D8, D9, D10, D11, D12, D13, D14, D15)$	
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

and the associated probability of occurrence for each scenario are presented in Table 3 where D_i denotes the blood collection demand in time block i .

It is important to study how a change in phlebotomist capacity will affect phlebotomist scheduling, essentially the impact on resource utilization. Meanwhile, a decrease in the available service time for scheduled blood draw assignments would allow the phlebotomists to have more time available for STAT tests, which are blood collections that have to be performed within the hour requested. Therefore, in the extended cases, three levels are considered for the phlebotomist capacity and

the available service time per hour for phlebotomists. The three levels of phlebotomist capacity are 34, 25, and 17 phlebotomists, while the three levels of available service time for the phlebotomists are 50, 45, and 40 min per hour. The purpose of analyzing different phlebotomist capacity levels is to determine if the blood collection demand can be fulfilled using less phlebotomists. For hospital laboratories to maximize phlebotomist utilization, it is also imperative to analyze different available service time levels as this will determine if the current blood collection demand can be met utilizing only a portion of the available phlebotomist service time. In both cases, if underutilization is present, the hospital laboratory management can cross train the phlebotomists to perform other laboratory operations or reduce the number of phlebotomists within the facility to maximize utilization and prevent phlebotomist idleness.

11. Results and discussion

11.1. Workload distribution over hours

The aim is to determine if there are hours that have higher workloads and to identify which hours they are, such that laboratory management can schedule phlebotomists accordingly. For the time blocks with multiple hours, the average workload per time block has been divided by the number of hours in the time block to accurately represent the hourly workload. The hourly workload is represented in number of blood collections assigned. The two-stage stochastic programming model used the input data provided in Table 3 to determine the number of phlebotomists that should be scheduled in each shift based on the workload difference in the time blocks. The two-stage stochastic programming model allows for the postponement of regular blood collection orders, which means some blood collections, i.e., workload, can be rolled over to the next time block to help achieve phlebotomist workload balance.

Figures 2 and 3 show a couple of sample scenarios to illustrate the comparison among the blood collection demand per hour (BCD/h), the total workload per hour (TW/h), and the average workload per phlebotomist per hour (AW/P/h). For each of the scenarios displayed in Figures 2 and 3, it can be concluded that the heuristic optimal solutions obtained from the two-stage SILP model produced a more smooth and balanced workload for phlebotomists within and between shifts. When comparing the three curves for each scenario, there is significant fluctuation in the blood collection demand per hour and the total workload per hour. However, the average workload per phlebotomist per hour presents much less variation and proves the two-stage SILP model was successful in balancing the workload for the phlebotomists scheduled. The remaining 14 scenarios displayed similar trends as shown in Figures 2 and 3.

This finding proves to be beneficial for healthcare management, as the hospital laboratory utilized for this case study currently schedules the least amount of phlebotomists during the time blocks with the highest workloads, which correspond to the evening shifts. Based on interviews with the hospital laboratory manager, their current scheduling policy has a high likelihood of producing work overload for the phlebotomists scheduled during evening shifts. Therefore, it is imperative for laboratory managers to acknowledge the importance of scheduling the number of phlebotomists for a shift that will best match the anticipated blood collection demand and allow for balanced workload among the phlebotomists scheduled.

11.2. Impact of phlebotomist capacity on the number of phlebotomists scheduled in each shift

Nine different cases were tested using the two-stage SILP model to analyze changes in the available service time per hour and varying phlebotomist capacity levels to determine the effect this will have on the number of

Figure 2. Comparison between blood collection demand and workload in scenario 2 of the base case. (Color figure online).

Figure 3. Comparison between blood collection demand and workload in scenario 10 of the base case. (Color figure online).

phlebotomists to schedule for each shift. Figures 4 and 5 illustrate the number of phlebotomists and the percentage of phlebotomists, respectively, to be scheduled for each shift over the course of a week. Table 4 provides the maximum workload for each of the nine cases obtained from the heuristic optimal solutions.

It was determined from each case tested that phlebotomist underutilization was present based on the maximum phlebotomist working minutes per shift in Table 4. The hospital laboratory could fulfill their current blood collection demand using only a portion of their current phlebotomist capacity. There are 400 min available per shift for each phlebotomist to perform blood collections in the first three cases, 360 min for the next three cases, and 320 min for the last three cases. According to the results of the heuristic optimal solutions summarized in Table 4, the phlebotomists are only using a portion of that available time for each case. To address the underutilization, there are two separate strategies that

could be implemented to increase phlebotomist utilization. The first strategy would involve determining the number of minutes the phlebotomists are idle and then identify other tasks they could perform. Therefore, if the laboratory management decides to keep a 134 phlebotomists on staff, a viable option would be to cross train the phlebotomists to perform other laboratory tasks to reduce phlebotomist idleness. The blood collection procedure takes place in the pre-analytical stage of the laboratory process and with proper training there could be opportunities for the phlebotomists to perform tasks in the remaining two stages of the laboratory process (the analytical stage and the post-analytical stage). The second strategy would be to determine how many phlebotomists are needed for dedicated blood collections. If the hospital laboratory management desires for the phlebotomists to only perform blood collections and not perform other laboratory tasks, they will need to reduce their current workforce to increase resource utilization.

Figure 4. Number of phlebotomists scheduled per shift for all cases. (Color figure online).

Figure 5. Percentage of phlebotomists scheduled per shift for all cases.

Table 4. Workload comparison for experimental design.

Cases for experimental design	Maximum workload per shift (in min)
34 phlebotomists: 50 min/h (base case)	110.15
25 phlebotomists: 50 min/h	149.12
17 phlebotomists: 50 min/h	217.33
34 phlebotomists: 45 min/h	111.46
25 phlebotomists: 45 min/h	149.14
17 phlebotomists: 45 min/h	210.39
34 phlebotomists: 40 min/h	112.33
25 phlebotomists: 40 min/h	147.68
17 phlebotomists: 40 min/h	215.76

11.3. Weekly scheduling template for phlebotomist scheduling

The purpose of the two-stage SILP model is to help laboratory management create optimal phlebotomist schedules that will minimize work overload. The results of the model indicated there were certain time blocks with a higher blood collection workload and therefore would require a larger number of phlebotomists to be available during the corresponding shifts. As mentioned previously, the late evening time blocks correspond with the higher blood collection workload due to physicians wanting patient test results to be available once they arrive in the following morning. Table 5 represents a weekly phlebotomist scheduling template for the case

study presented in this research. This scheduling policy will allow the hospital laboratory in a local healthcare system to reduce the work overload experienced by the phlebotomists in their facility. The proper scheduling of team members can reduce overload and improve the quality of the workplace for the team as a whole (Fanjiang, Grossman, Compton, & Reid, 2005).

12. Conclusion

In this paper, an optimization model is presented as a quantitative approach to address phlebotomist scheduling in hospital laboratories. Designed as a two-stage SILP, the model provides a planning environment for decision makers via the scenarios, allowing the incorporation of quantitative information from the analysis of different blood collection demands gathered from the hospital laboratory. This model can assist decision makers by answering such questions as “How many phlebotomists should be allocated to each shift?”, and “How can phlebotomist utilization be increased?”

This study makes a contribution to the literature by formulating one of the first optimization models developed for phlebotomist scheduling in hospital laboratories. By using stochastic programming, the study considers the stochastic nature of phlebotomist scheduling—an

Table 5. Weekly phlebotomist scheduling template with 25 phlebotomists available.

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Shift 1	6	4	3	1	1	3	5
Shift 2	0	0	2	0	2	1	1
Shift 3	1	0	2	1	1	0	2
Shift 4	2	1	1	3	1	3	1
Shift 5	0	2	0	6	3	2	0
Shift 6	0	1	0	1	0	0	0
Shift 7	3	4	5	0	2	0	0
Shift 8	1	2	2	2	3	5	5
Shift 9	7	7	5	10	4	6	6
Shift 10	4	2	4	1	7	5	4

important characteristic to be considered. The two-stage SILP model developed in this study captures the uncertainty associated with the blood collection demand. This model provides decision makers a quantitative approach to determine scheduling policies in order to reduce work overload and ensure the effectiveness of the hospital laboratory facility. Although phlebotomist underutilization was shown to be present, laboratory management can select to cross train phlebotomists to perform other tasks in the laboratory process or reduce phlebotomist capacity to include only the number of phlebotomists required for dedicated blood collections. This paper introduces the importance of determining optimal scheduling policies in the laboratory medicine area of healthcare delivery systems and encourages additional researchers to conduct future research in this field.

13. Implications for hospital laboratory management

The study presented in this paper provides a number of implications for management in hospital laboratories. This research addresses optimizing phlebotomist scheduling to decrease work overload and recommends hospital laboratory management to consider the negative impact of work overload on patients when developing phlebotomist schedules. To support this perspective, the methodology developed in this paper aims to minimize phlebotomist work overload when determining scheduling policies based on the random blood collection demand experienced in hospital laboratory facilities.

The results of the case study reveal that in order to minimize work overload, the phlebotomist capacity must be in alignment with the blood collection requests from physicians. This observation implies that the match of phlebotomist capacity and blood collection demand could reduce work overload. Therefore, the management should focus on the patterns of the blood collection demand, which will provide insights into the number of phlebotomists required for each shift.

Since the amount of blood collection requests is an uncertain factor, the two-stage SILP model developed can be used to determine an optimal scheduling policy in an uncertain environment. Finding an analytical solution to a two-stage SILP model can be challenging without the necessary expertise; however, the new heuristic algorithm developed in this study allows laboratory management to provide the necessary inputs for the model, select run using the GAMS software, and the optimal scheduling output will then be provided. Through utilizing a quantitative approach, this significantly minimizes subjectivity of judgment and permits analysis of the relationship among variables. The presented research intends to encourage laboratory managers to make use of quantitative models, in addition to qualitative approaches when making decisions related to phlebotomist scheduling.

14. Limitations and recommendations for future work

The developed model and applications of the proposed methodology involve certain limitations. Firstly, it required significant effort to gather and analyze quantitative data such as the blood collection demand over a period of time. However, in order to make reasonable decisions, quantitative data are essential. Due to many possible blood collection demand scenarios, the two-stage SILP model only considers the blood collection demand scenarios with the highest probability of occurrence. This approach has some drawbacks such as considering only a certain number of discrete outcomes and ignoring others, although, in practice, many organizations function using this type of analysis due to resource constraints. In general, this approach does not impact the theoretical aspect and stochastic structure of the developed model, or the results from an accuracy perspective. To examine all possible scenarios of the variables, Monte Carlo simulations would be a potential approach to utilize (Bayraksan, 2005; Shapiro, 2003). Through allowing sampling from probability distributions for each variable and producing thousands of possible scenarios, Monte Carlo simulations offer a more realistic and comprehensive solution method to stochastic programs.

Secondly, the computational problem of solving large scale stochastic programs might be a challenge in the application phase. The literature suggests some reliable heuristic techniques to solve such problems (Dantzig & Infanger, 1993; Dempster et al., 1983). However, these techniques may not guarantee an optimal solution, but in many cases provide near-optimal solutions as did the proposed heuristic algorithm in this study.

Finally, this paper provides a real-life application of the model using a hospital laboratory in a large urban health care system. For future work, the application can be improved in a variety of ways. Instead of considering only the scenarios with the highest probability of occurrence, Monte Carlo simulation (Shapiro) could be applied to examine all possible scenarios, and then the outcome could be compared with the results obtained in this study to determine if there is a significant difference.

Disclosure statement

No potential conflict of interest was reported by the authors.

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