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EVALUATING STAFFING LEVELS IN MILK LAB USING DISCRETE EVENT SIMULATION

Mandana Rezaeiahari
Antonije Lazic

Department of Health Policy and Management
University of Arkansas for Medical Sciences
4301 W. Markham St.
Little Rock, 72205, Arkansas

ABSTRACT

This study uses discrete event simulation (DES) to evaluate various staffing levels at a milk lab in an academic medical center. The studied milk lab operates 10 hours a day and 7 days a week and processes on average 45 orders from a 64-bed Neonatal Intensive Care Unit (NICU). We categorized the orders into simple and complex orders. The ranges for percentages of simple and complex orders were obtained by reviewing the historical data of orders at the milk lab. A DES model was then built to evaluate the number of required technicians at the milk lab by varying the number of orders as well as the percentage of complex orders. The performance measures studied in our simulation model were the makespan and utilization of the milk lab technicians. Based on the results, three technicians is a reasonable level of staffing conditional on timely start of the orders.

1 INTRODUCTION

Research has demonstrated positive associates between breast milk and an infant's health and strength of the immune system (O'Hare et al. 2013). Human milk contains hormones, immune cells, enzymes, and other modulators that improve infant development and reduce the probability of infant mortality (Kim et al. 2013). Given that "preterm birth is the leading cause of newborn death" utilizing breast milk has become a vital component in various neonatal intensive care unit (NICU) departments (O'Hare et al. 2013).

Centralized milk labs with standardized storage, preparation, and administration guidelines improve the safety and quality of the milk (Gabrielski and Lessen 2011). Evidence suggests that preparation of milk feeds does not require trained nurses (Barbas 2013). Additionally, dedicated milk lab technicians who are responsible for the storage and preparation of human milk could reduce nurses' time away from the patient's bedside and increase their time with direct care activities (Gabrielski and Lessen 2011). The allocation of milk feeding preparation from nurses to technicians resulted in a daily savings of $767 in one hospital (Brock et al. 2016). Similar hospitals with centralized milk labs store the labeled milk from mothers and donors in a centralized preparation room. Milk lab technicians are then responsible for thawing the proper volume of the milk, adding necessary fortifiers and relabeling the containers to identify both patient and the contents (Steele et al. 2015).

A majority of the studies related to milk labs focus on the quality and safety of the feedings. A study compared the incidence of infant formula infection in a centralized location versus nurses preparing the formula at the bedside (Steele and Short 2008). The result indicated that formulas prepared at the bedside are "24 times more likely to be contaminated" than formulas prepared in a centralized location. The results of the study are conclusive in that a centralized location for milk preparation reduces the incidence of contamination in milk. The Children's Hospital of Illinois implemented a six-sigma project in order to reduce the incidences of mothers receiving the wrong breast milk (Drenckpohl et al. 2007). Gabrielski and Lessen (2011) created a centralized process for milk storage, preparation, and the administration of feedings that improved the safety and quality of the process and increased the time nurses spend on direct care of patients.

Milk labs often prepare orders in batches and 12-hour or 24-hour volumes are usually prepared within each batch (Steele et al. 2015). Depending on the needs and workflow of the NICU, milk labs utilize various preparation times for processing the orders. Some milk labs only prepare orders in the mornings or afternoons and some prepare orders in both mornings and afternoons. Decisions regarding the frequency of preparation times, length of the preparation times, and the number of milk lab technicians are directly affected by the number of daily orders and percentage of daily complex orders. In this study, we categorized the orders into simple and complex orders. Simple orders are orders that require no fortifiers or one of the liquid fortifiers. Complex orders are defined as orders that require one or multiple powdered fortifiers and require a greater amount of time for preparation as solid fortifiers need to be mixed until no visible clumps are present within the milk order. Given that the number of orders and the percentage of complex orders fluctuates daily, milk labs are at the risk of overtime, overutilization, or underutilization of resources. This study was initiated due to the daily variation of staffing hours for milk lab technicians in an academic medical center. The number of technicians on each day was not based on the actual need of the milk lab which resulted in underutilization or overutilization of technicians. The shortage of milk lab technicians necessitated overtime pay of technicians, temporary recruitment of a higher paid position such as a dietician, and involvement of milk lab supervisors in technician activities. On the other hand, underutilization of technicians meant that an additional technician was paid to provide no additional benefit to the milk lab.

To combat these issues, our study determined proper staffing level using DES for varying levels of order volumes and complexities in order to maximize usage of financial resources. In this study, due to the work flow limitations from the NICU, we only assumed that preparation time occurs in the afternoon and once milk lab technicians start preparing the orders, they continue to finish the orders by the end of the shift.

The remainder of this paper is structured as follows. Section 2 provides a relevant background of the problem. Section 3 outlines the details of the baseline model. Section 4 includes the simulation model and the results of the what-if scenarios. Section 5 concludes the paper and discusses the streams for future research.

2 LITERATURE REVIEW

Healthcare systems have undergone huge changes mostly due to the changes in business models and pavement reforms. These changes have caused a shift from fee-for-service payment models to value-based care models where the focus is on value rather than volume. On the other hand, employment of healthcare occupations is projected to grow 14 percent from 2018 to 2028 which is faster than the average for all occupations (US Bureau of Labor Statistics 2020). The increased cost of doing business in healthcare has made healthcare organizations seek operational efficiency to reduce costs.

Staffing decisions in healthcare has presented as the one with the biggest impact on cost efficiency and quality of care in the US (Kolker 2018). Heavy attention has been given to the problem of nurse staffing in the literature. While nurse staffing is an important problem, little or no attention has been given to the problem of milk lab technicians staffing. While there are a relatively smaller number of factors to be considered in the milk lab technician staffing model compared to the nurse staffing model, there are several similarities between the two models. One of the key factors in the majority of nurse staffing literature is the inclusion of patient acuity and uncertainty in patient demand. Likewise, in our proposed milk lab technician staffing model, we model acuity as complexity of the orders from the NICU. Additionally, we model uncertainty as the variability in the number of daily orders coming from the NICU (which itself is driven by the number of infants in NICU).

Recently, operations research techniques including optimization, queuing theory, simulation, and forecasting have been largely used to determine staffing decisions (Saville et al. 2019). The key contribution of operations research techniques is their power in problem structuring, handling complexities, and numerical experimentations (Saville et al. 2019). Unlike traditional staffing models that mainly rely on expert opinion to determine staffing levels implicitly, operations research techniques can explicitly optimize staffing levels based on a set of performance metrics (Saville et al. 2019).

Discrete event simulation (DES) provides a cost-effective evidence-based approach to decision making and resource allocation in healthcare. DES has been overwhelmingly used in solving operational problems including but not limited to outpatient scheduling, inpatient scheduling and admissions, emergency room simulation models, physician and healthcare staff scheduling, bed sizing and planning, room sizing and planning, staff sizing and planning and etc. (Roberts 2011). Here, we reviewed several relevant papers that have used DES to address staffing decisions in healthcare.

Reynolds et al. (2011) used DES to estimate the impact of changes in prescription workload, staffing levels and skill-mix, and utilization of the dispensaries' automatic dispensing robots on the mean prescription turnaround times and percentage of prescriptions completed within 45 min. Siddiqui et al. (2017) used DES to estimate nurse staffing level in perianesthesia care units. They used time-varying patient flow, patient acuity and nurse protocol as inputs of their simulation model and found that the traditional nurse to patient ratios systematically underestimate nurse staffing needs. DeRienzo et al. (2017) developed a simulation tool to help healthcare mangers plan for staffing needs in a hospital NICU. They studied the effect of changes in staffing, patient acuity and referral patterns on length of stay and number of deaths at NICU. Baril et al. (2020) used DES to determine how different treatment protocols (for oncology patients) and nurse patient ratios affected nurses' workload. A staffing related study used DES to show different staffing levels of pathologists affects turnaround time for cytology reports (Pongjetanapong et al. 2019). Zouri et al. (2019) presents a case study for using DES to examine the impact of variability in patient volume on resource allocation for a Rehabilitation Hospital.

Previous success of DES usage in related healthcare issues to our own made the model appear as an attractive solution to solve our issue. To the best of our knowledge, there is no study addressing staffing decisions in milk labs using the DES approach. The contribution of our proposed staffing model is to determine the staffing decisions based on evidence and historical data using the DES approach. The implications of our model are operational efficiency and ultimately cost-savings for the academic medical center.

3 BASELINE MODEL

3.1 Process Map

The entire daily activities of milk lab technicians are divided into are four major steps: (1) inspection, (2) travel to milk station to grab milk delivered by mothers, (3) sorting, weighing, labeling and storing milk into fridges, (4) and preparing the orders. Steps 1 through 4 are illustrated in Figure 1. Steps 1-3 are routine activities that are completed before noon therefore they do not affect the completion time in the afternoon. However, time to prepare and complete the orders in Step 4 depends on the number of orders and complexity level of orders. Step 4 is completed in the afternoon followed by receiving the orders from the NICU. Preparation time starts between 12:30 p.m. to 1:00 p.m. after a waiting time of around 30 minutes. We investigated the causes of this waiting time and found that this delay was due to the late orders coming from the NICU. In this paper, we simulated Step 4 as none of the earlier steps had any impact on the completion time of the orders.

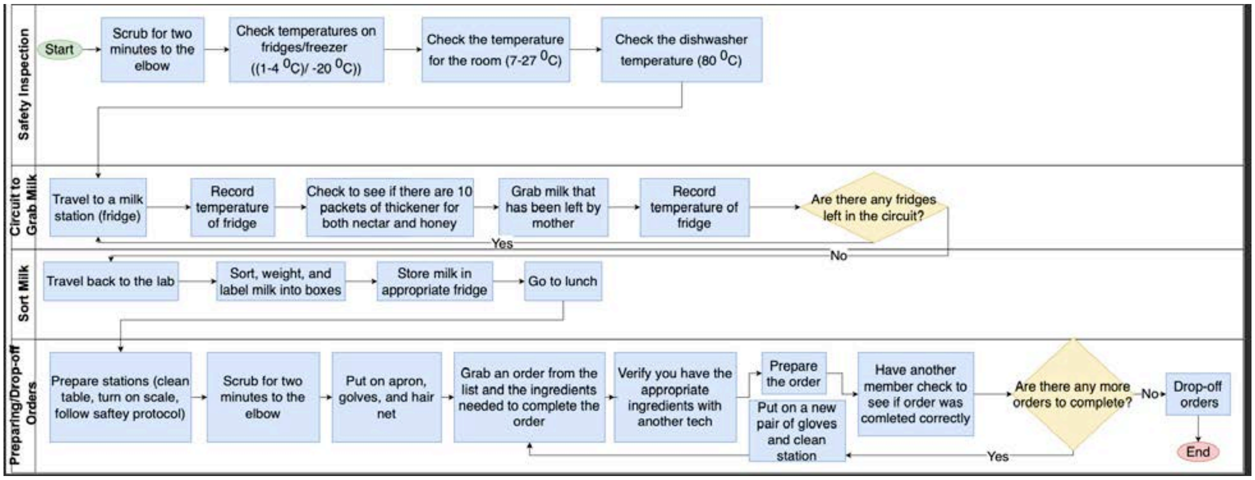

Figure 1: Milk lab process map.

3.2 Initial Staffing Ratio

The initial staffing mix consisted of 2 supervisors and 8 technicians who rotated based on a 4-on 3-off work schedule. A typical shift consisted of one supervisor and three to four technicians.

We performed preliminary data analysis with the historical data (January 2019- June 2019) that includes supervisors' hours, technicians' hours, and the number of completed daily orders. We found a significant negative correlation between supervisor hours and technician hours ($r=-0.26$, $p<0.001$) which indirectly alludes to the fact that supervisors were involved in technician activities when there was a shortage of technicians. Additionally, we observed large variation in the number of daily hours worked for supervisors (stdev=3.24 hours) compared to technicians (stdev=6.85 hours) between January 2019 to June 2019 which shows a variation in the number of available technicians.

3.3 Historical Data Analysis

In order to determine the ranges for the number of orders in the simulation model, descriptive analysis of the number of daily orders between January 2019 and September 2019 was used (Min.: 35.00, 1st Qu.: 41.00, Median: 45.00, Mean: 45.17, 3rd Qu.: 48.50, Max.: 57.00).
Processing time of the orders vary depending on the complexity level of orders. Based on the input from the senior technician, orders were divided into simple versus complex orders.

Complex orders are defined as powdered orders that have one or multiple ingredients of the following: Enfacare, Gentlease, Prosobee, PurAmino, Enfamil NeuroPro, Enfamil Human Milk Fortifier, Nutramigen, Tolerex, Simlac PM 60/40, Pregestimil, Ca+ Tribasic Phosphate.

Simple orders are orders that require no fortifiers or contain one of the liquid fortifiers of the following: Enfacare 22kcal, Gentlease 20kcal, Sterile Water, Nutramigen 20kcal, Nutramigen 40kcal, Pregestimil 20kcal, Pregestimil 24kcal, Prosobee 20kcal, Enfamil NeuroPro 20kcal, Enfamil NeuroPro 24kcal, Enfamil Premature 20kcal, Enfamil Premature 24kcal, Enfamil Premature 30kcal, Enfaport 30kcal, Similac Human Milk Fortifier, Similac Liquid Protein, Enfalyte.

A total of 12,468 milk lab orders from January 2019 to June 2019 were reviewed and organized to determine the percentage of complex orders per month. Table 1 summarizes the number and percentage of complex orders at the milk lab between January 2019 to June 2019.

Table 1: Number and complexity of orders at the milk lab during 2019.

Month	No. of simple orders	No. of complex orders	Percentage of Complex Orders
January	1117	293	20.78%
February	1079	126	10.46%
March	1146	266	18.84%
April	1208	206	14.57%
May	1357	191	12.34%
June	1194	165	12.14%

4 SIMULATION MODEL

To reproduce the order preparation process, a discrete event simulation model is used. The simulation model was developed with Simio. For the purpose of this research, the order is an entity that has two types: simple versus complex. Each milk lab technician is assigned with a work station and all technicians start processing the orders at the same time. The following assumptions were considered for the simulation model: (1) All orders arrive in batches at the same time, (2)Technicians take a 10 minute break.

4.1 Processing Time

We specifically simulated the activities of milk lab technicians in the afternoon due to the fact that orders are received by the milk lab between 12:30 to 1:00 p.m. Table 2 presents the tasks a technician performs and the associated service time.

Table 2. Service times in the milk lab.

Technicians Tasks	Time Intervals	Cumulative Probability
Prepare stations (minute)	Constant (1)	-
Scrub and put on apron (minute)	Constant (2)	-
Grab the orders and the ingredients needed from the list (minute)	[15 19], [20 24], [25 29], [30 34], [35 39]	0.22, 0.52, 0.77, 0.93, 1.00
Verification of the ingredients verbally with another technician (second)	Constant (5)	-
Prepare simple orders (minute)	[4 6], [7 8], [9 10], [11 12], [13 14]	0.11, .39, 0.61, 0.79, 1.00
Prepare complex orders (minute)	[9 13.5], [13.5 18], [18 22.5], [22.5 27]	0.2, 0.42, 0.83, 0.92, 1.00
Have other technician check the completed order (second)	[15 24.8], [24.8 34.6], [34.6 44.4], [44.4 54.2], [54.2 64]	0.30, 0.59, 0.81, 0.93, 1.00
Change gloves and cleaning stations (second)	[14 19.4], [19.4 24.8], [24.8 30.2], [30.2 35.6], [35.6 41]	0.15, 0.55, 0.85, 0.96, 1.00
Drop-off orders (minute)	[20 28], [29 37], [38 46], [47 55], [56 64]	0.13, 0.33, 0.53, 0.93, 1.00

4.2 Model Validation

After construction of the simulation study in Simio, we compared the results of our simulation model with the actual data. Table 3 shows a sample of actual data collected from the milk lab. For example, on day 1 of our data collections, there were 3 technicians and the milk lab had 46 orders among which 8 of them were complex. The simulation model was then run for each day for 100 replications and the averages of simulated makespan on each day were compared to the actual completion times using t test. We found no significance difference between the simulated results and the actual makespan shown in Table 3 (P-value = 0.72).

Table 3: Data collected from milk lab for validation of simulation study.

Day	No. of Technicians	No. of Orders	No. of Complex orders	Actual Makespan (minute)	Simulated 95% CI Makespan (minute)
1	3	46	8	254	[250 278]
2	3	47	9	262	[259 283]
3	4	49	7	220	[218 247]
4	3	51	6	260	[264 290]
5	4	51	9	235	[230 251]
6	4	51	7	280	[220 251]
7	4	51	8	265	[235 249]
8	4	51	10	267	[241 271]
9	4	52	11	269	[246 276]
10	4	50	8	249	[238 250]
11	4	51	8	239	[235 249]
12	4	50	10	284	[237 268]
13	4	50	8	232	[238 250]

4.3 What-if Scenarios Analysis

A total of 36 scenarios were evaluated by varying the number of orders, the number of technicians and the percentage of complex orders (Table 4). The performance measures used in the study are utilization of technicians and makespan (total time required from the start to the end of processing the orders). As can be seen in Table 4, the number of technicians varies between 3 and 4 as the milk lab required staffing for at least 2 technicians at any given time.

As mentioned earlier, the milk lab receives daily orders from NICU between 12:30 p.m. to 1:00 p.m.; therefore, in order to guarantee that the results of the simulation model are valid even under the worst case scenario, we started the simulation at 1:00 p.m for each day.

Table 4: Scenarios used in the simulation study.

Scenarios	**Total. Orders**	**No. of Technicians**	**% Complex Orders**	**Scenarios**	**Total. Orders**	**No. of Technicians**	**% Complex Orders**
Scenario 1	35	3	10%	Scenario 19	35	4	10%
Scenario 2	35	3	20%	Scenario 20	35	4	20%
Scenario 3	40	3	10%	Scenario 21	40	4	10%
Scenario 4	40	3	20%	Scenario 22	40	4	20%
Scenario 5	43	3	10%	Scenario 23	43	4	10%
Scenario 6	43	3	20%	Scenario 24	43	4	20%
Scenario 7	45	3	10%	Scenario 25	45	4	10%
Scenario 8	45	3	20%	Scenario 26	45	4	20%
Scenario 9	48	3	10%	Scenario 27	48	4	10%
Scenario 10	48	3	20%	Scenario 28	48	4	20%
Scenario 11	50	3	10%	Scenario 29	50	4	10%
Scenario 12	50	3	20%	Scenario 30	50	4	20%
Scenario 13	52	3	10%	Scenario 31	52	4	10%
Scenario 14	52	3	20%	Scenario 32	52	4	20%
Scenario 15	54	3	10%	Scenario 33	54	4	10%
Scenario 16	54	3	20%	Scenario 34	54	4	20%
Scenario 17	57	3	10%	Scenario 35	57	4	10%
Scenario 18	57	3	20%	Scenario 36	57	4	20%

Figure 2 shows the effect of numbers of orders and percentage of complex orders on the makespan for the number of technicians equals to 3 and 4. As expected, the increase in complexity level of orders increases the makespan. Other important observation from Figure 2 is that when the milk lab utilizes 3 technicians, there will be approximately half an hour overtime (considering start time at 1:00 p.m. and end time of milk lab at 6:00 p.m.) when the number of orders exceeds 50 regardless of the percentage of the complex orders. On the other hand, utilizing 4 technicians will result in significant idle time for the technicians when orders are less than 50 with any percentages of complex orders.

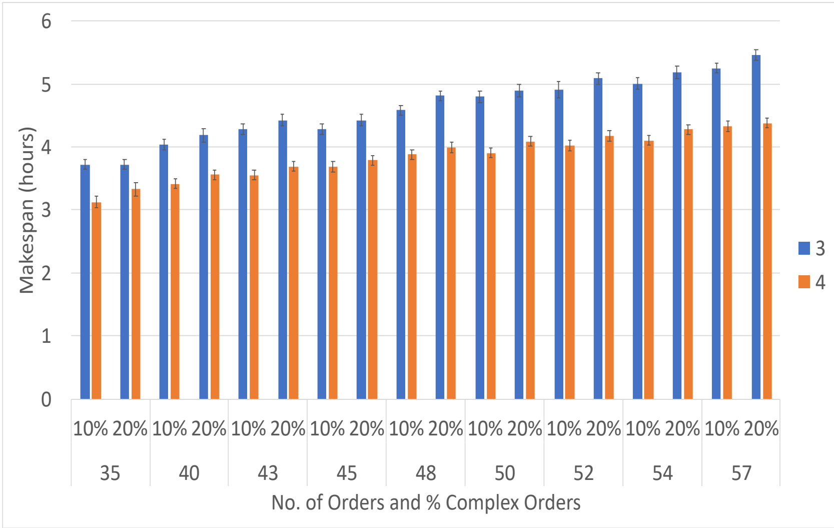

Figure 2: Effect of complexity and order volume on makespan.

We also evaluated the utilization of technicians. Figures 3 and 4 represent the utilization of technicians across various scenarios when the milk lab utilizes 3 and 4 technicians. At each order size, the increase in the percentage of the complex orders does not change the utilization of the technicians significantly; however, in Figure 3 when the number of orders increases to 52, utilization of all the technicians increases significantly compared to the minimum level of orders (i.e., 35).

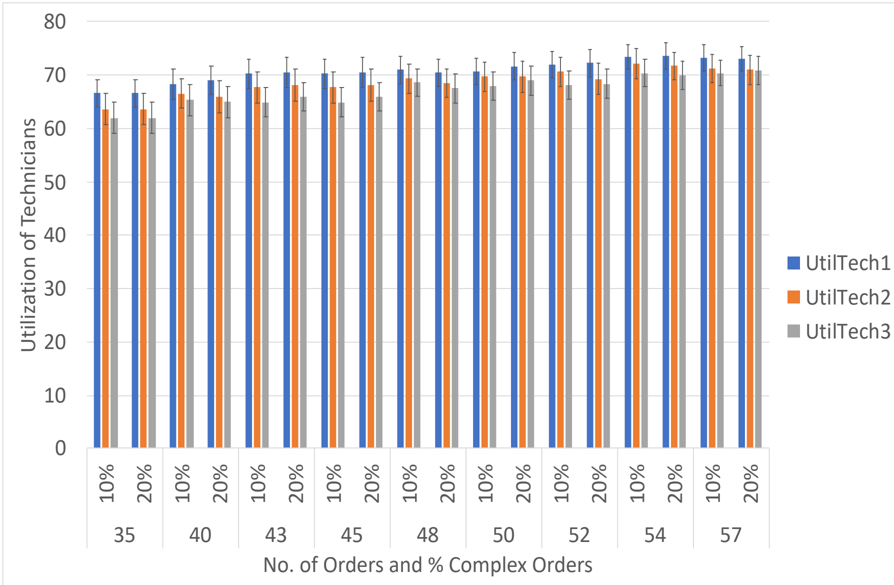

Figure 3: Effect of complexity and order volume on the utilization of three technicians.

In Figure 4, when the number of technicians increases to 4, utilization of the technicians does not change based on the percentage of complex orders but utilization of all the four technicians increases significantly when the number of orders increases to 57 compared to the minimum level of orders (i.e., 35). Additionally, utilization of the technicians drops significantly as compared to when there are 3 technicians across all orders sizes (Figure 4). Specifically, utilization of all of the technicians drops to less than 65% when the number of orders is less than 40 which this low level of staff utilization is not desired in the milk lab.

Based on the discussion provided above regarding both the makespan and utilization of the technicians, it is best to use four technicians only if the number of orders exceeds 50; however, since orders arrive at the milk lab around noon, it is hard to make daily staffing decisions in advance. Therefore, based on our discussion with the milk lab supervisors, we identified that if the milk lab utilizes three technicians but all technicians start processing the orders at noon, the milk lab can finish all orders with up to 57 orders with any complexity level before 6 p.m. Utilizing three technicians will also enhance utilization of all technicians effectively. However, this recommendation can change in the future depending on the increase in the number of NICU beds and/or any changes due to the safety protocols that could impact any of the assumptions made in this study.

One important factor to make sure all orders can be fulfilled using three technicians before 6 p.m. was identified as timeliness of orders from the NICU to the milk lab. We identified that in order for the milk lab to start processing the orders at noon, the NICU staff should make sure that all orders are ready to be sent to the milk lab not later than noon.

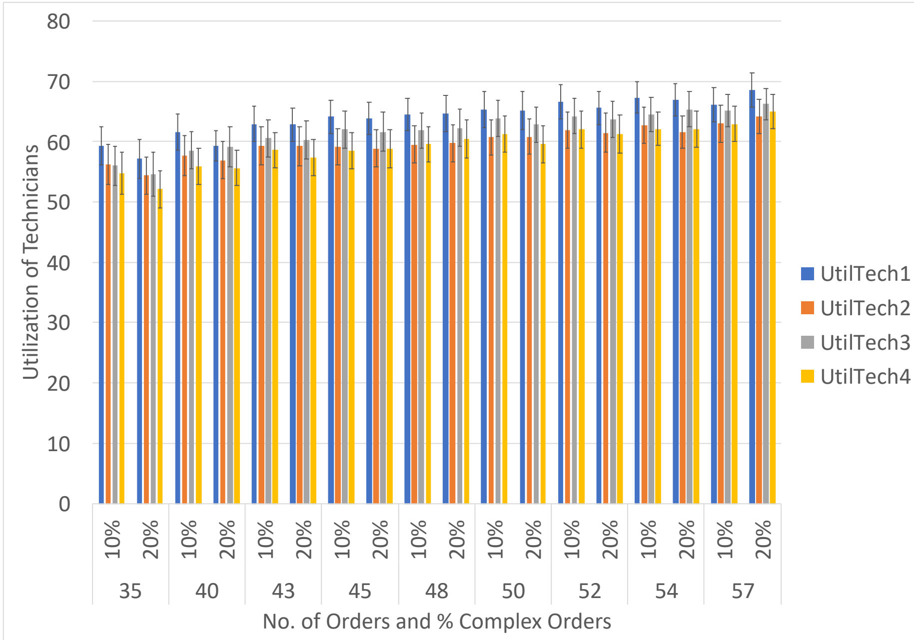

Figure 4: Effect of complexity and order volume on the utilization of four technicians.

5 CONCLUSIONS

In this study, we used discrete event simulation to evaluate various staffing levels at a milk lab in an academic medical center. The milk lab operates seven days a week, with ten hours shifts. Historically, the number of technicians at the milk lab was not proportionate to the number of orders and the percent of complex orders. In the simulation model, we evaluated the what-if scenarios by changing the number of orders and the percentage of complex orders. Based on our results, if the number of orders exceeds 50, it is recommended that the milk lab utilizes 4 milk lab technicians to finish all orders before the end time of the milk lab. This recommendation is only valid if we assume the start time at 1:00 p.m. If there’s a possibility of starting the orders at noon, milk lab can complete all orders of up to 57 (with any percentage of complex orders) before 6 p.m. with only 3 technicians. Suggestion for future research includes the effect of staffing levels on the rate of adverse events such as wrong order labels or wrong feedings.

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AUTHOR BIOGRAPHIES

MANDANA REZAEIAHARI is an Assistant Professor in the Department of Health Policy and Management at University of Arkansas for Medical Sciences. She holds a PhD in Industrial and Systems Engineering from State University of New York at Binghamton. Her research interest is in predictive analytics, simulation, and optimization, and she has relevant research experiences in the application areas of healthcare operations management and health disparities. Her email address is mrezaeiahari@uams.edu.

ANTONIJE LAZIC is a graduate assistant for the College of Public Health at the University of Arkansas for Medical Sciences. He holds a Masters in Health Administration from the University of Arkansas for Medical Sciences and will begin a PhD program in Health Services and Sciences in the Fall of 2020. His research interest is in barriers to access, optimization of clinical resources, and data analytics, and he has research experience in productivity, staffing, simulation, and patient flow. His email address is alazic@uams.edu.