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Using discrete-event simulation to address COVID-19 health and safety guidelines in outpatient laboratory clinic

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Abstract

Simulation has, over multiple decades, achieved a remarkable record of improving operational efficiency and effectiveness in many areas – manufacturing, supply chains (including commercial transportation and logistics), health care, public-sector transport, service industries, and military operations. About ⅔ through the twentieth century, simulation's earliest successes appeared in the manufacturing sector. These successes began with attention to value-added operations (e.g., at machines often entailing high capital investments) and rapidly spread to the non-value-added but very necessary material-handling requirements within factories. SARS-CoV-2, (COVID-19) has caused a rapid, widespread change in patient care across the globe. New health and safety guidelines have been established by the Centers for Disease Control and Prevention (CDC) (Health Care Guidelines, 2020). Still, it has been left to individual facilities to address and implement solutions to new standards for social distancing and cleanliness. Here we develop a discrete-event simulation model to simulate an outpatient laboratory clinic, including check-in and patient interaction, to determine if changes lead to increased efficiency and reduce patient wait times, without increasing staffing or additional resources. Under the aegis of the University of Michigan Medical Group (UMMG), this simulation is validated against real data of waiting time at the University of Michigan Canton Health Center (UMCHC) during the height of the pandemic.

Keywords: Discrete-event process simulation, Health care operations, Laboratory clinic, Queuing improvement

1. Introduction

Discrete-event process simulation achieved its first shining successes in the manufacturing sector. More recently, its use has expanded into analyses of supply-chain and warehousing operations, various service industries (e.g., hotels, retail stores), call centers, public transport (e.g., urban and interurban trains, operations in airports), government operations (e.g., military, operations in courthouses), and health care. Health care applications of simulation are remarkably broad, extending across emergency departments, hospital operating, recovery, and birthing rooms; scheduling of nurses and anesthesiologists, and clinics (including dental clinics). The practitioner Edgar J. Figueredo has recently published a comprehensive survey of simulation applications in health care (Figueredo, 2016). For example, a valuable use of simulation to support preventive health care (colonoscopy appointments) is documented in (Martin et al., 2020). The work (Kobayashi et al., 2018) describes the use of simulation to establish scenarios to train health-care professionals in correct and effective maintenance of hand hygiene (clean hands!). As a more broadly based example, (Ahmad et al., 2020) documents the use of simulation in the management of hospital resources to reduce patients' waiting times.

Relative to the context of the simulation analysis undertaken here, UMCHC is a multidisciplinary clinic serving more than one hundred thousand patients annually with primary care and specialty practices. Collocated clinics have shared waiting space that has been reconfigured to support social distancing guidelines during COVID-19. Due to seating limitations, the issues of

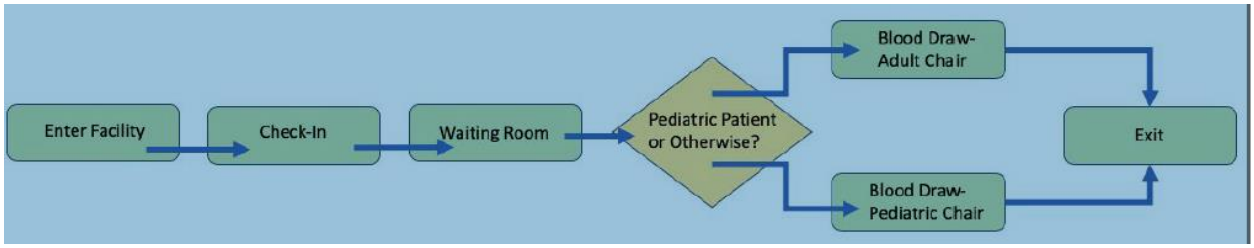

Figure 1. Patient flow at the blood draw area.

throughput, wait times, and total length of stay were identified as an opportunity for improvement. UMMG's Continuous Improvement department was asked to study the current state and offer recommendations for ways in which clinical workflows can be streamlined, so that patient safety and total length of stay is minimized. Discrete-event process simulation, as described in this paper, was a valuable and powerful ally in achieving significant improvements in performance metrics.

The remainder of this paper is organized as follows: Section 2 provides an overview of the clinic's work and operating procedures. Section 3 documents the collection and analysis of the input data required by the simulation. Section 4 describes the construction, verification, and validation of the simulation model. Section 5 discusses the output of the model and the decisions and conclusions reached from that output, and Section 6 gives indications of future extensions and expansions of this work.

2. Overview of the clinic and its operations

The University of Michigan Canton Health Center (UMCHC), which opened in 2000, provides a wide range of medical services (diagnostic, curative, and consultative) to its patients. These services include, but are not limited to, rehabilitation after trauma or injury, eye care, hepatology, computed tomography ("CAT scans") and ultrasound, nutritional consulting, lactation consulting, and more. The clinic is open six days a week (except Sundays), with twelve-hour days Monday through Thursday. Demand for these services from the clinic is steady and has been gradually increasing for more than a decade.

A "central vortex" of clinic operations is the blood draw operation, which almost all patients (and many of these pediatric) require. The recent and ongoing COVID-19 pandemic, with its requirements for "social distancing," had exacerbated bottlenecks already existing in this blood-draw area. Therefore, in keeping with long-standing advice to simulation analysts to judicially restrict model scope ((Centeno and Díaz 2015), whose advice is even given in the context of simulations on behalf of health care), and also in view of tight time constraints, this study confined itself to the blood-draw operation. Primary goals were to reduce the number of patients in the area at any one time and to reduce average and maximum queueing time; these goals and performance metrics being closely correlated. The basic and deceptively simple workflow in this operation is shown in Figure 1 (top of this page).

Patients arrive at the facility, walk back to the check-in desk and then wait to be retrieved by a laboratory technician when a chair is available. Between uses of any chair, the chair must be thoroughly sanitized. If the patient is a pediatric patient, i.e., a child five years or younger, that patient has a dedicated blood draw chair and needs the attention of two technicians. Non-pediatric patients are divided into three categories: Adult, adolescent/geriatric, and respiratory. The adult and adolescent/geriatric categories are distinguished only by walking speed. Respiratory patients not only have a slower walking speed, but also must go to a special station. These patient demographics are unique at UMCHC due to the sharing of space with obstetrics/gynecology and pediatrics clinics on site. All other patients go to one of three adult chairs and need the attention of only one technician. Once the blood draw is complete the patient leaves the building with no further interactions. Six patients per day on average are respiratory patients and therefore require employees to wear full personal protective equipment [PPE], leave the laboratory, escort the patient to a separate area to perform the draw, and return to the laboratory where they remove the PPE. These patients arrive at random intervals and require twenty minutes of staff time before exiting the system. The number of technician resources varies throughout the day and is also dependent on the staffing at other sister facilities. Technicians are also responsible for sanitization procedures, running the check-in desk, and preparing the blood specimen.

3. Input data and its analysis

Direct observation of arrival data and accompanying analysis confirmed arrivals to be a Poisson process with arrival rates varying by time of day over the twelve-hour period applicable Mondays through Thursdays. Since no performance metric problems were unique to Fridays or Saturdays, the simulation runs always lasted up to 12½ hours, under the assumption (in which the clients concurred) "We'll simulate a twelve-hour day, and the last entering patients have always been served within half an hour of closing the entry door." Among all arriving patients, the mix was 6% children, 71% adults, 21% adolescents/geriatrics, and 2% respiratory, independent of the hour of the day. After fitting observed data using the statistical package Stat::Fit® (Benneyan, 1998), walking speeds were modeled as triangular distributions. Similarly, service times at the check-in desk were triangularly distributed and both blood-draw service times were lognormally distributed.

4. Model Construction, Verification, and Validation

The clients and analysts agreed upon the use of the Simio® [SIMulation with Intelligent Objects] software package, (Smith, Sturrock, and Kelton, 2018) provided within the University of Michigan analytical software suite. This package has many advantages, some of which are shared by worthy competitors in the marketplace (Abu-Taieh and El-Sheikh, 2009):

1. Provision of standard constructs for entity arrival, entity departure, service to entities, resources (static or mobile), etc.
2. Ability to represent complex logical decisions with no knowledge of a programming language required
3. Ability to construct a useful animation (2D or 3D at a mouse click) and superimpose it atop an AutoCAD® drawing of the facility layout; this animation conveniently provides many niceties such as clearly visible simulation-clock time, the ability to easily change the color of an entity when desired (e.g., if the entity balks or reneges from a queue), and server icons that change color to indicate status (busy, idle, down, blocked, off-shift)
4. Availability of data tables to specify movement patterns relative to entity type (which enables a non-technical client to understand and become confident in the model logic more readily)
5. Extensive debugging tools
6. Strong separation of model verification and validation work from comparative evaluation of subsequent scenarios.

Verification of the simulation model used several widely recognized and effective techniques (Sargent, 2015) and (Law, 2019), including:

1. Allowing only one entity to enter the model and following its progress;
2. Inserting one entity of each type (e.g., pediatric or not) into the model and following the entity's progress;
3. Comparing the animation with client expectations;
4. Conducting "walkthroughs" among the team members to examine model logic (Myers, 1975);
5. Ensuring that all portions of the model (e.g., Servers, Paths,….) were visited in a run of sufficient length;

Validation of the model was greatly aided by use of the Electronic Health Records rigorously maintained by the clinic. These meticulous records contain data on patient arrivals, stations visited, waiting times, and service times for each patient on each working data. Observational data were compared to the EHR to confirm the accuracy of the simulation model when run under the current operating conditions (i.e., the "base case"). Results for easily reviewed and highly important performance metrics including queue length, the average length of stay, and patient mix were monitored during this validation work. This validation work was made more convenient because Simio® provides an "Arrival Table" capability enabling the analyst to tell Simio® "Here's yesterday's arrival data (arrival times of patients, types of patients….) – run the model with it," whereupon the model results can be compared with "what actually happened yesterday." After correcting several modeling errors, these comparisons matched within 3½%. One of the instructive errors thus exposed and removed involved the lognormal probability distribution, which has two common but mismatching parameterizations (Goos and Meintrup, 2015). Comparing the base case schedule to both historical and anecdotal evidence provided both the analysts and the client managers with confidence in the model's validity. This confidence provided a firm foundation for running the various proposed scenarios to be described next.

5. Results of the simulation model

During experimentation, the model was deemed to represent a terminating system, since the clinic was open for 12-hour days and actually operated slightly longer, to finish serving those patients who arrived shortly before closing time. Therefore, warm-up time for all simulation runs was set to zero. A quota of 100 replications per scenario simulated produced sufficiently narrow confidence intervals for performance metrics to guide management decisions.

Three experiments were run. In all of them, standard and trusted output analysis techniques (Currie and Cheng, 2013), such as the construction of confidence intervals and comparison by Student-*t* hypothesis tests, were used to distinguish statistically significant from statistically insignificant differences. The first examined scheduling alternatives which could potentially increase staffing at peak times, as follows:

1. Base case of current schedule; total of five workers
2. Clone of base case with worker three scheduled time changed to 10am-6pm; total of five workers
3. Clone of base case including all staff available with none being on vacation and a different scheduled time for worker four; total of six workers (actually implementing this alternative would require "workers on call" to substitute for workers taking vacation)
4. An additional staff member. Total of 7 workers

This experiment produced the following performance metrics, as summarized in Table 1 (times are in minutes):

Table 1. Results of staffing change investigations.

Scenario	Avg TIS	Pediatric chair utilization	Adult chairs utilization	Max Q length	Max time in queue
1	8.6	13.9%	33.2%	6.8	14.6
2	10.4	13.3%	34.1%	8.2	24.1
3	7.6	11.7%	32.2%	4.5	7.4
4	7.5	6.3%	31.0%	3.3	4.4

Based on these results, the analysts concluded that having six or seven workers staffing in the laboratory shows a reduction in maximum queue length, time in system, and wait time for patients. Changing schedule times made the queue, and maximum wait times, longer as seen in Table 1. This experiment clearly demonstrated that to realize a meaningful reduction in time in system and queue length, the number of workers should be at minimum six.

The second experiment, building upon the first, examined the possibility of allowing an adult patient to use the pediatric station when a child was not using it and conversely, as follows:

1. Base case (exactly as before, repeated for convenience)
2. Clone of base case with adults allowed to use pediatric chair and vice versa
3. Clone of scenario 2 with additional staff member, hence total of 7 workers
4. Clone of base case with no vacations assumed (as in Scenario 3 in the first experiment)

This second experiment produced the following performance metrics, as summarized in Table 2 (times are in minutes):

Table 2. Results of chair allocation policy investigations.

Scenario	Avg TIS	Pediatric chair utilization	Adult chairs utilization	Max Q length	Max time in queue
1	8.6	13.9%	33.2%	6.8	14.6
2	8.5	12.7%	25.2%	6.6	14.3
3	7.4	6.5%	23.4%	3.4	4.7
4	7.5	10.6%	23.7%	4.5	7.3

Based on these results, the analysts concluded that scenario three best improves overall patient experience with decreased length of time in the system, a small number of patients in queue, and low maximum wait times for the patient in queue. Scenario two has a very limited impact on system performance as seen in Table 2. Given this information, adding extra chairs does not significantly improve key performance metrics unless at least six workers are present.

The third experiment, building upon both the first and the second, examined the possibility of changing arrivals to appointment-based and concurrently changing some worker schedules in a quest to "level-load" the facility. It comprised these scenarios:

1. Base case (exactly as before, repeated for convenience)
2. Base case with level-loaded worker schedules across hours
3. Appointment-based arrivals and chairs not reserved for pediatric or for adult patients
4. The scenario 4 worker schedule from the first experiment and by-appointment, arrivals
5. The scenario 4 worker schedule from the first experiment and base-case arrivals

This third experiment produced the following performance metrics, as summarized in Table 3 (times are in minutes):

Table 3. Results of arrival scheduling investigations.

Scenario	Avg TIS	Pediatric chair utilization	Adult chairs utilization	Max Q length	Max time in queue
1	8.6	13.9%	33.2%	6.8	14.6
2	9.4	14.1%	35.8%	8.4	21.0
3	9.2	12.2%	26.2%	7.2	20.1
4	8.7	7.9%	33.9%	5.9	12.4
5	8.8	7.3%	32.4%	4.7	8.9

Hence, the team recommended UMCHC take a phased approach to implement solutions while continuing to build out the model for additional insight via the inclusion of variables excluded from this solution.

Phase 1 - Interim solutions that may be implemented immediately

1. Further explore various staffing models within the simulation to match historical interarrival times and maintain six personnel per day
2. Allow use of the currently pediatrics chair by all patients

Phase 2 - Long term, permanent solutions

1. Back-fill laboratory technicians while on vacation or sick to allow for at least six workers at the Canton location, especially on Mondays
2. Investigate the physical layout of the shared waiting space to get as many patients as close to the laboratory entrance as possible while maintaining social distancing

Phase 3 - Scale

1. Expand the simulation to explore the remaining areas of CHC not included in the scope of this project
2. Expand the project to the remaining 140 outpatient clinics at Michigan Medicine

6. Conclusions and further work

The COVID-19 has placed increasing amounts of pressure on healthcare facilities to provide efficient and effective patient care while still limiting contact and exposure. The UMCHC outpatient lab has seen no decline in patient demand and increasing wait times. To make a data-driven decision to reduce patients' total length of stay, a simulation model was built to reflect the day-to-day operation of the laboratory. In total, three experiments were run to compare the base case (or current state) model to potential alternatives. These three experiments included modifying the existing technician schedule, altering the station utilization, and moving to an appointment-based clinic (versus walk-in).

The final results and recommendations are valid, but expansion of the simulation to include more input variables and data is planned, and will result in more accurate output statistics. However, the implementation of simulated changes has already resulted in an improved patient experience and improved KPIs. Further simulation is warranted to explore the experimental impacts across a week-long simulation.

Experiment two scenario four, having a minimum of six workers scheduled in a day and utilizing the pediatric chair for adults, is the best option without adding resources. If Canton Health Center is the most important facility among the three ambulatory care units, priority should be placed on fully staffing Canton first. This scenario would realize an average of a one-minute reduction in patient total length of stay and 50% reduction in total patient wait time.

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