Original Research

DIGITAL HEALTH

Digital Health
Volume 7: 1–8

DOI: 10.1177/20552076211040987
journals.sagepub.com/home/dhj
SAGE

More from less: Study on increasing throughput of COVID-19 screening and testing facility at an apex tertiary care hospital in New Delhi using discrete-event simulation software

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Abstract

Background: One of the challenges has been coping with an increasing need for COVID-19 testing. A COVID-19 screening and testing facility was created. There was a need for increasing throughput of the facility within the existing space and limited resources. Discrete event simulation was used to address this challenge.

Methodology: A cross-sectional interventional study was done from September 2020 to October 2020. Detailed process mapping with all micro-processes was done. Patient arrival patterns and time taken at each step were measured by two independent observers at random intervals over two weeks. The existing system was simulated and a bottleneck was identified. Two possible alternatives to the problem were simulated and evaluated.

Results: Scenario 1 showed a maximum throughput of 316. The average milestone times of all the processes after the step of “Preparation of sampling kits” jumped 62%; from 82 to 133 min. Staff state times also showed that staff at this step was stretched and medical lab technicians were underutilized. Scenario 2 simulated the alternative with lesser time spent on sampling kit preparation with a 22.4% increase in throughput, but could have led to impaired quality check. Scenario 3 simulated with increased manpower at the stage of bottleneck with 26.5% increase in throughput and was implemented on-ground.

Conclusion: Discrete event simulation helped to identify the bottleneck, simulate possible alternative solutions without disturbing the ongoing work, and finally choose the most suitable intervention to increase throughput, without the need for additional space allocation. It therefore helped to optimally utilize resources and get “more from less.”

Keywords

Discrete event simulation, health care simulation, health care reengineering, COVID-19 testing, resource optimization

Submission date: 17 February 2021; Revision date: 5 July 2021; Acceptance date: 3 August 2021

Background

COVID-19 has posed numerous challenges and tested the limits of health care infrastructure. It has posed challenges on many fronts and testing for COVID-19 has been a major one. Some studies have raised concerns that testing in India has not been up to the mark.[1] In the wake of the COVID-19 pandemic, a testing facility was planned,

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designed, and operationalized in an apex tertiary care hospital in New Delhi. There has been increasing pressure to increase the throughput (number of patients tested per day) of the facility especially when COVID-19 cases were on the rise.

The COVID-19 screening and testing facility was created in the area of the erstwhile Employee Health Scheme outpatient department, considering its peripheral location with good connectivity. This helped in segregating patients going for testing from the other patients. Necessary structural reengineering was done with limited resources available during the lockdown. Necessary manpower including doctors, data entry operators (DEOs), medical lab technicians (MLTs), patient care coordinators (PCCs), hospital attendants, and sanitary attendants was trained and deployed. Processes and standard operating procedures were designed in line with the institute's infection control guidelines.

In the light of mounting pressure, the challenge was to increase the number of tests being done per day. It was also pertinent to maintain social distancing, avoid overcrowding and long queues in view of COVID-19, which also necessitated an increase in throughput. The facility was studied in detail to look for any scope for expansion. The facility was open for 8 h on all working days from 9 a.m. to 5 p.m. with a 1 h lunch break and hygiene interval from 1 p.m. to 2 p.m., making it net 7 working hours.

There were two PCCs deployed in the registration desk, two DEOs for online registration (entering data into hospital information system), four doctors for taking history and determining the need for COVID-19 testing, three staff for preparing sample collection kit, and finally five MLTs were collecting swabs from five counters. Increasing working hours had its own challenges as it would require an additional working shift to be added. Besides at this point utilization of different cadres was not clear. So any blanket increase in manpower could have led to underutilization.

Also, the area allotted for the facility is in contiguity with the emergency department, which makes any extra space allocation difficult. Therefore, it became pertinent to increase throughput within the available space and the existing working hours. Any possible alternatives/interventions had to be tested before implementation to ensure the existing work does not suffer. Different operational research tools and techniques were considered and discrete event simulation (DES) was found to be suitable.

DES being a computer-based modeling methodology is flexible and intuitive.[2] It can simulate dynamic behaviors of complex interactions between individuals, population, and their environment.[3] It enables to compare available alternatives and identify the most efficient and effective one. DES offers an advantage over other techniques such as decision trees or Markov models in being able to model even complex systems.[4] DES is a valuable tool for investigating system capacity and throughput. The use of DES models with health care applications includes hospitals, outpatient clinics, emergency departments, and pharmacies.[5]

DES helps decision-makers by simulating the "What if" scenarios without meddling with the existing systems, which is a huge advantage in times of crises like this. In a review by Zhang,[4] DES was found to have numerous applications ranging from disease distribution, disease progression modeling, screening modeling, and health behavior modeling to the most common use in health and care systems operations. Therefore, it was decided to use DES software (health care version) to address the challenge of increasing the throughput of the COVID-19 testing facility.

Aim

To explore opportunities to increase the throughput of the COVID-19 testing facility using DES software.

Methodology

Study setting: COVID-19 screening and testing facility at an apex tertiary care teaching institute in New Delhi.
Study design: Cross-sectional interventional study.
Study duration: September 2020 to October 2020.

A detailed process mapping of the facility was done (Figure 1). There were largely three stages of processes viz, registration, medical examination, and sample collection. Each stage had further micro-processes. Once the patient arrives, he/she is sent to the registration desk where PCCs hand them over forms to collect requisite information. The patient then proceeds to the online registration desk where DEOs enter the details in the hospital information system. From here on all the patient details, samples, etc., are linked to their unique hospital ID (UHID).

The next stage is medical examination wherein doctors in personal protection equipment take a detailed history from patients and based on Indian Council of Medical Research guidelines determine if COVID-19 testing is required or not. If the doctors decide that COVID-19 testing is not required, the patients' exit. If testing is required, then the patient waits in the waiting area till another team of doctors prepares the sample collection kit. This is one of the quality control checkpoints wherein the patient details/UHID are cross-checked, bar codes are stuck to the viral transport media and made into a kit which is handed over to the patient. The patient then goes to the sample collection window where the MLT collects the sample through a see-through glass with gloves. The patient exits after sample collection.

Time taken at each step in the process was calculated by measuring them in-person by the two independent

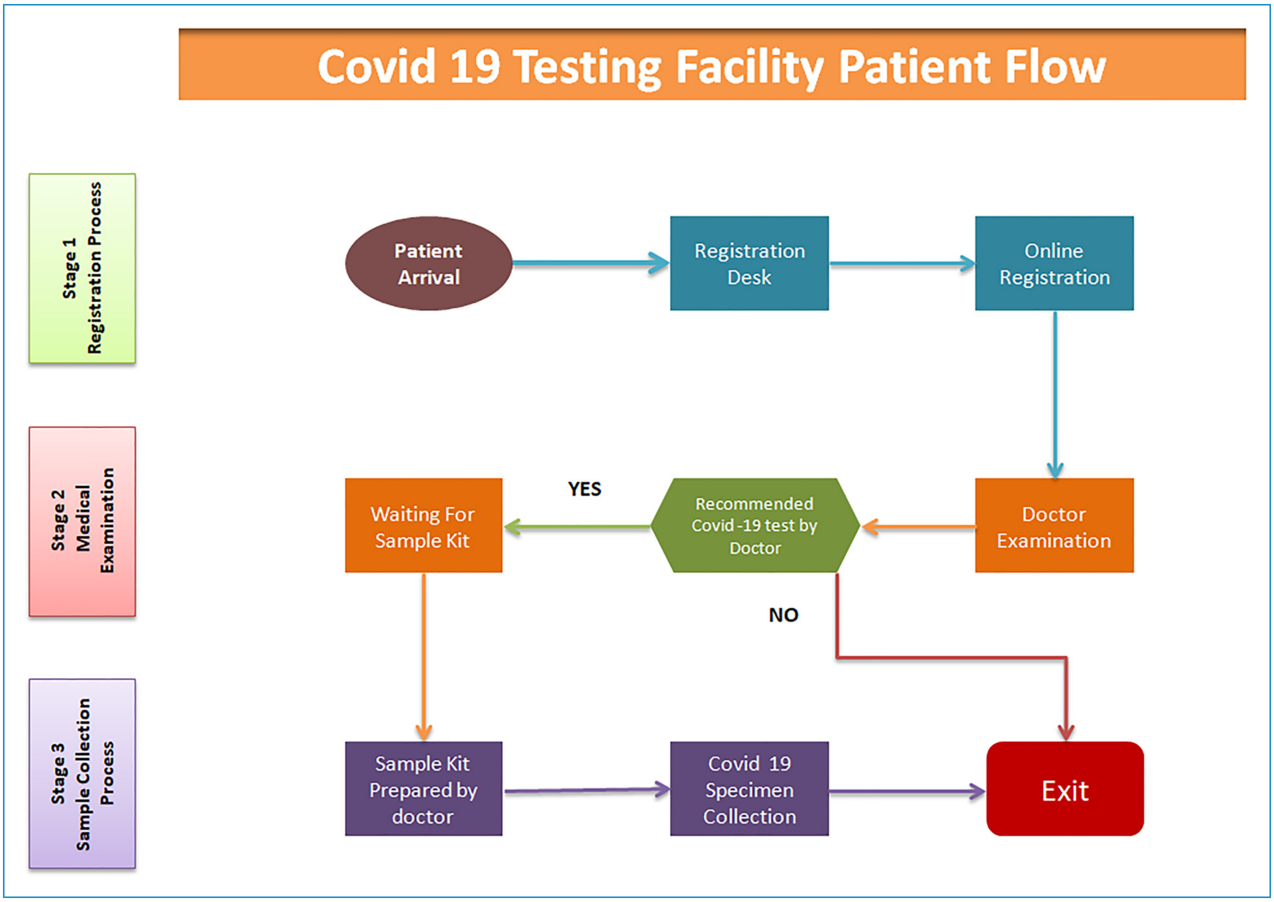

Figure 1. Process mapping of patient flow.

observers, at random intervals spread over 2 weeks. Random sampling over 2 weeks helped to get a longitudinal picture, minimizing bias and controlling for any intra-day or inter-day fluctuations. Two independent observers provided better inter-rater reliability. A number of patients and their arrival patterns were also observed and tabulated similarly by two independent observers.

With all the requisite data, models (scenarios) were built on Flexsim Healthcare software (DES software). Scenario 1 was that of the existing situation. This was simulated to identify the bottleneck(s) in the entire process. Once bottlenecks were identified, possible solutions were simulated in Scenarios 2 and 3. They were evaluated for their on-ground feasibility. The alternative that was feasible on-ground was selected for final implementation. The increase in throughputs was compared and documented on-ground as well.

Results

Scenario 1

The existing system was simulated in Scenario 1 (Figure 2). It was found on a simulation that the maximum throughput per day was 316, which closely corroborated with on-ground observations and data collection.

This gave valuable insights. The average milestone times of all the processes after the step of "Preparation of sampling kits" jumped 62%; from 82 to 133 min. This indicates some dampening factors at the step of "preparation of sampling kits" that were slowing down the entire process (Figures 3 and 4).

On further analysis, Staff state times showed that doctors involved in "preparation of sampling kits" spent almost all their time in performing the task, indicating that this resource was stretched. MLTs who were involved in sample collection had very little proportion of time spent in performing the task and spent more than two-thirds of their time waiting for the next task, indicating underutilization. It also indicated that the bottleneck was at the step of "preparation of sampling kits" (Figure 5).

Thus, scenario 1 helped to pinpoint the bottleneck. It was clear that the step of preparing sampling kits was the pain point. The slowness in the system was due to this step and was responsible for the overall lower throughput per day. On further detailed analysis, this step involved generating bar codes, sticking them, cross-checking patient

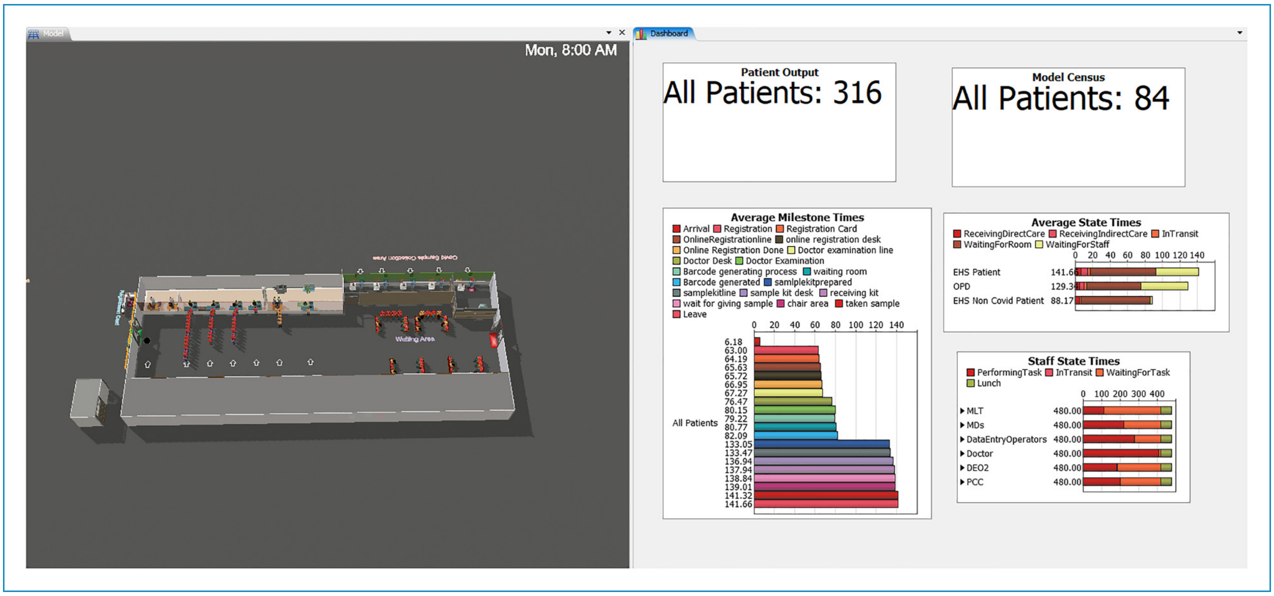

Figure 2. Scenario 1 simulation of an existing system.

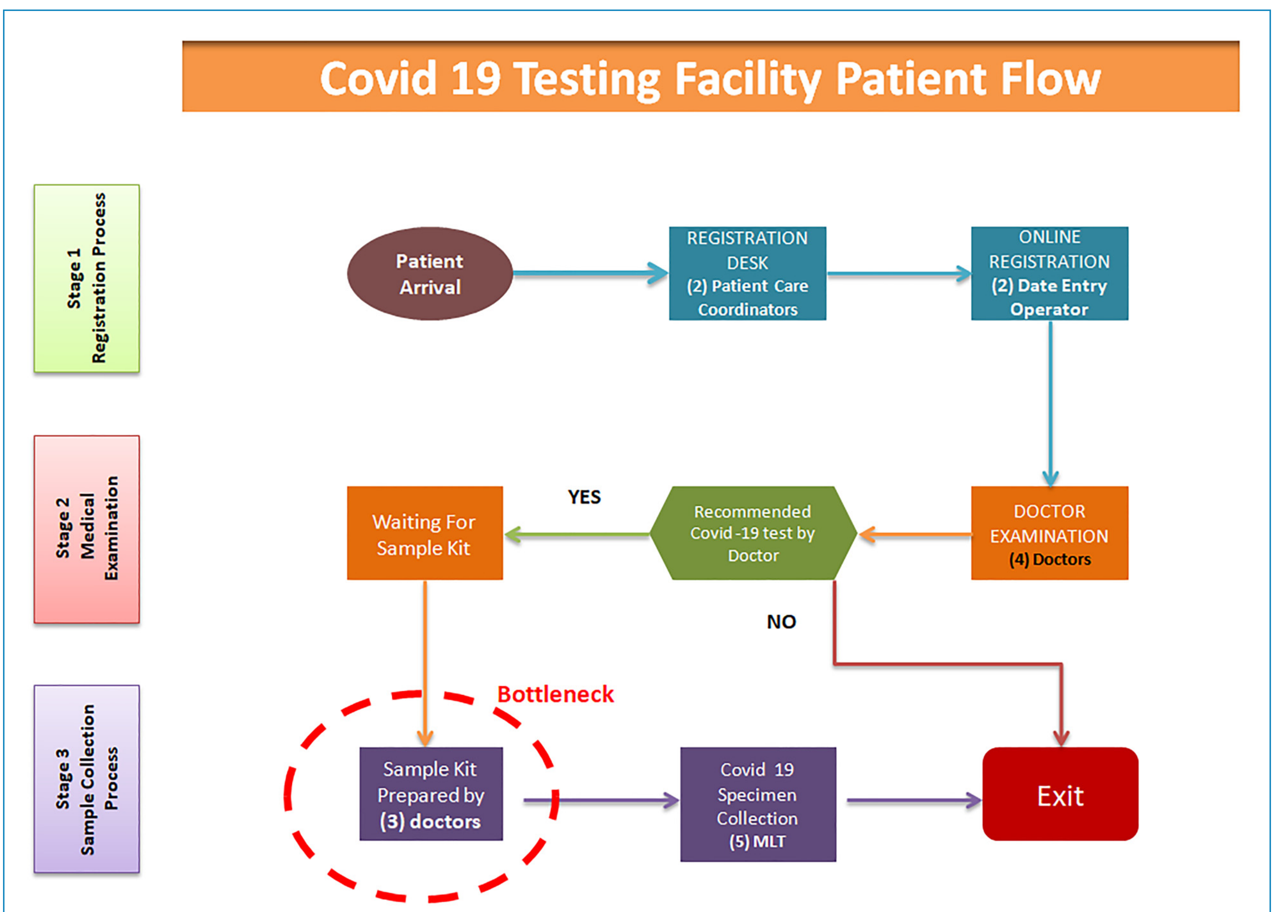

Figure 3. Bottleneck in the entire process.

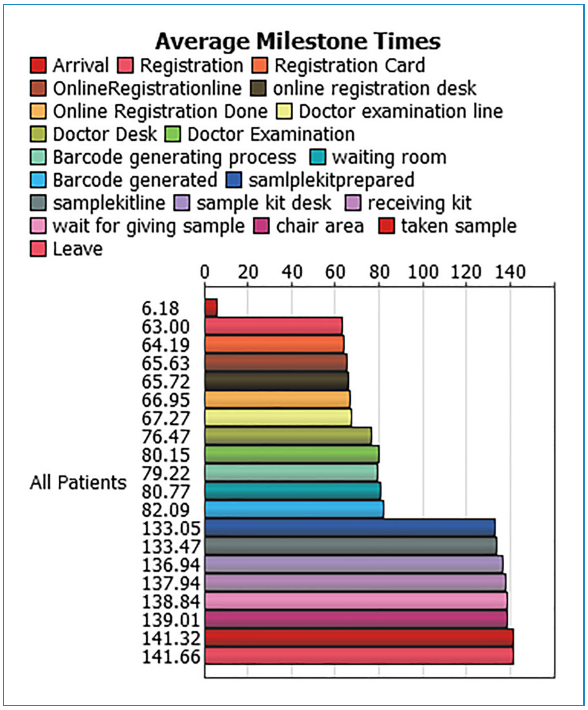

Figure 4. Average milestone times. Increased after the "preparation of sampling kits."

details, and finally creating a sampling kit. These were taking an average of 4 min per patient and there were three staff involved in the process.

So, there were two ways in which this problem could be solved. First, decrease the time taken per patient and second was to increase the number of staff. The first alternative was simulated in scenario 2 (Figure 6) and the second alternative was simulated in scenario 3.

Scenario 2

Scenario 2 showed a 22.4% increase in throughput; from 316 to 387. This was a significant improvement which

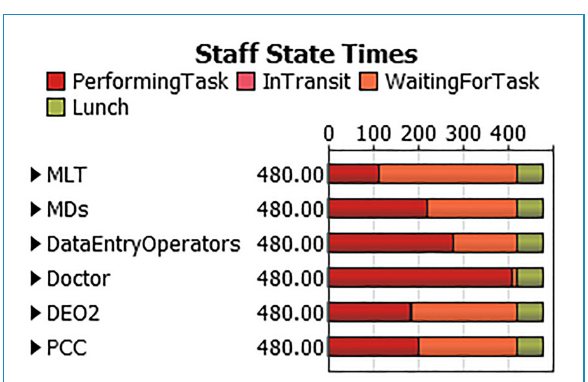

Figure 5. Staff state times. Doctors overstretched and underutilization of medical lab technicians (MLTs).

also improved MLT utilization. But, there were on-ground limitations. Decrease in the time entailed cutting short the process, which was crucial from a quality checkpoint of view. This would have clearly jeopardized the quality check and thus was not a desirable option.

Scenario 3

Therefore, the next alternative of increasing the number of staff at this step was simulated in Scenario 3 (Figure 7). It showed a 26.5% increase in throughput; from 316 to 400. This was a desirable improvement that decreased the pressure on staff and improved utilization of MLTs which are evident from both average milestone times and staff state times. Besides, there were no apparent on-ground limitations/challenges, which made this a desirable choice.

The intervention was carried out by adding three more staff at this step, taking the total manpower deployed to 6. Independent observers carried out their observations and collected data. It was found to closely corroborate with the findings from the simulation in terms of improved throughput and better staff utilization.

Discussion

Information technology (IT) enabled systems have been making inroads in health care. Right from managing patient medical records, maintaining informational continuity[6] to managerial data and feedback systems,[7] IT systems have been found to improve performance. Software with operational research tools have also been in use for more than two decades now[8] and have been catching pace over the years finding wider applications/use cases.

Baril et al.[9] studied how a business game can be used jointly with DES to test scenarios defined by team members during a Kaizen event. They aimed at rapid and successful implementation of the solutions developed during the Kaizen. Patient delays before receiving their treatment were reduced by 74% after 19 weeks.[9]

DES has also been found instrumental in reducing waiting time in the radiation therapy unit in Canada. Babashov et al.[10] in their study identified sensitive and non-sensitive system parameters. It provides a template approach for other cancer programs, using their respective data and individualized adjustments, which may be beneficial in making the most effective use of limited resources.[10]

Many other studies have also used simulation modeling in the field of radiation therapy to explore target waiting times through varying capacities[11] and to analyze the number of linear accelerators to achieve shorter waiting times.[12] Kapamara et al.[13] and Proctor et al.[14] used DES modeling to understand the treatment process, complexities, patient flow, and bottlenecks at the radiotherapy unit.

A recent study by Reese et al.[15] published in 2020 was carried out in Ambulatory Surgical Center in Seattle

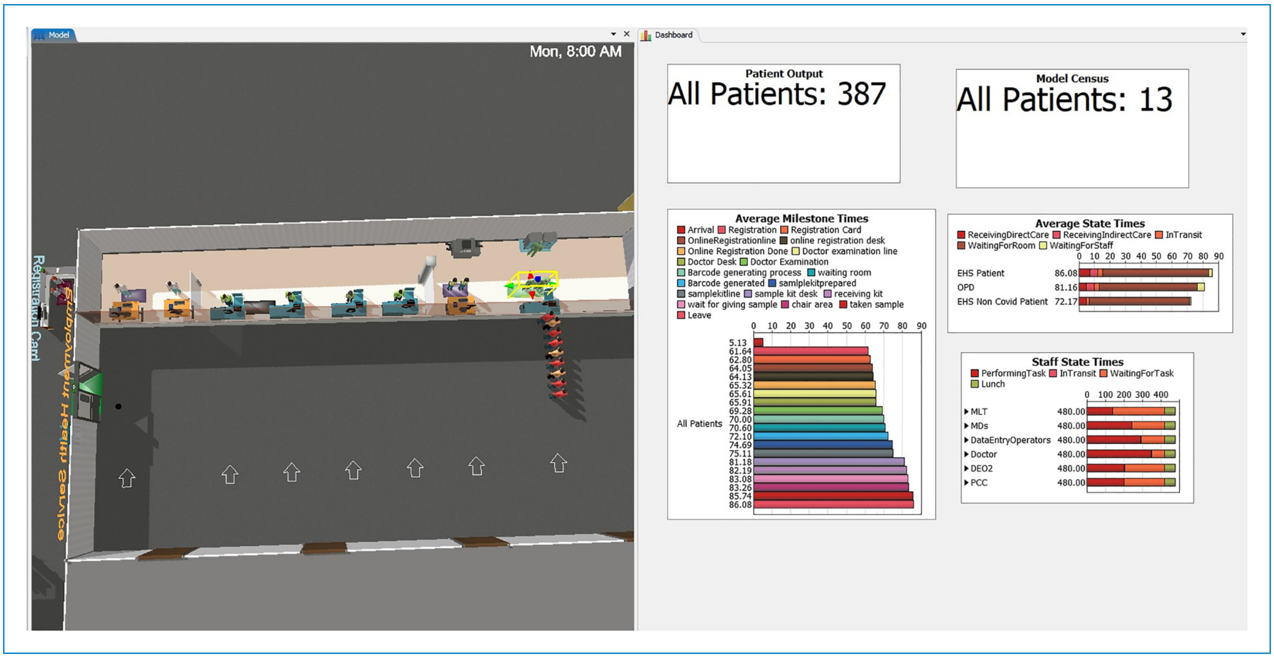

Figure 6. Scenario 2. With decreased time at the step of preparation of sampling kits.

Children's Hospital to identify throughput capacity as the number of operating rooms was increased from three to four, while the post-anesthesia care unit remained constant at 14 beds. The aim was to determine the number of patients who could receive care while minimizing the duration of crowding.[15] DES helped them achieve this objective by augmenting administrative decision-making.

DES has also been used for studies involving disease distribution. More than half of the International Classification of Diseases-10 chapters have been covered by DES studies.[4] DES is also being used for disease progression modeling, wherein DES is commonly employed to transparently conceptualize and construct the course of diseases, health states transition and disease-related events patients will go through under different interventions.[16,17] It helps by comparing different treatment alternatives at a medical level in terms of resources consumed, health outcomes, or both.

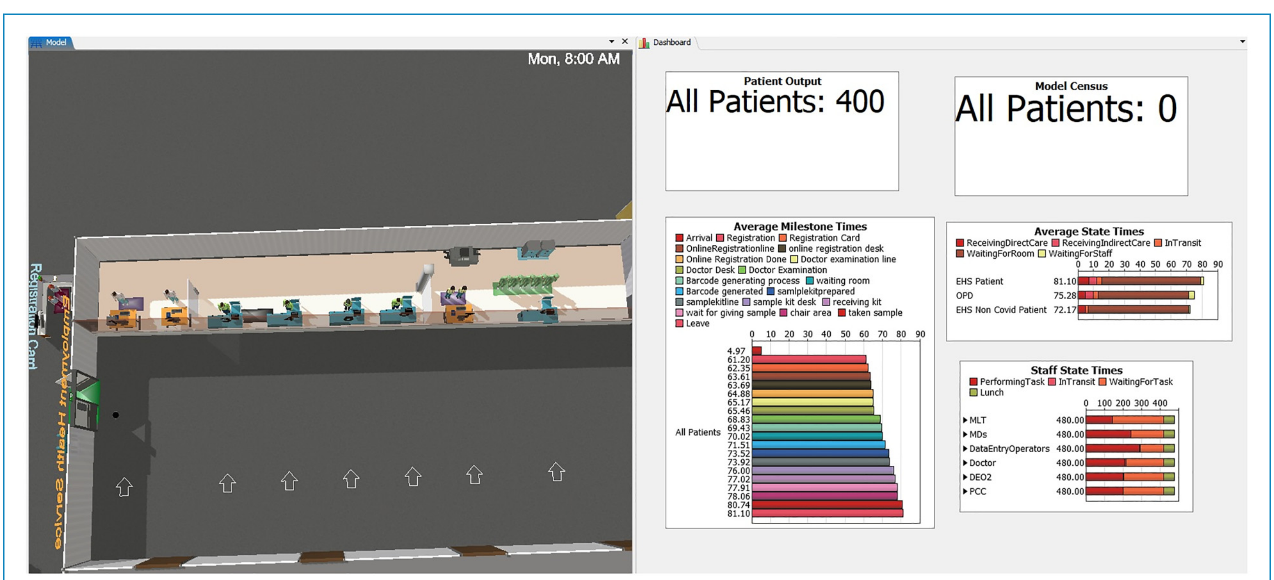

Figure 7. Scenario 3. With increased manpower at the step of preparation of sampling kits.

DES has also been applied for evaluating different disease screening modalities. Some studies have used DES to investigate the costs and health outcomes of different mammographic follow-up schedules,[18,19] alternative breast cancer screening programs,[20,21] as well as the routine performance of a mammography facility under different operational conditions.[22] They help to compare the health benefits (quality-adjusted life-years) vis-a-vis cost incurred, which is useful for administrative decisions.

DES has also been used for human behavioral modeling wherein cognitive and behavioral aspects involved in health programs are evaluated. Smoking behaviors, quit attempts, relapses, and sets of events corresponding to smoking-cessation behaviors were simulated by DES structures with the intention to identify the most cost-effective smoking-cessation strategies for diverse populations.[23] Brailsford et al.[24] modeled behavioral aspects of a breast cancer screening program.

The most common application of DES is in health and care systems operations. It assists administrative decisions by providing valuable insights into the complexity of the systems.[25] The current study is also a testament to how valuable DES can be in augmenting decision-making in terms of resource allocation and optimization. The bottleneck could be precisely identified and available alternatives could be simulated and tested out without disturbing the ongoing work, which is a huge advantage. Also, any blanket increase in manpower would have led to the under-utilization of other cadres, therefore pinpoint identification of the problem was crucial in the optimization of resources.

Conclusion

DES therefore has been proven to be a valuable tool in the evaluation of systems, identification of specific problem statements, creating possible alternatives, testing them out without disturbing the running system, choosing the best available alternative, and implementing them on-ground. The predominant advantage is the ability to create "What if" scenarios and test them before tweaking the systems on-ground. This is especially important during crises such as the current one, wherein any disturbance/disruption in the functioning of the running system cannot be afforded considering the criticality of the situation. Intervention based on the findings from the simulation (DES) helped in improving throughput within the existing facility without the need for any additional space. Identification of the specific bottleneck helped to increase only that specific manpower, thus saving valuable resources at a crucial time during the pandemic. It therefore helped achieve "more from less," when it was needed the most.

Acknowledgements: We would like to thank Ms Shubhangi Khare (Patient Care Manager) and Mr Amit Gautam (PCC) for their assistance during data collection.

Contributorship: All authors were involved in planning, designing, and conducting this study. NRG and AK wrote the first draft of the study protocol which was then refined by the other authors. HV, ARS, and DKS were instrumental in data interpretation and in designing intervention. RP and DCJ were instrumental in data collection and executing the intervention. NRG and AK wrote the first draft of the manuscript which was edited and approved by the other authors.

Declaration of Conflicting Interests: The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Ethical approval: We confirm that guidelines on patient consent have been met and any details of informed consent obtained are indicated within the text of the submitted manuscript. We confirm that Ethical Committee approval was sought where necessary and is acknowledged within the text of the submitted manuscript.

Funding: The authors received no financial support for the research, authorship, and/or publication of this article.

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