

Study to assess the utility of discrete event simulation software in projection & optimization of resources in the out-patient department at an apex cancer institute in India

Angel Rajan Singh | Anant Gupta  | Sidhartha Satpathy | Naveen Gowda

Department of Hospital Administration,
All India Institute of Medical Sciences,
New Delhi, India

Correspondence

Anant Gupta, Department of Hospital
Administration, All India Institute of Medical
Sciences, C-19 East of Kailash, New Delhi
110065, India.

Email: anant933@gmail.com

Abstract

Background and Aims: A study was done to create and run a discrete event simulation in the outpatient department (OPD) of a tertiary care cancer hospital in North India to project and optimize resource deployment.

Methods: The OPD process & workflow as per the expected load at tertiary care cancer hospital were finalized with various stakeholders in a focused group discussion. The finalized OPD process & workflow along with the OPD Building plans were utilized to develop a discrete event simulation model for the OPD at a tertiary care cancer hospital using a discrete event simulator. The simulation model thus developed was tested with incremental patient loads in 5 different scenarios/“What if” situations (Scenario 1–5). The data regarding initial patient load and resources deployed was taken from on-ground observations at the tertiary care cancer hospital.

Results: It was found that rooms and doctors were over-utilized and support staff utilization remained low. This was implemented with a lesser waiting time for patients. No additional support staff was provided thus improving utilization of existing staff and saving on resources. The simulations enabled us to deploy resources just when it was required, which ensured optimal utilization and better efficiency. The peak census helped us to determine the capacity of the waiting area in different scenarios with incremental patient load and resource deployment.

Conclusion: The simulation software was very helpful, as “what if scenarios” could be created and the system tested, without disturbing the normal functioning of OPD. This enabled decision-making before making on-ground changes which saved a lot of time and money. Also, the processes of the old system were reengineered to fit the needs of changing times.

KEYWORDS

cancer, discrete event simulation, OPD, resource management

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1 | BACKGROUND AND AIMS

Healthcare is growing more complex with the mandate expanding from the primary function of providing care to include economic, legislative, and social conditions that have led to the rise of numerous ancillary services. These have necessitated multiple new processes and systems which are closely intertwined. According to the World Health Organization,¹ a good health system requires “a robust financing mechanism; a well-trained and adequately paid workforce; reliable information on which to base decisions and policies; well-maintained facilities and logistics to deliver quality medicines and technologies.”

Today, healthcare organizations are challenged by pressures to reduce costs, improve coordination and outcomes, and be more user-friendly. Yet, at the same time, healthcare delivery is increasingly challenged by entrenched inefficiencies and suboptimal outcomes. These have, over a period of time, brought in new concepts/approaches that can better manage and optimize healthcare systems which are generally referred to as “Healthcare Engineering.”²

Data is a key driver for any healthcare engineering project. Globally, healthcare organizations are trying to harness “big data” to create actionable insights. Healthcare Analytics as a way of transforming data into actions is gaining ground. In essence, Data analytics should help in connecting the dots and making sense of the data which in turn can assist in decision making.^{3,4}

There are many operations research tools that are helpful in this regard. Among them, discrete event simulation (Simulation) has the capacity to model complex situations with the inherent advantages of interactive visualization. Even users who are not operation researchers or industry engineers can understand, develop, and validate the system better. It can describe a complex real-world system while accurately representing stochastic elements. Users can ask “what if?” questions and design new systems.⁵ There are several types of simulation: discrete event, continuous, and agent-based. In a discrete event model, items (e.g., patients, medical orders, etc.) flow through a network of components. Each component performs a function (e.g., magnetic resonance imaging) before the item (e.g., patient) moves on to the next component (e.g., service). So every component needs to be studied individually and they were not part of a continuous methodology, which is why discrete event simulation was used.

Simulation can act as a forecasting tool where the performance of an existing system with changes in operating conditions can be evaluated. This enables hospital administrators to experiment with different management policies in a multitude of possibilities without interfering with the normal functioning of the healthcare facility.⁵ Thus, simulation gives an edge to the administrators.

The parent institution has an outpatient department (OPD) footfall of around 12,000 patients per day.⁵ The huge patient load has put tremendous pressure on existing systems and infrastructure. Long waiting times are a common occurrence, affecting overall patient experience, which has also been reflected through the in-house feedback system.⁶

The lessons learned from the parent institution have prompted the use of new tools and techniques for resource optimization in the tertiary care cancer institute. The cancer institute is an apex center for translational research in the prevention & care for India-centric cancers and is the flagship project of MoHFW. The institute was recently inaugurated and is being operationalized in phases. Patient load is expected to increase rapidly and this makes it pertinent to scientifically design processes and optimizes resource allocation for more efficiency and better outcomes.

Discrete event simulator (DES) over the years has found numerous applications including modeling Lean process for reducing patient delays,⁷ reducing the turnaround time for patients,⁸ predicting and planning for staffing needs⁹ and developing high-fidelity simulation models for quality improvement (QI).¹⁰ Various studies around the globe have conducted DES in outpatient or the emergency department.^{5,11–18} Simulation modeling has been shown to be a valid, decision support tool for informing service planning but few studies are done in healthcare settings.^{19–22} Some of the DES studies report results²³ while few report the implementation strategy.^{24–27} Studies have shown engaging key stakeholders in the simulation modeling process is critical to the success of the implementation.²⁸ The studies done in various settings are also highlighted.^{5,29}

Therefore, it was decided to leverage DES to model the processes and functioning of the cancer institute to help the timely, efficient deployment of resources. Also when the new institute starts there are new processes that are to be set up and process reengineering need to be done. It was seen that the patients usually have two to three visits to a hospital just for a single consultation which was an important barrier in follow-up visits, which needed streamlining. Hence a study was done to run discrete event simulation in OPD of cancer institute to project and optimize the resources and also to do process validation.

2 | METHODS

The study design is a simulation model based on focused group discussions. The study setting was a tertiary care hospital that was recently inaugurated. The hospital has around 700 beds dedicated to cancer treatment making it one of the largest cancer hospitals in the country and a total of 250 beds were to be started in Phase I.

1. To build a simulation model of the outpatient department at the institute using Discrete Event Simulation Software.

Methodology: As part of the research project, the OPD process & workflow as per the expected load at the institute have been finalized with various stakeholders in a focused group discussion. The various stakeholders were the Head, and key faculty from the Department of Medical Oncology, Surgical Oncology, Radiotherapy, Onco-anesthesia& Palliative Medicine, Laboratory Medicine, Radiology, Nuclear Medicine, and Hospital Administration.

The finalized OPD process & workflow along with the OPD Building plans were utilized to develop a discrete event simulation model for the OPD at the institute by using healthcare-specific discrete event simulation software, Flexsim Healthcare.

To simulate a real-world situation data was triangulated from the key stakeholder, physical data collection from the OPD, mapping the process of gathering patient datasheets, taking records from medical records, etc. we had gone to the OPD in Cancer Hospital and followed the patient journey from the start to the end of treatment and seen the various pathways and noted the time of patients with service delivery. These data sets were then taken to key stakeholders who validated the process and refined the delivery details.

2. To simulate different scenarios with incremental patient load in OPD at the institute on the simulation model and identify bottlenecks, if any.
3. To suggest possible solutions/give recommendations for improvements based on findings from simulation of the sequence of scenarios.

The simulation model thus developed was tested with incremental patient loads in five different scenarios. The five different scenarios were finalized after running multiple iterations and combinations and getting them finalized by the key stakeholders taking into account the physical infrastructure and the resident manpower which were the key constraint. The key stakeholders took the decision on the final parameters for the simulation. There are four categories of validation activities to take into account when defining decision support models for healthcare systems: data validity, conceptual model validity, computational verification, and operational validity. The data was historical from a cancer hospital to mimic the real-time scenario and the management of the hospital validated the model framework. The validation and verification of DES were conducted by a group of clinicians who defined the path of patient movement and workflow. The model was run without error and was assumed to be working. The data regarding initial patient load and

resources deployed was taken from on-ground observations at the institute OPD. Each scenario tested incremental patient load, identified the bottlenecks, and thus recommend additional resources to ease the bottlenecks. These were then simulated in the subsequent scenarios thus giving us a longitudinal picture of how the system has evolved with the incremental workload.

A novel approach of combining Discrete Event Simulation, Simulation-Based Multi-Objective Optimization (SMO), and Data Mining techniques were used to reach the results and enable the health provider with decision making. The model was made by inputs and data of the cancer hospital which was used to run DES and further SMO was done to arrive at certain data points, and finally, Data Mining was done to arrive at the optimum resources. The management was forwarded the results of the data obtained for the final decision.

The result were reported as the mean for the wait times. Data analysis was done in Flexsim software. Proportions were reported for utilization of staff and patients.

3 | RESULTS

Different scenarios/"What if?" conditions were simulated during the operationalization of NCI OPD to facilitate decision-making. In all the scenarios the focus was on improving the overall patient experience by optimally deploying and utilizing resources. The parameters include average patient waiting times, census, throughput, staff utilization parameters, utilization of screening rooms, utilization of Disease Management Group (DMG) rooms, and time at which OPD finishes. The dashboards function in the software provides a real-time update on these parameters and thus it is easy to obtain a longitudinal trend over a period of time.

The decision points were for the deployment of staff (different cadres), the size of the waiting area, and the opening up of additional

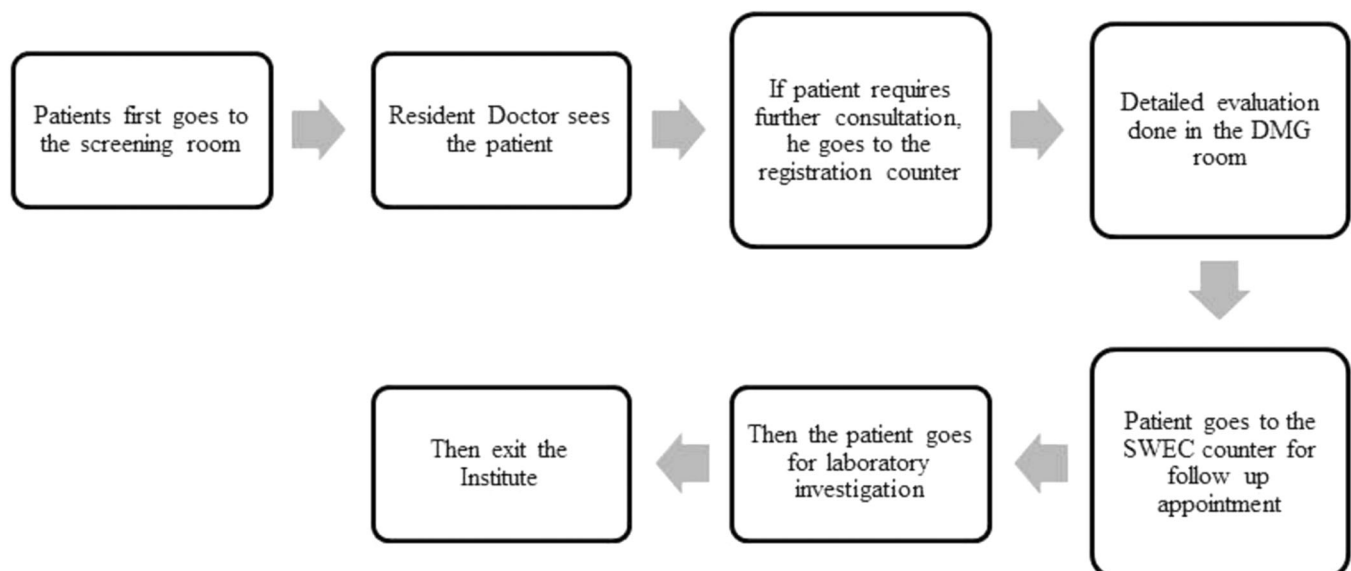


FIGURE 1 Schematic representation of process flow of patient

floors for patient care with a focus on a better patient experience. The simulation model has helped to strike a fine balance to minimize the waiting times by optimally deploying resources. The general tendency towards a blanket increase in manpower could be circumvented as the models provided a real-time picture of staff utilization and staff state times. They also helped to identify the main bottlenecks in the overall process.

The process flow of patients at the cancer institute is that the patient first goes to the screening room where the doctor first screens and decides if the patient has to be registered under the institute. Subsequently, the patient goes to the registration counter, gets the card made and proceeds to the DMG room where a detailed evaluation is done. Subsequently, the patient goes to the SWEC [Single Window Exit Counter] where fees for tests are paid, and then samples are drawn in the sample collection area by a lab technician, following which the patient leaves the OPD (Figure 1).

The different scenarios that were modeled are as under: the summary of findings of the above-mentioned scenario is mentioned in Table 1.

4 | SCENARIO 1

The initial patient load was about 40 patients per day. The resources deployed were 2 screening rooms (with 2 doctors), 2 DMG rooms (with 2 doctors), 1 receptionist, 2 patient care coordinators (PCCs), and 1 lab technician. With these resources, the OPD finished at 3 pm which was also what we could see on ground (Figure 2).

The peak census at any given point of time was 25, based on which the capacity of the waiting area was kept at 30 initially. This helped to provide seating for patients while they wait for consultation. We could see that utilization of DMG rooms (83.58%) and utilization of doctors in DMG rooms (83.5%) were high and were likely to become a bottleneck with any increase in workload. The staff state times also reflected the same. The utilization of receptionists however was barely around 11% which clearly indicated that there was no need to augment in the near future. The average waiting time for patients was around 100 min towards the end of the OPD.

5 | SCENARIO 2

In the second scenario patient load was increased to 60 patients per day in the simulation model. With the same resources as in Scenario 1, the OPD did not finish at 3 pm. Instead, 20 patients were yet to be seen with an average waiting time of 115 min. The utilization of DMG rooms and doctors in DMG rooms was around 89%. The utilization of screening rooms and doctors there was about 83%. The average state times of the doctors and patients reflected the same. The peak census crossed 40 patients. The capacity of the waiting hall was increased to 50 which provided seating arrangements for patients waiting. The OPD got over around 5 pm which was corroborated on ground (Figure 3).

TABLE 1 Summary of simulation of different scenarios

Scenario no.	Patient load	Resources deployed	OPD finish time	Utilization of DMG (denominator)	Utilization of doctors (denominator)	Average wait times
1	40	2 screening rooms (with 2 doctors), 2 DMG rooms (with 2 doctors), 1 receptionist, 2 PCCs (patient care coordinators), and 1 lab technician	15:00 h	83.58% (360 min)	83.5% (360 min)	100 min (10–125)
2	60	2 screening rooms (with 2 doctors), 2 DMG rooms (with 2 doctors), 1 receptionist, 2 PCCs (patient care coordinators) and 1 lab technician	Did not finish at 15:00 h still 20 patients remain	89.0% (360 min)	89.0% (360 min)	115 min (12–135)
3	100	2 screening rooms (with 2 doctors), 2 DMG rooms (with 2 doctors), 1 receptionist, 2 PCCs (patient care coordinators) and 1 lab technician	Did not finish at 15:00 h still 58 patients remain	93% (360 min)	90.0% (360 min)	138 min (21–156)
4	100	2 screening rooms (with 3 doctors), 2 DMG rooms (with 4 doctors), 1 receptionist, 2 PCCs (patient care coordinators) and 1 lab technician	Did not finish at 15:00 h still 20 patients remain	81% (360 min)	90% (360 min)	138 min (22–158)
5	100	2 screening rooms (with 4 doctors), 2 DMG rooms (with 4 doctors), 1 receptionist, 2 PCCs (patient care coordinators) and 1 lab technician	14:10 h	81% (310 min)	82% (310 min)	81 min (1–99)

Abbreviations: DMG, Disease Management Group; PCC, patient care coordinators.

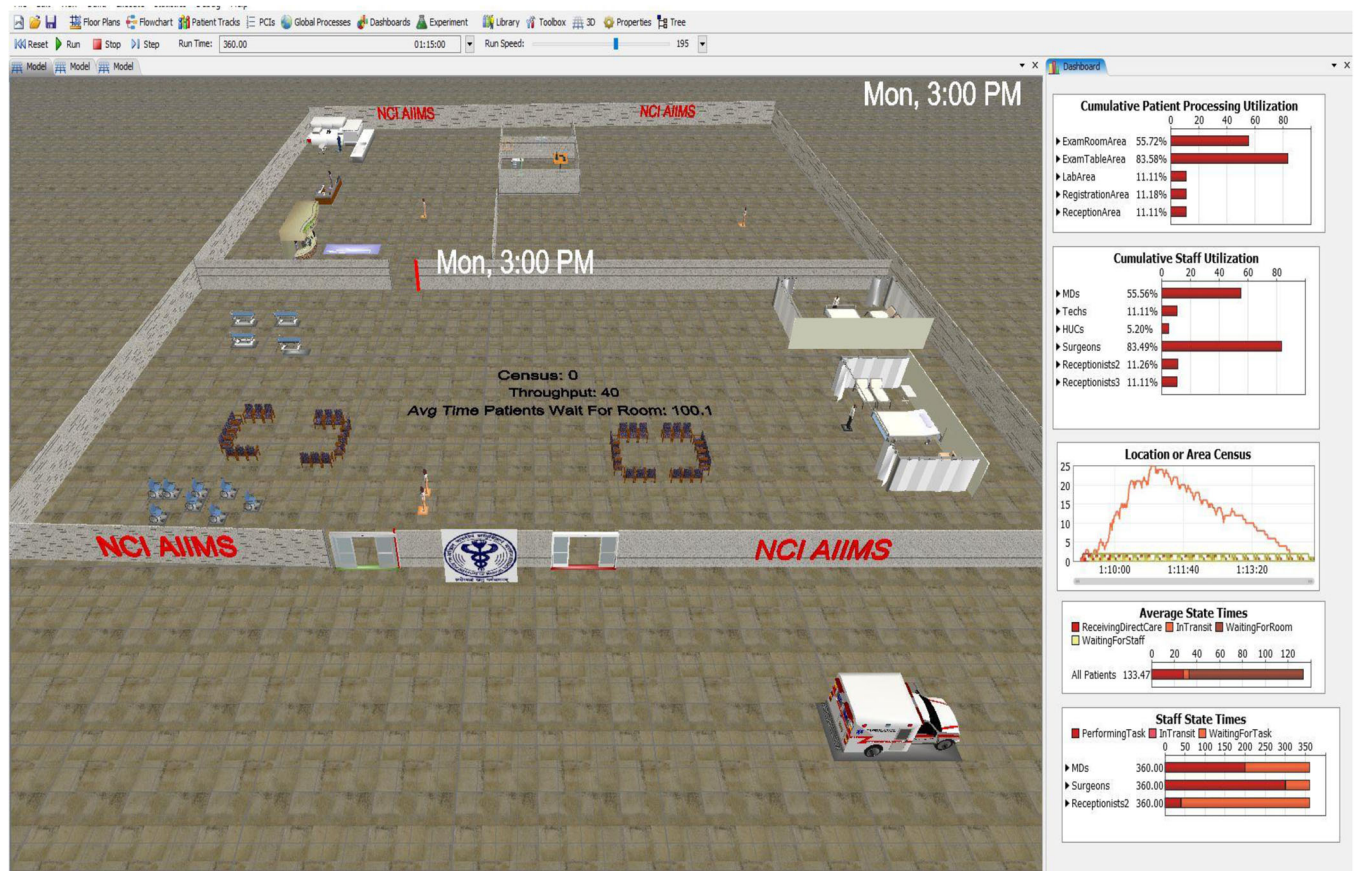


FIGURE 2 Simulation of Scenario 1

6 | SCENARIO 3

In the third scenario patient load, the patient load was increased to 100 patients per day with the same resources in Scenario 1, and a simulation was run. The OPD did not finish at 3 pm and 58 patients were still waiting to be seen at 3 pm. The peak census had crossed 80 which called for more waiting areas. The average wait time increased to 138 min. Utilization of screening rooms and doctors there had crossed 93% and utilization of DMG rooms and their doctors had crossed 91%. The staff state times reflected the same. Utilization of reception area, lab area, lab technicians, receptionists, and PCCs all remained barely around 20% (Figure 4).

7 | SCENARIO 4

In the fourth scenario, the manpower was increased for a patient load of 100 patients per day in the simulation. Based on the staff utilization seen in Scenario 3, an additional 1 doctor was deployed in the screening area and 2 additional doctors were deployed in DMG rooms. That makes a total of 3 doctors in the screening area and 4 doctors in DMG rooms. There were some improvements with the average waiting time coming down to 128 min, with about 24 patients remaining to be seen at 3 pm in the OPD waiting area.

The utilization of DMG rooms and their doctors cooled down to 81% but utilization of screening rooms and their doctors continued to be more than 90%. The peak census came down to a little above 60 which decreased the waiting area required. The utilization of other staff increased but continued to be around 40% (Figure 5).

8 | SCENARIO 5

In the fifth scenario, an additional floor was opened to cater to the load of 100 patients per day. Based on utilization figures from scenario 4, the screening room was found to be the bottleneck. Therefore all the DMG rooms were now shifted to the first floor and the capacity of screening rooms increased on the ground floor. With the increased manpower and additional floor opened, the OPD finished at 2:10 pm itself with the average waiting time dropping dramatically to 81 min. The utilization of screening rooms and their doctors cooled down to around 81% and that of DMG rooms and their doctors hovered around 82%. The peak census came down to a little below 60 which decreased the need for any further expansion of waiting areas. The utilization of other staff slightly increased but still didn't mandate any further augmentation (Figure 6).

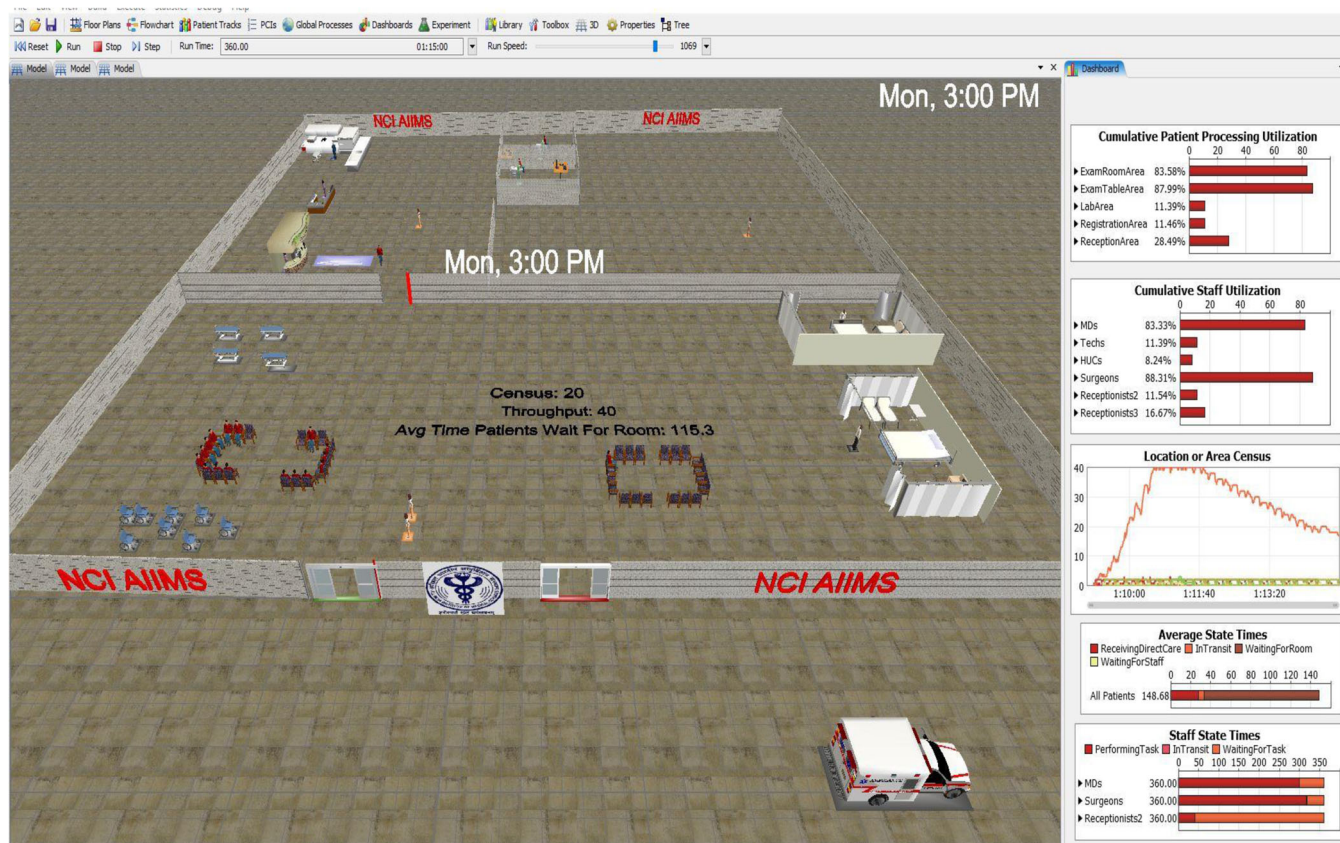


FIGURE 3 Simulation of Scenario 2

9 | DISCUSSION

The simulation models built on the discrete event simulation software, Flexim healthcare, have been helpful in decision making during the operationalization of OPD services at the NCI, AIIMS. The model built in scenario 1 with 40 patients per day and the said resources, very closely resembled the on-ground situation when the OPD was operationalized.

Subsequently, planning was done for the periodic deployment of resources to ensure their optimal utilization. Early deployment, especially of manpower would have led to idling and wastage. In Scenario 2 the patient load was increased to 60 per day. In this case, it was noted that the OPD would go on until 5 pm. The bottleneck was noted to be the DMG room and doctors. The utilization of support staff like the receptionists, lab technicians, and PCCs was barely around 11%. The peak census crossed 40. Therefore, these mandated increases in waiting hall capacity and augmentation of DMG rooms.

Subsequently, the simulation was run with a higher patient load of 100 patients per day. In Scenario 3 this load was tested with the existing resources of Scenario 1. It clearly reflected the system was on the verge of failing as less than half the patients were seen by 3 pm with long waiting times and utilization of doctors in screening and DMG rooms clearly crossing 90%. The peak census crossed 80. These indicated requirements for augmentation at levels of waiting

areas, screening rooms, and DMG rooms. Utilization of support staff however remained around 40%.

Therefore it was suggested to augment with two more DMG rooms (with 2 additional doctors) and one more screening room (with 1 additional doctor). This was simulated and tested on the software in Scenario 4. The augmentation of resources slightly eased the system by bringing down waiting times but still, 24 patients remained to be seen at 3 pm in the OPD.

Besides this, utilization of screening rooms and its doctors continued to be more than 90% which turned out to be the bottleneck. Also as the peak census was high, there was also a need for a larger waiting area which put pressure on space as only the ground floor of the OPD block was initially operational.

It was, therefore, now suggested to increase the screening rooms and its doctors. Considering the need for space, it was decided to operationalize the first floor of the OPD and shift all 4 DMG rooms there. This was simulated in Scenario 5 on the software. It was found that by operationalizing the new floor and adding just one extra screening room (with 1 extra doctor), the average wait time dramatically dropped to around 80 min with the OPD finishing by 2:10 pm. The utilization of screening rooms, DMG rooms, and doctors also hovered around a little above 80%, which indicates optimal utilization.

The utilization of support staff has slowly increased with patient load. Utilization of lab technicians (32%) & PCCs (18%) remained low

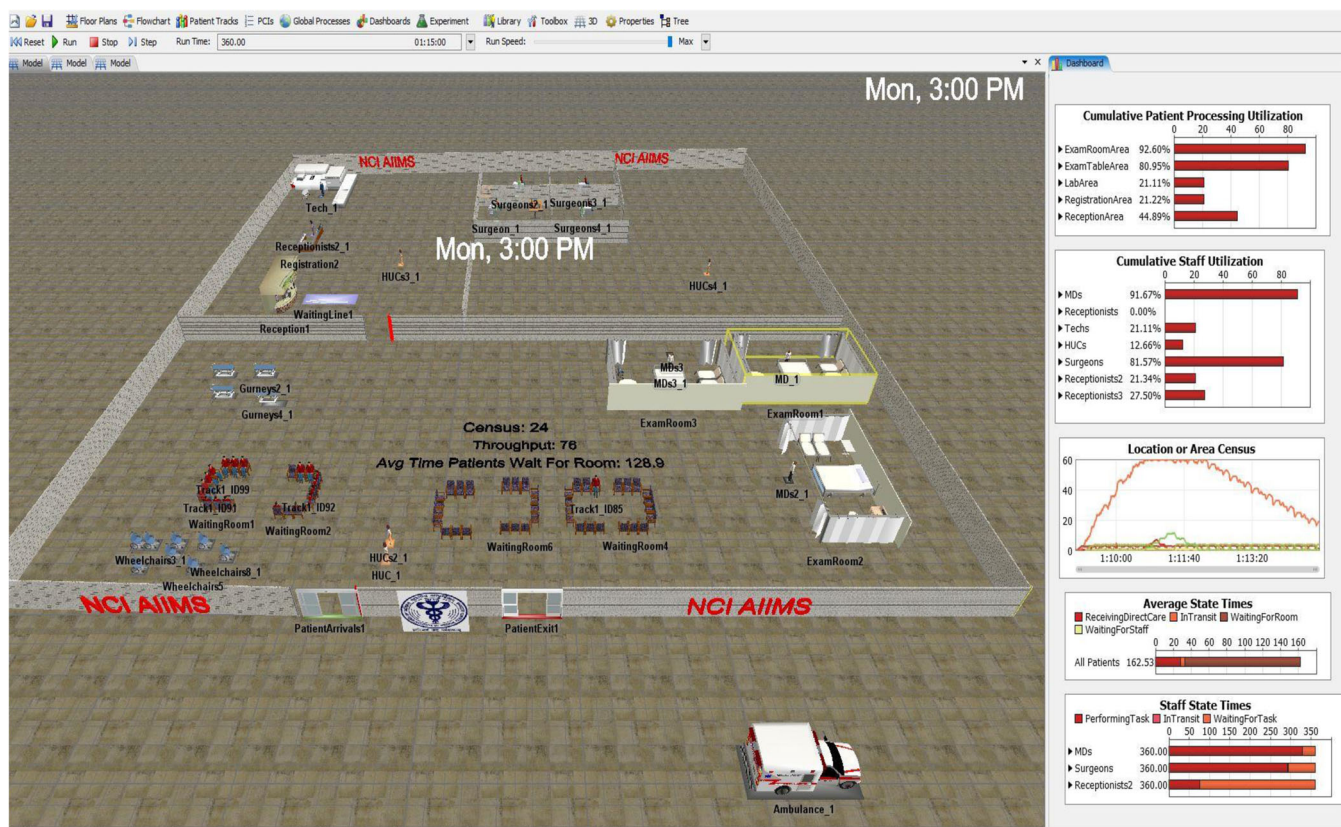


FIGURE 5 Simulation of Scenario 4

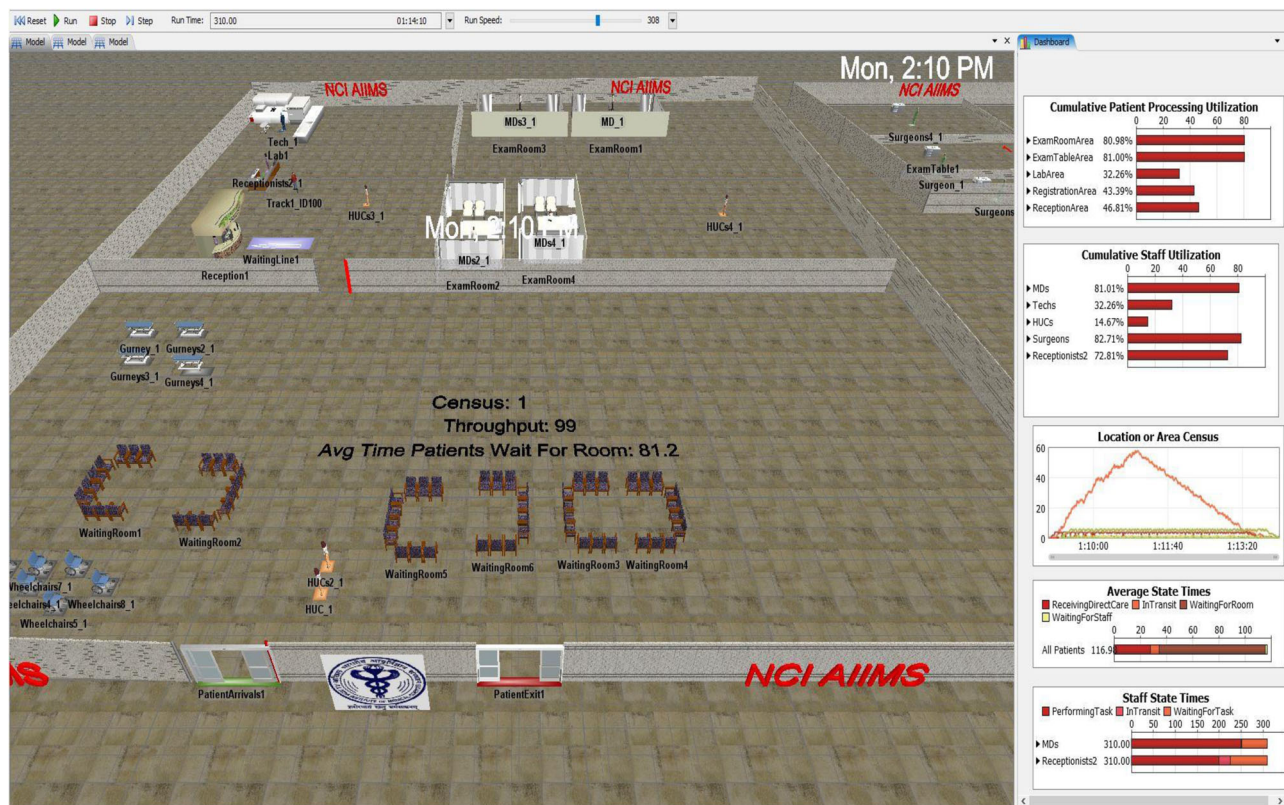


FIGURE 6 Simulation of Scenario 5

The orthopedic OPD ward in a large Thai public hospital was modeled using Discrete-Event Stochastic simulation.³⁰ Key performance indicators (KPIs) were used to measure effects across various clinical operations during different shifts throughout the day. By considering various KPIs such as wait times to see doctors, the percentage of patients who can see a doctor within a target time frame, and the time that the last patient completes their doctor consultation, bottlenecks are identified and resource-critical clinics can be prioritized. The simulation model quantifies the chronic, high patient congestion that is prevalent in Thai public hospitals with very high patient-to-doctor ratios. They have shown how DES models can be used as decision-support tools for hospital management. The findings of the above study were similar to our study where the bottlenecks were identified and discussed with key stakeholders for smoother process flow.

The simulation must be read as a proposed model near to real-world but it may vary in different settings and work cultures and should be modified accordingly.

10 | CONCLUSION

The simulation software was very helpful, as “what if scenarios” could be created and the system tested, without disturbing the normal functioning of OPD. This enabled decision-making before making on-ground changes which saved a lot of time and money. It helped us to determine the capacity of the waiting area, resource utilization, bottleneck identification, average staff state times, average patient waiting time, operationalization of green-field projects, and resource deployment.

Therefore, discrete event simulation has served as an important tool for decision-making. There are many more applications of this tool like integration with Kaizen activities, and alignment with QI programs among others which needs to be explored.

AUTHOR CONTRIBUTIONS

Conceptualization: Angel Rajan Singh. *Data curation:* Anant Gupta, Naveen Gowda. *Formal analysis:* Anant Gupta. *Investigation and methodology:* Angel Rajan Singh, Anant Gupta, Sidhartha Satpathy. *Project administration, resources, software:* Angel Rajan Singh. *Supervision:* Angel Rajan Singh, Sidhartha Satpathy. *Validation:* Angel Rajan Singh, Anant Gupta. *Visualization:* Angel Rajan Singh, Anant Gupta. *Writing—original draft:* Angel Rajan Singh, Anant Gupta, Naveen Gowda. *Writing—review and editing:* Sidhartha Satpathy. All authors have read and approved the final version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Dr. Anant Gupta had full access to all of the data in this study and takes complete responsibility for the integrity of the data and the accuracy of the data analysis.

TRANSPARENCY STATEMENT

Dr. Angel Rajan Singh affirms that this manuscript is an honest, accurate, and transparent account of the study being reported; that no important aspects of the study have been omitted; and that any discrepancies from the study as planned (and, if relevant, registered) have been explained.

ORCID

Anant Gupta  <https://orcid.org/0000-0003-3960-2204>

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