Simulation-Based Optimization of Outpatient Appointment Scheduling in a Vietnam's Oncology Hospital

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Abstract: ***This study aims to reduce outpatient waiting times at the Breast Division of a major oncology hospital in Ho Chi Minh City using discrete-event simulation (DES) and OptQuest optimization. A DES model was developed in Arena software to simulate hospital operations, encompassing patient flow through registration, consultation, testing, and pharmacy. The model considered both walk-in and appointed patients. Optimization via OptQuest focused on inter-appointment times and appointment volumes under two policies: strict-time and flexible-time entry. The current system showed an average wait of 163.46 minutes. Policy 1 reduced waiting to 112.77 minutes with 39 patients at 7-minute intervals, outperforming Policy 2 (132.46 minutes, 42 patients at 5-minute intervals). Policy 1 met national standards and is recommended for implementation.***

Keywords: discrete-event simulation, OptQuest, outpatient scheduling, healthcare optimization, patient waiting time

1. Introduction

Healthcare systems worldwide face persistent challenges in managing patient flow and minimizing waiting times, particularly in specialized outpatient departments. Extended waiting times not only diminish patient satisfaction but also impact clinical outcomes, staff morale, and overall healthcare quality [1]. The Institute of Medicine recommends that 90% of patients should meet their physicians within 30 minutes of scheduled appointments [2], yet this standard remains elusive in many healthcare settings. In Vietnam's healthcare system, patient congestion represents a critical operational challenge. Ho Chi Minh City's Department of Health reported a 13.6% increase in medical checking arrivals in 2024 compared to 2023, exacerbating existing overcrowding conditions [3]. Previous studies at Vietnamese hospitals have documented mean waiting times ranging from 42.05 to 104.1 minutes [4], [5], [6], significantly exceeding international benchmarks.

Discrete-event simulation (DES) has emerged as a powerful methodology for analyzing and improving healthcare operations without disrupting daily activities [7]. DES enables the replication of complex system behaviors, capturing stochastic variations in patient arrivals, service times, and resource availability. When combined with optimization techniques, DES provides a robust framework for identifying optimal operational strategies [8].

This research employs DES integrated with OptQuest optimization to develop an evidence-based appointment scheduling system for the Breast Division of the Consultation Department in a major oncology hospital in Ho Chi Minh City, Vietnam. The study's objectives are threefold: (1) construct a simulation model representing current system for baseline assessment, (2) identify optimal appointment scheduling parameters through OptQuest optimization, and (3) evaluate compliance with national healthcare standards while maximizing patient satisfaction. This study holds significance in providing actionable, simulation-based solutions to a pressing challenge in Vietnam's healthcare—minimizing outpatient waiting times while adhering to national standards.

2. Literature Review

2.1 Discrete-Event Simulation in Healthcare

Outpatient appointment scheduling has received considerable research attention due to its impact on reducing patient waiting times and improving service quality. Luo et al. (2016) identify two components of waiting time: indirect (the delay from desired to assigned appointment) and direct (from arrival to consultation) [9]. This study focuses on direct waiting time because it directly affects patient satisfaction. Various quantitative approaches, including queuing theory, mathematical optimization, and simulation, have been used to address this problem, with DES standing out for its operational flexibility and practicality.

Wijewickrama and Takakuwa (2005, 2008) used DES to develop and extend appointment scheduling systems for outpatient departments under realistic conditions, including no-shows, variable consultation times, and physician lateness [10], [11]. Their studies identified several efficient scheduling rules but emphasized that no single approach dominates in all scenarios. Similarly, Jamjoom et al. (2014) and a related study in China [9], [12] applied DES to analyze outpatient appointment systems, focusing on factors such as patient unpunctuality, no-shows, and walk-ins. Both studies

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demonstrated that optimal scheduling could significantly reduce patient waiting times—by up to 26.3% and 34%, respectively—without additional resources.

Yeon, Lee, and Jang (2010) investigated an ophthalmology department in Korea, where multiple doctors shared resources. Their DES model highlighted that individually optimal schedules for each doctor do not necessarily lead to the best overall system performance, underscoring the importance of considering system-wide interdependencies when designing scheduling policies [13].

2.2 OptQuest Optimization

Simulation optimization is an increasingly valuable approach for improving resource allocation and overall performance in complex healthcare systems. Among the available tools, OptQuest stands out for its integration with simulation platforms (e.g., Arena, Simul8, Simio) and its ability to combine various metaheuristics (e.g., tabu search, scatter search, neural networks, integer programming) to explore solution spaces effectively. [14] developed a state-dependent simulation optimization model using Arena and OptQuest to dynamically reallocate admission staff based on real-time queue thresholds, resulting in reduced patient waiting times and increased throughput compared to fixed resource strategies. [15] has compared techniques like Response Surface Method, Radial Basis Function, and Artificial Neural Networks with OptQuest, finding that while OptQuest delivered near-optimal solutions, metamodels provided faster results under tight time constraints. In [16], OptQuest has been applied to optimize physician and nurse allocation in hospital emergency departments, achieving 8% improvement in patient flow and reducing overcrowding. Overall, OptQuest's ability to find near-optimal configurations makes it suitable for both operational and tactical decision-making in healthcare environments.

3. Methodology

Due to the complexity of the hospital's operation, DES is an ideal approach to replicate the dynamic behavior of this system without interfering with day-to-day activities. This study aims to simulate outpatient operations, evaluate patient waiting times, and identify improved appointment scheduling policies to enhance service efficiency. The research process begins with developing a DES model to replicate the hospital's outpatient department operations, evaluates current system performance, and subsequently tests various appointment scheduling policies optimized by OptQuest.

3.1 Discrete-Event Simulation

Following the simulation framework by [17], the DES process consists of four main phases: (1) Problem formulation, setting objectives and overall design, (2) Model building and data collection, (3) Running of the model, and (4) Implementation, illustrated in ***Figure 1***.

3.2 OptQuest Optimization

OptQuest for Arena has been used to search for optimal solutions. When OptQuest is opened, it checks the Arena simulation model and loads data from the model into its own database. An optimization model in OptQuest considers several major elements, which are:

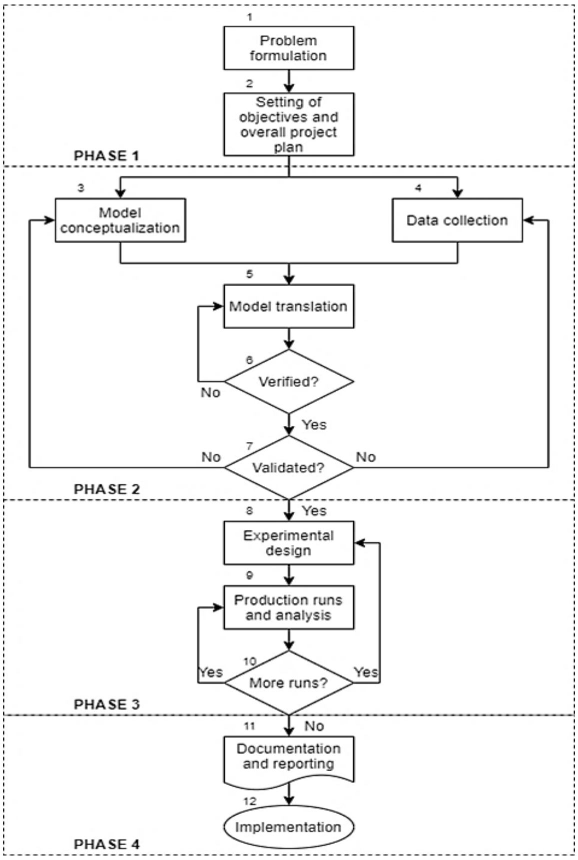

Figure 1: Steps in the simulation study

- *Controls:* Variables or resources that can be meaningfully adjusted to impact the performance of the simulation model.
- *Responses:* An output from the simulation model.
- *Constraints:* Relationships among controls and/or responses.
- *Objective:* A mathematical response or an expression used to represent the model's objective in terms of statistics collected in the simulation model.

Once set up, OptQuest runs the simulation iteratively, testing different combinations of inputs using heuristic algorithms. It returns the best solution that satisfies all constraints while optimizing the chosen objective. The optimal values are then input back into the simulation for validation through multiple replications to ensure statistical reliability.

4. Discrete-Event Simulation Model

4.1 Model Development

4.1.1 Conceptual Model

A conceptual model was developed, as illustrated in ***Figure 2***. Specifically, a normal medical procedure for each outpatient is as follows. For new patients, after entering the hospital, they are required to obtain a Personal Health Record Book at the Reception Desk and fill in their information. However, in this conceptual model, it is assumed that all patients already have their Personal Health Record Book in the first place. Patients will register at the Registration counter and pay the consultation fee at the Payment counter to acquire a consultation order number. They will sit in the waiting room and only go into the consulting room when they see their order number on the digital panel. Once they have entered the consulting room, the patients will have a vital checkup (i.e., measuring blood pressure, weight, etc.) with the nurse. When the checkup is done, they will wait and receive consultation with the doctor.

Figure 2: The outpatient flow diagram

After the first consultation, based on the given Paraclinical Test Request form, some patients will be requested to get several laboratory tests (lab tests) in order for the doctor to diagnose their health problems, while some can just get the medicine and leave the hospital. The patients who need lab tests will register and pay the lab test fees at the Registration and Payment counter, before taking all of the required tests at the lab test rooms. Once they get the lab test results at the Result counter, the patients will return to their initial consulting room to get the second assessment. Later, based on the patients' needs, some will go to the Pharmacy to buy medicine or immediately leave the hospital.

4.1.2 Assumptions

- In this study, the simulation focuses on the hospital's operations during weekdays only, from 07:00 to 12:00 and 13:00 to 16:30, including a lunch break (12:00–13:00). Although the hospital operates from 05:00 to 19:00 daily, weekend and overtime services are excluded, resulting in a 9.5-hour simulated service time per day.
- All patients are assumed to already have a Personal Health Record Book, so time for obtaining or filling it out is omitted. Minor time components such as health declarations and movements between departments are also excluded due to their minimal impact compared to waiting and consultation times.
- The model considers only outpatients visiting the Consultation Department (both insurance- and service-based), excluding those requiring cancer screening, surgeries, or hospitalization. Admissions are limited to 07:00–11:00; patients arriving later must register for another day.
- Patients are divided into Type I (breast) and Type II (thyroid, ENT, general, and gynecological), with this study focusing on Type I. All patients are same-day patients, completing consultations, tests, and follow-ups within the day. Those unable to finish within the timeframe are excluded from the analysis.
- Patient punctuality is assumed; early or late arrivals are not considered. Medical staff remain continuously available during work hours and do not leave their posts. Patients are not reassigned to different doctors and always return to the same doctor for follow-ups.
- Patients choose queues with the fewest waiting individuals and enter consultation rooms only when the queue has fewer than two patients and the nurse is idle. Staff complete ongoing tasks before breaks, accepting reduced rest periods if necessary.
- Lab tests follow a set order: medical tests, diagnostic imaging, and functional exploration. Patients register and pay for all required tests at once after the initial consultation and collect all results together before any follow-up consultation.

4.1.3 Data Collection and Analysis

Data was collected over two weeks during weekdays from 07:00 to 16:30, primarily through direct observation and patient interviews. Key data categories include patient arrivals, inter-arrival times, registration durations, vital checkup and consultation times, testing procedures, result collection, medication pickup, resource availability, and staff schedules. Collected data was analyzed using Arena's Input Analyzer to identify appropriate statistical distributions.

4.1.4 Model Translation

A discrete-event simulation model was developed using Rockwell Automation Arena, Version 14.0. The model replicates each step of a typical outpatient visit, with each simulation run representing one working day with a replication length of 570 minutes, using minutes as the base time unit.

4.2 Model Verification

Verification ensures that the operational model accurately represents the conceptual model in terms of system structure, component assumptions, input values, abstractions, and simplifications [17]. In this study, the operational model was rigorously reviewed by several experts with extensive experience in Arena simulation, particularly in hospital and healthcare applications, to confirm that it faithfully captures the conceptual design. Furthermore, sensitivity analyses were conducted by adjusting various input parameters to examine the logical consistency of the model outputs. For instance, an increase in patient volume appropriately resulted in longer average waiting times and higher resource utilization. Similarly, higher percentages of patients requiring paraclinical tests led to a notable reduction in resource idle times, confirming expected system behavior. To ensure input parameter integrity throughout the modeling process, ReadWrite modules were integrated to export key operational data—such as doctor service times, nurse service times, and testing durations—to text files. These exported datasets were then analyzed using Arena's Input Analyzer to verify their consistency with the specified input distributions. Overall, this verification process demonstrated that the implemented model accurately reflects the conceptual model and preserves the intended system logic.

4.3 Model Validation

Validating input-output transformation has been used as a technique to validate the model. The data that are used to validate the operational model includes:

- Y_1: average total time in the system of patients
- Y_2: average waiting time of patients

Using data from 20 simulation replications, a two-tailed t-test was applied. For both metrics, the calculated t-statistics were well within the critical values at a 95% confidence level, indicating no significant difference between the model outputs and actual data. Specifically, the average total time in the system ($\overline{Y}_1$ = 181.01 minutes) and average waiting time ($\overline{Y}_2$ = 163.46 minutes) closely matched the observed values of 180.70 and 163.10 minutes, respectively.

To further substantiate the validation, confidence interval testing was applied to estimate whether errors between expected values and confidence interval bounds exceeded the critical difference, with both metrics showing expected values within their respective confidence intervals and all best-case and worst-case errors below the critical threshold, confirming model validity without requiring additional replications.

4.4 Results

4.4.1 Patient Waiting Time

Since this model does not account for patients' moving time between rooms and laboratories, each patient's waiting time is calculated as follows: *Waiting time = Total time in system – Value-added time*, where value-added time refers to the actual time patients spend receiving services from nurses, doctors, lab technicians, or other medical staff.

After running 20 replications of the Arena simulation model, the results show that the mean waiting time for outpatients in the current system is 181.01 minutes, or approximately 3 hours. Individual waiting times vary widely, ranging from 0 minutes (indicating no waiting at any stage) to as high as 426.23 minutes (over 7 hours). A summary of the average patient waiting times is presented in ***Figure 3***.

Overall, the results show that nearly 35% of patients wait less than 60 minutes in the hospital. In contrast, more than 50% of patients experience waiting times ranging from 180 to 360 minutes. Several factors may contribute to these longer delays. Patients who require multiple lab tests must queue at several different service points, increasing their total waiting time. Additionally, delays in receiving lab test results can further prolong the overall process. Finally, hospital overcrowding often leads to high workloads for individual service providers, resulting in longer queues and extended waiting times for patients.

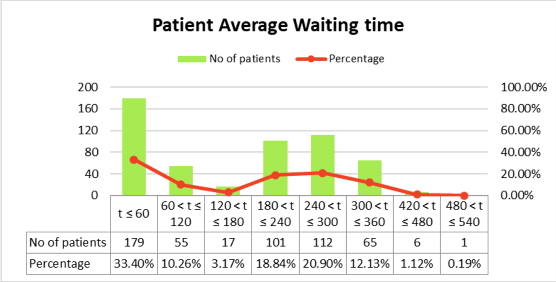

Figure 3: Patient average waiting time in the current system

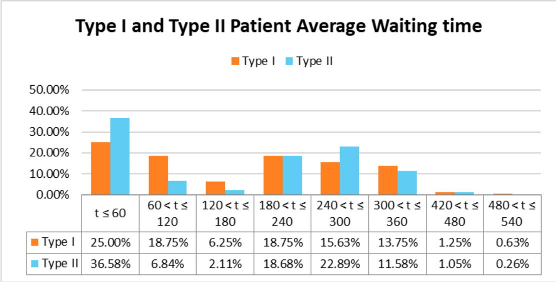

Figure 4: Average waiting time of Type I and Type II patients in the current system

As shown in ***Figure 4,*** a large proportion of both Type I and Type II patients wait less than 60 minutes for their medical procedures. However, in the 60 to 180-minute range, Type I patients clearly account for a higher percentage than Type II patients. For waiting times between 180 and 240 minutes, the proportions of Type I and Type II patients are similar, at around 18%. Notably, in the 240 to 300-minute range, the percentage of Type II patients surpasses that of Type I. Beyond 300 minutes (up to 540 minutes), Type I patients consistently represent a higher percentage compared to Type II patients.

4.4.2 Resources Scheduled Utilization

As illustrated in ***Figure 5***, currently, General Doctor 2 has the highest utilization among all doctors, exceeding 75%. Among the breast division doctors, Breast Doctor 1 and Breast Doctor 2 also show relatively high utilization rates, at 70.40% and 71.11%, respectively. The utilization of Breast Doctors 3 and 4 is slightly lower but still substantial. Overall, doctors in the breast division exhibit comparatively high scheduled utilization.

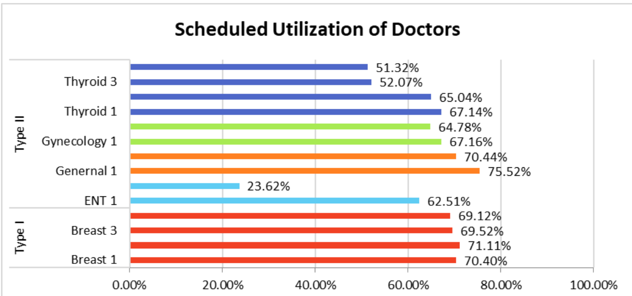

Figure 5: Scheduled utilization of doctors in the current system

Figure 6 shows that among the nurses, Thyroid Nurse 1 has the highest utilization at over 41%. In the Type I (Breast) division, both Breast Nurse 1 and Breast Nurse 2 show relatively higher utilization compared to nurses in other divisions. Overall, the resources in the Breast division are operating at a high level of scheduled utilization, reflecting their heavy workload.

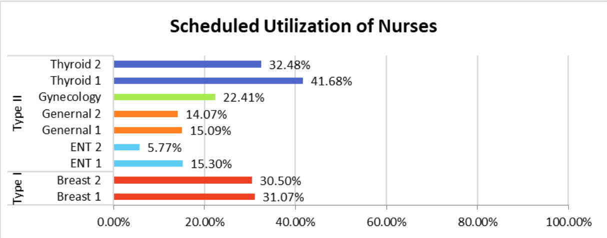

Figure 6: Scheduled utilization of nurses in the current system

4.4.3 Performance Evaluation Based on Medical Standards

(a) Length of Medical Procedure

Simulation results were benchmarked against the Ministry of Health of Vietnam's official guidance on outpatient procedures (Decision No. 1313/QĐ-BYT, 2013) [18]. This guidance outlines expected durations for medical procedures based on the number of lab tests required:

- 0 lab tests: ≤ 2 hours (120 minutes)
- 1 lab test: ≤ 3 hours (180 minutes)
- 2 lab tests: ≤ 3.5 hours (210 minutes)
- 3 lab tests: ≤ 4 hours (240 minutes)

Table 1 presents a comparison between simulated output and the benchmarks. The system meets standards for procedures with 0 or 1 lab test for both patient types. However, when patients require 2 or more lab tests, total time exceeds Ministry standards by more than 40 minutes on average. This suggests inefficiencies in handling patients with more complex diagnostic requirements and highlights areas for improvement in process management and resource allocation.

Table 1: Comparison of current system output and the guidance of Ministry of Health regarding the length of waiting time

	Number of lab tests	*Current System*	*Guidance*	*Satisfied?*
Type I	0	64 mins	< 120 mins	Yes
	1	176 mins	< 180 mins	Yes
	2	262 mins	< 210 mins	No
	3	290 mins	< 240 mins	No
Type II	0	43 mins	< 120 mins	Yes
	1	177 mins	< 180 mins	Yes
	2	259 mins	< 210 mins	No
	3	283 mins	< 240 mins	No

(b) Consulting Room Capacity

According to the guidance in [18], by 2020, the number of patients per consultation room during office hours should be limited to 35 to ensure consultation quality. During peak seasons, this number may increase by up to 30%, allowing a maximum of 46 patients per room.

As shown in ***Table 2***, for both Type I and Type II patients, the number of patients in most consulting rooms remains within acceptable limits, except for the Thyroid 1 room. This room currently accommodates nearly 10 more patients per doctor than the recommended threshold. Although the shorter service times in the thyroid division prevent long waiting times and system bottlenecks, the high patient load raises concerns about consultation quality and doctors' ability to maintain a positive attitude under pressure.

Table 2: Comparison of current system output and the guidance of Ministry of Health regarding consulting room capacity

Consulting room	Doctor	Number of patients	Satisfied?
Breast 1	Doctor 1	42	Yes
	Doctor 2	42	Yes
Breast 2	Doctor 3	41	Yes
	Doctor 4	41	Yes
Thyroid 1	Doctor 1	56	No
	Doctor 2	54	No
Thyroid 2	Doctor 3	44	Yes
	Doctor 4	43	Yes
ENT 1	Doctor 1	34	Yes
ENT 2	Doctor 2	33	Yes
General 1	Doctor 1	40	Yes
General 2	Doctor 2	37	Yes
Gynecology	Doctor 1	31	Yes
	Doctor 2	30	Yes

5. OptQuest Optimization

To overcome the limitations of conventional appointment scheduling models that focus solely on doctor consultations, this study develops a comprehensive and holistic simulation-based optimization framework that includes ancillary processes such as laboratory testing and pharmacy visits. The OptQuest for Arena tool is used to identify optimal scheduling configurations that minimize patient waiting time while satisfying operational and regulatory constraints.

5.1 Optimization Framework

5.1.1 Assumptions

This simulation model inherits all assumptions of the current system mentioned in *Section 4.1.2* but with some modifications. Patients book appointments via mobile application and pay online. Upon arrival, they receive consultation tickets from self-service registration kiosks. 7.7% of patients arrive late with delay drawn from UNIF(0,15) minutes, while the remainder arrive early or on time with UNIF(-15,0) minutes. All patients must arrive before 12:00. A single doctor is designated for appointed patients. Additionally, two appointment policies are considered:

- Policy 1 (Strict-time entry): Patients may only enter the consulting room at their scheduled appointment time.
- Policy 2 (Flexible-time entry): Patients may enter the consulting room earlier than scheduled if the doctor is idle and ready.

5.1.2 Optimization Setups

- Controls. (1) Time interval between successive appointments (ranging from 1 to 15 minutes), (2) Number of appointment slots scheduled per day (ranging from 35 to 45)
- Responses. (1) Number of appointed patients who arrive before 12:00, (2) Average waiting time of appointed Type I patients, (3) Arrival time of the last appointed patient
- Constraints. (1) The number of scheduled appointments must equal the number of patients who arrive before

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12:00, (2) All appointed patients must arrive before 300 minutes (12:00 PM), (3) At least 38 patients must be scheduled
- Objective. Minimize the average waiting time of appointed Type I patients

5.2 Optimization Results

After running the optimization problem, the set of values for the controls that optimizes the associated objective is shown in ***Table 3***. Policy 1 (patients can only proceed at their appointment time) achieved an average waiting time of 112.77 minutes with 39 appointed patients at 7-minute intervals; Policy 2 (early patients can proceed if resources are idle) resulted in 132.46 minutes with 42 appointed patients at 5-minute intervals.

Table 3: Controls in OptQuest optimization model of Policy 1 and Policy 2

	Inter-arrival time	Number of appointed patients
Policy 1	7 mins	39 patients
Policy 2	5 mins	42 patients

5.3 Discussion

For Policy 1, using the result from the above optimization problem as the input of the simulation model and running the model for 20 replications, the obtained mean waiting time of appointed Type I patients is 112.77 minutes. Compared with the guidelines issued by the Ministry of Health, the result is presented in ***Table 4***. For Policy 2, the obtained mean waiting time of appointed Type I patients is 132.46 minutes. Compared with the guideline issued by the Ministry of Health, the result is summarized in ***Table 5***.

Table 4: Comparison of Policy 1 output and the guidance of Ministry of Health regarding the length of waiting time

	Number of lab tests	*Total time in system*	*Guidance*	*Satisfied?*
Policy 1	0	28 mins	< 120 mins	Yes
	1	133 mins	< 180 mins	Yes
	2	213 mins	< 210 mins	No*
	3	239 mins	< 240 mins	Yes

** Although the result slightly exceeds the benchmark, the deviation is minimal and considered operationally acceptable.*

Table 5: Comparison of Policy 2 output and the guidance of Ministry of Health regarding the length of waiting time

	Number of lab tests	*Total time in system*	*Guidance*	*Satisfied?*
Policy 2	0	30 mins	< 120 mins	Yes
	1	162 mins	< 180 mins	Yes
	2	240 mins	< 210 mins	No
	3	269 mins	< 240 mins	No

Overall, although Policy 2 allows for a greater number of daily appointments and permits patients to receive consultation earlier when the doctor is idle, the average waiting time for appointed patients remains higher compared to Policy 1. Furthermore, Policy 1 ensures that the total time patients spend in the system aligns with the benchmarks set by the Ministry of Health. Optimization using OptQuest under Policy 1 exhibited significant efficiency improvements, demonstrating that this approach successfully optimizes the trade-off between resource utilization and patient throughput within the healthcare system. By considering the interdependent workflows of doctors, nurses, lab technicians, and administrative staff, the OptQuest framework delivers a holistic and system-oriented scheduling solution that enhances overall healthcare performance.

6. Conclusion

This study developed a discrete-event simulation (DES) model to represent the real-life operations of the Breast Division of the Consultation Department in a major oncology hospital in Ho Chi Minh City. To further improve patient flow and reduce waiting time, two appointment scheduling policies were tested through a simulation-based optimization using OptQuest for Arena. The objective was to minimize the average waiting time of appointed patients while accounting for system-wide resource constraints. Results showed that Policy 1—which restricts patients from entering the consultation room before their scheduled time—consistently delivered lower average waiting times compared to Policy 2, despite the latter accommodating more appointments.

These findings suggest that incorporating simulation-based optimization into hospital operations can lead to data-driven, practical improvements in patient scheduling and service delivery. This work also contributes to the literature by integrating appointment policies directly into a simulation-optimization model—an approach not widely explored in prior studies. Although the model does not currently consider no-show patients, multi-server systems, or service disruption, future studies are encouraged to expand in these directions for broader applicability. Future extensions should also explore the integration of predictive analytics and adaptive scheduling to further enhance healthcare delivery in complex, high-volume environments.

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Pham Huynh Tram received her M.Sc. and Ph.D. degrees in Innovation in Manufacturing Systems and Technologies from Nanyang Technological University, Singapore. Her major fields of study include manufacturing systems, quality management, lean production, and simulation. She is currently a lecturer in the School of Industrial Engineering and Management at International University – Vietnam National University, Ho Chi Minh City, Vietnam. She has extensive experience in teaching and research, focusing on quality management, lean production, simulation modeling, and experimental design. Over the past years, she has actively contributed to both academic and industry collaborations and has guided numerous student projects in her areas of expertise. She has worked on various applied projects, such as improving operational effectiveness in hospitals, optimizing supply chains for agricultural products in southern Vietnam, enhancing logistics performance at Chu Lai port for THACO automobile, and improving warehouse operations at Saigon Coop.