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Optimizing Resource Allocation using Simulation-Optimization Approach at Private Specialist Centre

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ABSTRACT

Long waiting times refer to the prolonged length of time patients spend waiting for medical treatment. This is due to a lack of human resources or equipments such as doctors, nurses or treatment rooms. This study investigates the optimization of resources allocation in private specialist centre to address long waiting times and enhance operational efficiency. A simulation model was developed by using Discrete Event Simulation (DES) approach to represent the actual patient flow in the centre and identify system bottlenecks that contributed to the prolonged waiting times. To determine the most effective resource configuration, the DES model was optimized using the Simulation-Optimization capabilities of OptQuest in Arena software. The optimization process focused on minimizing the Total Average Waiting Time (TAWT) while adhering to operational constraints such as limited staff and equipment. The results significantly improved the Total Average Waiting Time (TAWT) by 52.74%, reduction from 234.26 minutes to 110.71 minutes. This finding highlights the effectiveness of Simulation-Optimization approach in healthcare resource planning and offers valuable insights for optimizing operations in private specialist centres as well as reducing the congestion.

Keywords: Discrete event simulation; linear programming; resources allocation

INTRODUCTION

Healthcare institutions are responsible for providing medical facilities and services to treat the diverse range of health issues affecting the population. Malaysia has a dual-tiered healthcare system with general revenue and taxation funding the public sector. This sector provides services with heavy subsidization and minimal user charges. On the other hand, the private sector largely gains its finances from out-of-pocket payments or private health insurance (Quek et al. 2014).

Congestion and long waiting time are among common issues faced by the healthcare providers around the world (Ibrahim et al. 2023). Long waiting time refers to the prolonged duration that a patient has to wait to receive a medical treatment (Harding et al., 2011). This happens due to the lack of resources or facilities provided by hospitals such as doctors, nurses and treatment rooms (Savioli et al. 2022). Patient Flow related to a movement of a patient through healthcare facilities and known as a critical issue that is often associated with problems involving congestion in the emergency department and inefficient scheduling (Digdarshinee 2024; Tlapa et al. 2020). The poorly managed patient flow in hospitals may result in poor health outcomes that include elevated revisits and death rates (Pearce et al. 2023). One of the problems faced is the long waiting time cause the non-optimal use of resources. As a result, this leads to patient dissatisfaction when seeking treatment and leads to poor quality services (Pearce et al. 2023; Sarwat 2021).

The management of the healthcare facilities has implemented various actions to address these issues. Adding and redistributing resources directly into the current system is a common thing that management does to address the problems encountered and is mostly done manually. This action can have implications that may endanger and disrupt the entire operation of the facility as well as increasing the operational cost (Wan Malissa 2018). Therefore, the management must study the patient flow and every detail of the operation before a final decision is made. This is to ensure all constraints on the system operation have been considered.

Previous studies have shown that computer simulation is one of the tools that can be used to analyze the problems. It has been widely used in most operating systems, such as the healthcare industry, manufacturing industry (to study the processes involved and product flow), logistics and transportation, banking, and military operations (Ibrahim et al. 2017). Discrete Event Simulation (DES), Monte-Carlo Simulation, System Dynamic Simulation, Agent-Based, and Continuous Simulation are the commonly used approaches that are effectively used in simulation (Ouhmidou et al. 2020). However, the most frequently used approach is DES since most of the researchers believe that DES gives a more accurate outcome compared to other approaches (Mohd Fadilah et al. 2023). Besides, their abilities to model a complex system is also promising (Baesler et al. 2003).

The simulation approach helped to improve and optimize the scheduling appointment system and manage the patients flow as well as minimize the patient waiting time (Aziati et al. 2018). DES is also helpful in decision making due to its ability in producing detailed analysis of operating system problems and making real-world system improvements (Abid et al. 2023). DES is also known as a very ideal tool to communicate with the end user because it gives a clear understanding through animation and graphic visualization where the management can visualize the patient flow and see the bottlenecks in the system (Forbus & Berleant, 2022). The simulation model can be used to analyse a variety of improvement scenarios through the concept of what-if (what-if) where decision makers can list the possibilities of improvement and see the impact of those improvements to the current system operations (Mohd Kamal et al. 2021).

Atalan & Keskin (2023) used DES in Arena software to evaluate the utilization rates of the employees such as dentists, orthodontists, assistants, and clerks in a dental clinic. The utilization rate is a measuring of employee productivity and calculated in percentage. The result revealed a significant improvement in the employee utilization rate. Fun et al. (2022) in their study used DES to analyze and improve patient flow in a specialist outpatient clinic which operating in dual practice system. Their results revealed how overlapping resources usage contributed to the congestion and long waiting times. Mohamed (2021) also used DES in his study to examine and improve patient flow within the emergency department of an Egyptian hospital. The simulation model effectively identified critical bottlenecks and resource constraints that contributed to the prolonged waiting times. Guo et al. (2020) used DES to analyze the flow of glaucoma's patients and identify the strategies to reduce the long waiting times. The study shows that by reallocating staff and reducing bottlenecks in diagnostic procedures led to reduction in waiting times. In other study, Wlamyr at el. (2022) demonstrated the effectiveness of DES in accurately modelling the flow of the patient arrivals. The findings show that DES is a powerful decision-support tool that enabling hospital administrators to test changes virtually before actual implementation has been done, thus minimizing the risk in decision making.

Implementation of DES approach alone is not sufficient because simulation model only provides approximate values and not the optimal values (Ahmad et al. 2012) and the findings from this approach are only based on the what-if concept and cannot be used as a single optimization (Zeinali et al. 2015). Besides, it requires huge amount of time when dealing with the large number of constraints (Wan Malissa 2018). Therefore, some researchers have combined this approach with the optimization approaches, such as Data Envelopment Analysis, Linear programming, Goal Programming, Data Mining, Heuristic, Machine Learning, Agent Based Optimization and others to solve operational issues in healthcare industry.

Simulation-optimization uses simulation analysis combined with optimization methods to improve system operations (Makarem et al. 2020). The simulation method such as DES can be used as a tool to visualize a stochastic patient flows, where variables such as patient arrival time and service time are varies. The model will be tested to identify the bottleneck in the system being studied, which are the activities contributed to the research problem. Then, the simulation model will be combined into optimization model, where the process will be interleaved to evaluate the system performance for each resource configuration proposed (such as the number of doctors and nurses), while optimization component uses selected algorithms to adjust the variables to achieve the main objective, for instance to minimize patient's waiting time or to maximize throughput. A number of series of improvement alternatives are proposed based on the objective setting. Hence, simulation optimization using simulation results to search for the most optimum solutions based on optimization criteria determined by decision makers (Yousefi et al. 2020).

The selection and implementation of suitable optimization methods to find optimum solutions is important. The advancement in optimization has introduced to the invention of intelligent search that is capable to search for optimum solution or near optimum against complex problems with a wider solution by exploring potential alternatives. Researchers actively developed solution procedures referred to as Meta-heuristic. It has been used widely in the healthcare systems to provide solution estimation to any complex problems (Yousefi et al. 2020). Meta-heuristic emerges with the aim to provide better solution based on high-level intelligent procedure integration and efficient computer implementations (Ghasemi & Khalili-Damghani 2021; Samat & Prakash 2021).

Meta-heuristic provided a method to improve heuristic performance significantly. The search strategy being suggested through Meta-heuristic methodology produces iterative procedures that are capable of releasing itself from local optimal points (Rezk et al. 2023). It can facilitate searching processes to reach optimum solutions. Hence, the combination of both methods is ideal as compared to other methods since they combine the SPD strength to handle uncertainty (for example random patient arrival time or diversity in service time taken for each patient) in the system under study. The Meta-heuristic efficiency in exploring solution space enables researchers to obtain better results faster than ever (Hejazi 2021).

There are several meta-heuristic techniques that are commonly used by researchers to solve their research problems. According to Fu et al. (2005), several well-known Meta-heuristic methods are Genetic Algorithm, Simulated Annealing, Tabu Search and Scatter Search. However, Tabu Search and Scatter Search are proven to be the most effective method and acts as a basis in most simulation optimization software development today (Du & Swamy 2016; Ghnatios et al. 2019). There is various simulation software in the market, which equipped with integrated optimizer modules to help researchers to find the best solutions in a complex system. For instance, the OptQuest optimizer in the Arena and Simul8 software or Experimenter optimizer in Flexsim software. Although there are wide selection of software available in the market, this study choses Arena due to its OptQuest engine capabilities that effectively handle stochastic problems, especially in healthcare service environment.

OptQuest uses the combination of three meta-heuristic methods to control solution searching process, that are:

1. Scatter Search: This technique is used to explore various combinations of variables systematically to ensure the search space is fully explored (Kalra et al. 2021)
2. Tabu Search: This method functioned to avoid the algorithm repeated itself on the same solution, hence enabling search process to release itself from local optima points to search better solutions (Desale et al. 2015).
3. Neural Networks: This component is used to learn the patterns from the simulation, then facilitate to improve searching process by expecting which area that can provide or potentially provide better results (Hejazi 2021).

Through the integration of these methods, OptQuest is capable of handling a complex clinic system that has stochastic elements. Consequently, it gives a solution that proposes the most effective number of staff and resources to minimize patient waiting time. The application of Simulation-Optimization using OptQuest is well-established in healthcare research. Previous studies have successfully utilized this approach to address various operational challenges, such as emergency department overcrowding and prolonged waiting times, staffs scheduling, and resource planning and allocation (Oluwasequn & Adeyi 2020; Eskandari et al. 2011; Baril et al. 2016; Zeigler & Hammadi 2017; Ahmed & Alkhamis 2009; Isken & Rajagopalan 2002).

Therefore, the aim of this study is to develop a simulation model for the specialist centre understudy. The simulation model represented the flow of the patient through the current system operation and will be used as an analysis tool to analyze the problems faced by the management. The results from the simulation model will be used to determine the optimal number of related resources which will assists in improving the patient's total average waiting times (TAWT). The patient flow simulation model will be developed using DES approach with Arena simulation software. This process is to identify the bottlenecks to the current system that contributes to a long waiting times of the patient (activities with the highest waiting times). Based on the simulation results, a mathematical formulation was constructed to be embedded into OptQuest optimizer to find an optimal configuration of resources. The constraints (staffs or resources availability) were discussed with the management based on their operational budget. The results from the optimization model will provide the optimal configuration of resources based on the predetermine operational budget, which is expected to improve operational efficiency. The findings of this study are expected to offer practical decision-making support for the healthcare managers and can benefit the healthcare industry by providing a systematic approach to improve the patient flow as well as reducing the patient's waiting time and enhance the resource utilization.

METHODOLOGY

SYSTEM BACKGROUND

This study focusses on a breast care specialist centre at one of the private hospital in Kuala Lumpur. This centre operates from 9.00 am to 5.00 pm daily with an average of 75 to 80 patients per week. The centre provide consultation and treatment services related to breast and endocrine diseases. The centre only serve patient with prior appointments scheduled while the walk-in patients are usually will be scheduled for the next visits except in urgent cases. Currently, the centre operates with 2 registration staffs, 2 primary triage nurses, 2 blood test nurses, 2 doctors, 2 mammogram staffs and 2 pharmacy staffs. There is 1 mamogram machine allocated in this centre. In order to develop the simulaton model, the data was collected through interviewing the administrators, documents reviewed and direct filed observations. Data regarding the service times for each activities was collected manually obtained through observation and some of the data was obtained from the specialist centre's system. The simulation model incorporates data such as patient arrival times, service durations for each stages, number of available resources and number of patients per day. For scheduled events, such as patient arrivals, a constant interval of 15 minutes was used based on the centre's appointment system. For service times where raw historical data were unavailable, triangular distributions were employed. The parameters for these distributions (minimum, most likely, and maximum values) were determined through interviews and consultations with senior staff nurse and managers to ensure the model accurately reflects real-world operational variations.

SIMULATION MODEL DEVELOPMENT

DES is designed to model systems where events occur at distinct, individual points in time (Zuo et al., 2019). There were several steps required to build a correct DES model. Figure 1 illustrates the process involved in DES modelling.

The first step of the simulation model is start with defining the problem, followed by setting the objectives. Then, a conceptual model and data collection. Conceptual modelling in the context of simulation involves the creation of abstract representation of real-world systems. This process involved understanding the relationships and behaviour of the system in achieving the objectives of the simulation model (Durán, 2020). To ensure the simulation model is reliable to be used for further analysis, the verification and validation processes was conducted using specific benchmarks. The verification was conducted through 2 methods: debugging tests and expert verification. The debugging test is used to ensure the model functioned correctly and to rectify any model logical structural errors. There is "check model" function available in Arena software to check for the errors. Once the model has passed the debugging test, then the expert verification was performed involving the senior manager, assisstant manager and senior staff nurse, which each of them has a clinical experience of more than 8 years. They will closely examined the patient flow, resources allocation, and service times for each activities involved to ensure it is correctly represent the flow.

After the model has been verified, a validation process was conducted. Validation is the process of checking two results to establish their consistency. It involves the comparison of the representation of a conceptual model to the real system. If the comparison shows consistency, then the model is valid otherwise, it is invalid (Kuo et al. 2023). In the validation process, the error percentage method is used to validate the model by compairing the outputs of simulation and outputs of the real system. If the percentage of error between the real system and the simulation model is less than 10% then the model is considered as a valid model and can be used for conducting further analysis (Dias et. al, 2022).

The outputs are measured by the number of patients in and out from the registration process, primary triage process, consulations process and mammogram test process. Equation (1) represents the formula to calculate the error percentage (EP), where OS is the simulation output and OR is the real system output. The results of the validation process will be discussed further in the Results and Discussion section.

$$\%EP = \frac{|OS - OR|}{OR} \times 100\% \tag{1}$$

OPTIMIZATION MODEL DEVELOPMENT

Once the model was completed and validated using the error percentage in Equation (1), the analysis was conducted to identify the bottlenecks of the system (the activities that contributes to the highest TAWT). The model is considered valid if the EP is less than 10% as presented in the next section, Results and Discussion. Based on the identified bottlenecks, the mathematical formulations were developed by utilizes the OptQuest, an optimization feature integrated in Arena software. It is formulated as in Equation (2) to Equation (10), where the objective function is to minimize the TAWT for patients, which is a stochastic output of the simulation model. OptQuest employs a combination of heuritics algorithms (Scatter Search, Tabu Search and Neural Network) to search for the optimal configuration of resources that can improved the objective function with maximum reduction in TAWT. The search is defined by the lower and upper limit of the operational resources provided by the management.

$$Min\ TAWT = f(x_1 + x_2 + x_3 + x_4 + x_5 + x_6 + x_7) \tag{2}$$

Subject to

$$2 \leq x_1 \leq 3 \tag{3}$$

$$2 \leq x_2 \leq 3 \tag{4}$$

$$2 \leq x_3 \leq 3 \tag{5}$$

$$2 \leq x_4 \leq 3 \tag{6}$$

$$2 \leq x_5 \leq 3 \tag{7}$$

$$1 \leq x_6 \leq 2 \tag{8}$$

$$x_7 = 2 \tag{9}$$

$$x_1, x_2, x_3, x_4, x_5, x_6, x_7 \geq 0 \tag{10}$$

Equation (2) of the formulation represents the average total waiting time based on the resources available. While Equation (3) to (8) represents the upper and lower limit for registration staffs, primary triage nurses, blood test nurses, doctors, mammogram staff, mammogram machine, and pharmacy staffs. Meanwhile, Equation (9) represents the constraint of pharmacy staff, where the number of staff is fixed. All lower and upper bound limitations are determined based on the information obtained from the specialist centre. Equation (10) represents the non-negativity constraints. The decision variables for this problem are as follows:

x_1= number of registration staff

x_2= number of primary triage nurses

x_3= number of blood test nurse

x_4= number of doctors

x_5= number of mammogram staff

x_6= number of mammogram machines

x_7= number of pharmacy staff

The optimization model will then suggest several alternative of resource configurations. These suggestions will be inserted separately into the simulation model to evaluate their impact on the TAWT. The configuration with the most reduction of TAWT will be selected as optimal solution and presented to the management of the specialist centre. The percentage improvement (PI) for each suggested alternatives will be calculated using Equation (11), where $TAWT_{SM}$ represents the total waiting time of the simulation model and $TAWT_{OM}$ represents the total waiting time of the optimization model.

$$\%\ PI = \frac{TAWT_{SM} - TAWT_{OM}}{TAWT_{SM}} \times 100\% \tag{11}$$

RESULTS AND DISCUSSION

VALIDATION TEST RESULTS

Table 1 presents the percentage error for the average total number of patients in and out. Meanwhile, Table 2 presents the percentage error of the average waiting time (AWT). The results demonstrate that the percentage error is less than 10%, indicating that the model simulation falls within the acceptable threshold and sufficiently reflects the real operations of the centre and able to be used for further analysis.

SIMULATION RESULTS

The simulation model was run with 12 replications. This number of replications yielded a sufficiently small half-width for the confidence intervals, and the simulation results have reached an acceptable level without requiring additional runs (Kelton et al. 2015; Wan Malissa 2018; Ahmad et al. 2012). Table 3 shows the outputs from the simulation model, regarding the AWT in minutes that patients experienced at each process. Based on the results, the TAWT of the patient was 234.26 minutes, indicating that patient needs to wait for almost 3.9 hours to complete all procedures. Meanwhile, Table 4 illustrates the utilization rate of the resources. According to Zulkifli et al. (2016) , an ideal resource utilization rate should typically range between 70% and 80% to maintain a balance between efficiency and service quality.

Based on the results, the utilization rate for primary triage nurse and doctors are exceeds the acceptable range of 70% to 80% as stated before, exceeding this threshold typically triggers significant queues and delays. Therefore, a modification of resources are required to improve the results.

TABLE 3. The average patient waiting time

Process	AWT (Minutes)
Primary triage	6.00
Consultation	56.53
Blood test	18.54
Mammogram test	143.21
Pharmacy	9.98
TAWT	234.26

TABLE 4. The utilization rate of resources

Resource	Utilization Rate (%)
Registration staff	68.91
Primary triage nurse	89.24
Blood test nurse	66.67
Doctors	93.51
Pharmacy	67.18

BOTTLENECKS IDENTIFICATION

Based on the results from Table 3, the bottlenecks to the system were identified in the mammogram test (143.21 minutes), the consultation (56.53 minutes) and the blood test (18.54 minutes). These are mainly because there is a shortage in number of staff and equipment. The centre has only two doctors, two nurses and two staff working with one mammogram machine. Hence, this leads to delays in providing services and disrupts the flow of patients. To manage these problems, increasing the number of staff and mammogram machine will help patients get seen quickly, reduce wait times and improve overall patient experience.

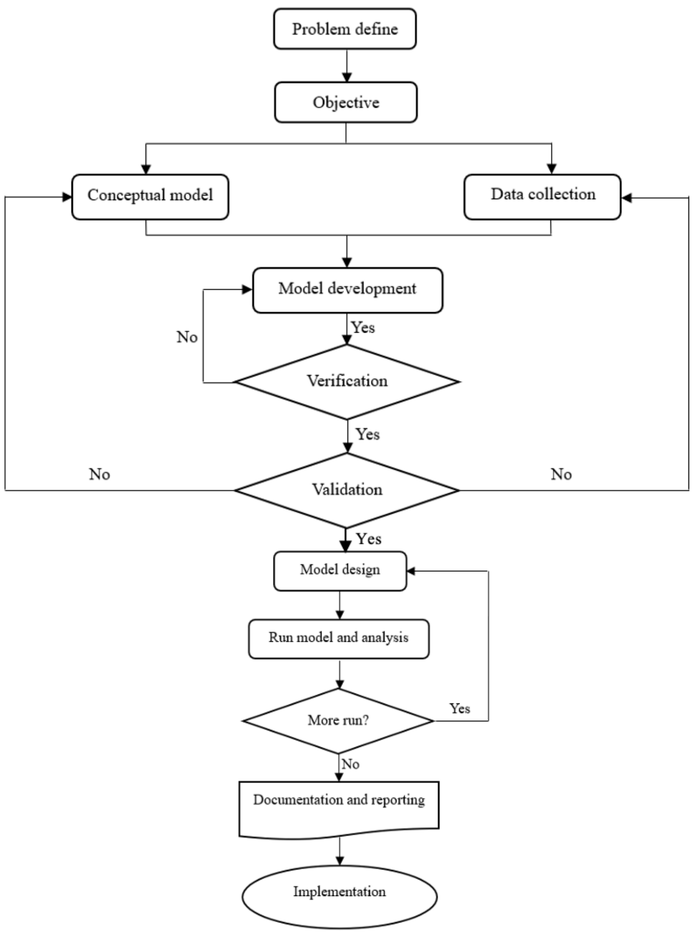

FIGURE 1. Steps in simulation modeling using DES approach

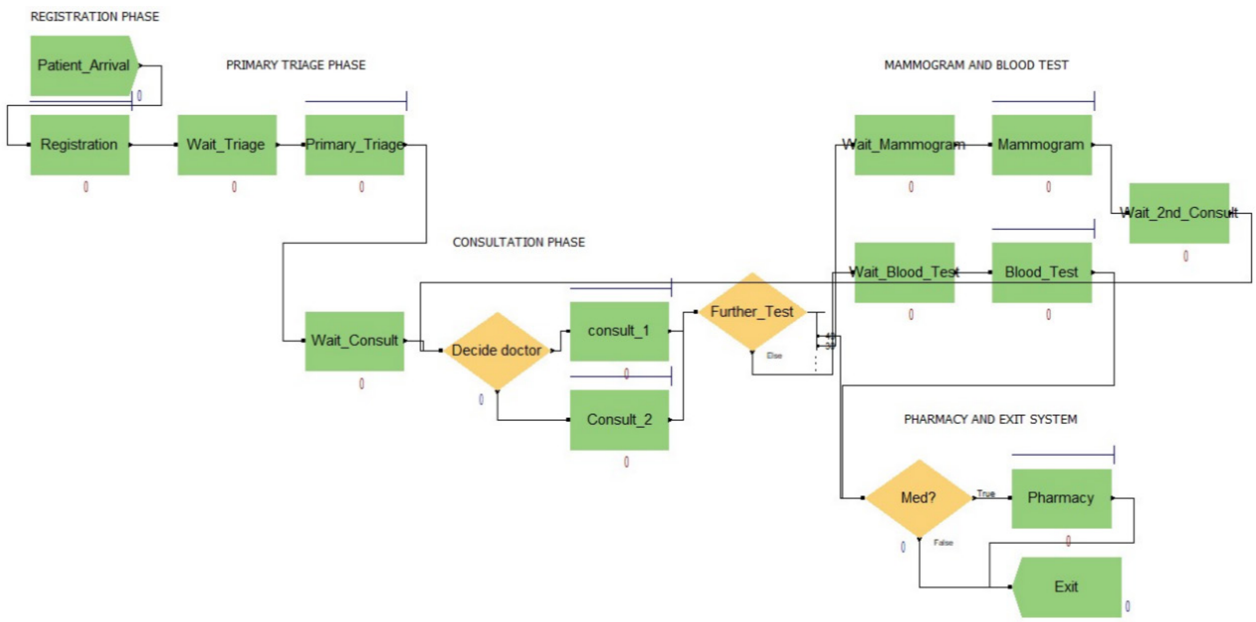

FIGURE 2. Patient's flow at private specialist centre

TABLE 1. Percentage error of the average total patient in and out

Process	Patient In	Patient Out	Actual record	Error (%)
Registration	76	76	76	0.00
Primary triage	76	76	76	0.00
Consultation 1	40	40	39	2.56
Consultation 2	36	36	37	2.70
Mammogram test	29	29	28	3.57

TABLE 2. Percentage error of the average waiting time

Process	Simulation	Actual	Error (%)
Primary triage	6.00	5.83	2.96
Consultation 1	57.28	61.88	7.44
Consultation 2	55.78	53.09	5.07
Blood test	18.54	17.97	3.17
Mammogram test	143.21	137.28	4.32
Pharmacy	9.98	9.45	5.61

OPTIMIZATION RESULTS

The best solution to solve the problem of patient long waiting times at the Breast Care Centre is through optimization method. The optimization model is built using the output of the simulation model. The objective of this optimization method is to minimize the TAWT by considering the limitation in the number of manpower and physical resources that the specialist centre can provide for each activity that contributes to the delayed in service.

The OptQuest was executed based on the mathematical formulation in Equation (2) to (11). There are 16 alternatives of resource configurations suggested by the OptQuest. These recommendations are inserted individually into simulation model to evaluate their TAWT. The solution with the lowest TAWT was selected and presented to the management. Table 5 shows the comparison of resource capacity between simulation model and optimization model.

TABLE 5. Comparison of resource capacity between simulation model and optimization model

Resources	Simulation model	Optimization model
Registration staff	2	2
Primary triage nurse	2	3
Blood test nurse	2	2
Doctors	2	3
Mammogram staff	2	2
Mammogram machine	1	2
Pharmacy staff	2	2
Objective function: 110.71 minutes		

The TAWT of the optimization model was compared to the TAWT of the simulation model to evaluate percentage of improvement using Equation (12). The results show that the improvement in TAWT is 52.74% with significant reduction of TAWT from 234.26 minutes to 110.71 minutes. Table 6 presents the comparison of percentage of improvement between the simulation model and the optimization model for each activity. Figure 3 shows the comparison of AWT for each activity before and after optimization phase with the highest % PI is in mammogram test activity, 61.77% and followed by consultation activity, 60.88%.

As shown in Table 5 and Table 6, minimizing TAWT required adding resources such as primary triage nurses, doctors and mammogram machines while maintaining other resources with low utilization to avoid inefficiency. Table 7 further shows that the resource utilization rates are also improved within the 70% - 80% acceptable range as stated by Zulkifli et al. (2016). The additional triage nurses speed up patient assessments, more doctors reduced consultation delays and extra mammogram machines addressed long waits for tests, significantly improving the overall patient flow, reducing waiting times and the resource utilization rates.

TABLE 7. The utilization rate of resources

Resource	Utilization Rate (%)
Registration staff	70.43
Primary triage nurse	71.79
Blood test nurse	69.78
Doctors	71.55
Pharmacy	69.57

CONCLUSION

This study effectively achieved its major objectives, which included the creation of a DES model of patient flow at the Specialist Centre using Arena simulation software. Through the simulation model, bottlenecks that contribute to the long waiting timea are identified. A mathematical formulation was developed, taking into account the resources limitation to achieve the optimal resource allocation. This has been done by utilizing the simulation-optimization function in Arena software namely, OptQuest. The simulation model was successful representing the current operation of the centre understudy, identifying the major bottlenecks, and highlighting that long waiting times were largely due to inadequate human and physical resources. The results from OptQuest provided actionable recommendations to optimize resource allocation, reduce waiting times and improve system performance (improved utilization rate).

This study recommends that the centre should increase its human resources, particularly in the primary triage process and consultation process. Additionally, physical resources should also be addressed, as the longest waiting times are observed during the mammogram test process. Therefore, the centre should consider adding one mammogram machine. These recommendations will help in reducing the waiting times and enhance overall performance. Although the proposed optimized configuration demonstrates a substantial reduction in patient waiting times, it is important to note that increasing resources such as specialists and medical equipment involves operational expenditures.

Future research should include the associated resource costs, such as salaries for medical staff and maintenance for equipment. It is crucial to ensure that the proposed configuration of resources remains within the operational budgetary and financially viable for the centre to implement. Furthermore, other patient categories, such as walk-ins, emergency cases and outpatients, to better understand the variability and unpredictability in patient flow and improve resource allocation. Additionally, the relationship between the centre activities and external diagnostic services, like CT scans, should be analyzed as inefficiencies in coordinating these services can create bottlenecks. Advanced simulation tools could be utilized to model the entire patient journey, providing a holistic approach to optimizing health operations and enhancing patient satisfaction.

TABLE 6. Comparison of AWT between the simulation model and the optimization model and its percentage improvement

Activities	AWT of Simulation Model (Minutes)	AWT of Optimization Model (Minutes)	Percentage Improvement (%)
Primary triage	6.00	5.98	0.33
Consultation	56.53	22.11	60.88
Blood test	18.54	17.91	3.40
Mammogram test	143.21	54.75	61.77
Pharmacy	9.98	9.95	0.30
TAWT	234.26	110.71	52.74

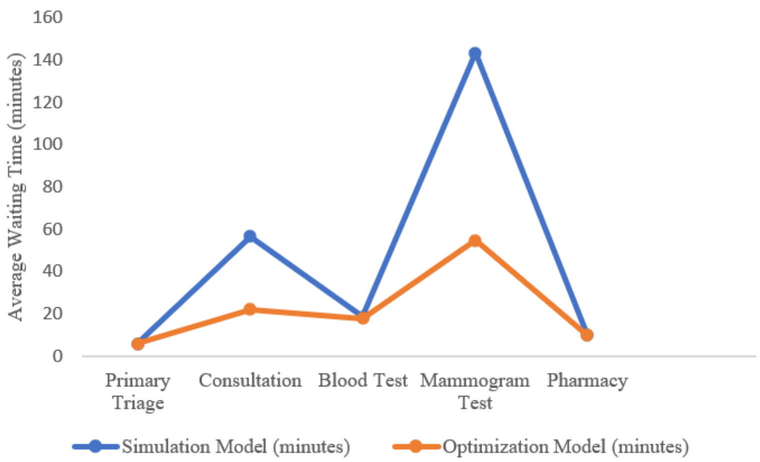

FIGURE 3. Comparison of AWT for each activity before and after optimization process

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DECLARATION OF COMPETING INTEREST

None.

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