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SIM-PFED: A Simulation-Based Decision Making Model of Patient Flow for Improving Patient Throughput Time in Emergency Department

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ABSTRACT Healthcare sectors face multiple threats, and the hospital emergency department (ED) is one of the most crucial hospital areas. ED plays a key role in promoting hospitals' goals of enhancing service efficiency. ED is a complex system due to the stochastic behavior of patient arrivals, the unpredictability of the care required by patients, and the department's complex nature. Simulations are effective tools for analyzing and optimizing complex ED operations. Although existing ED simulation models have substantially improved ED performance in terms of ensuring patient satisfaction and effective treatment services, many deficiencies continue to exist in addressing the key challenge in ED, namely, long patient throughput time. The patient throughput time issue is affected by causative factors, such as waiting time, length of stay, and decision-making. This research aims to develop a new simulation model of patient flow for ED (SIM-PFED) to address the reported key challenge of the patient throughput time. SIM-PFED introduces a new process for patient flow in ED on the basis of the newly proposed operational patient flow by combining discrete event simulation and agent-based simulation and applying a multi-attribute decision-making method, namely, the technique for order preference by similarity to the ideal solution. Experiments were performed on three actual hospital ED datasets to assess the effectiveness of SIM-PFED. Experimental results revealed the superiority of SIM-PFED over other alternative models in reducing patient throughput time in ED by consuming less patient waiting time and having a shorter length of stay. The findings also demonstrated the effectiveness of SIM-PFED in helping ED decision-makers select the best scenarios to be implemented in ED for ensuring minimal throughput time while being cost effective.

INDEX TERMS Emergency department, patient flow, simulation modelling, throughput time, decision making.

I. INTRODUCTION

The healthcare sector of every country has a sensitive setting and plays an important role in national politics [4]. Any deviation from the optimal health service places additional pressure on healthcare professionals [5]. The emergency department (ED) plays a central role in the furtherance of the objectives of a hospital to improve the quality of hospital services [6]. ED provides health services 24 hours a day for seven days a week to injured and sick patients, and medical tests are conducted in ED until the health conditions

of patients stabilize [7]. Notably, the function of ED is to treat patients in a critical or life-threatening situation and not to deal with patients that present low-acuity injuries or illnesses [8]. Thus, ED is the most challenging element of the healthcare system [9]. Patients expect well-organized services from a customer perspective. ED managers encounter difficulties in controlling problems related to process flow (patients and information), and these difficulties result in long patient time in ED [10]. Simulation models are effective tools for process modeling and improving healthcare processes and complex systems, such as ED [11], [12]. Simulation models are thus suitable for addressing problems in ED, where resources are scarce and patients arrive at irregular times [11].

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Several ED simulations models have been proposed to continuously improve ED services, maximize ED resources, and eventually ensure patient satisfaction and provide effective treatment services [9], [13], [14]. However, only a few ED models examine the operational patient flow process in ED with respect to reducing patient throughput time [15], [16]. These models include integrated safety simulation [1], agent-based simulation (ABS) [2], and interactive simulation-based decision support framework [3]. Patient throughput time is the total amount of time spent to serve a patient (from the patient's time of arrival to the time of exit from ED). The issue of patient throughput time relates to the long patient throughput time in ED. Patient throughput time is essential in obtaining patient satisfaction; providing quality treatment while reducing the throughput time of patients enhances ED performance in terms of achieving patient satisfaction and providing effective treatment services [1], [17]–[20].

Throughput time is also one of the essential aspects that exert significant effects on ED operations (e.g., patient flow) [21], [22]. Although the usefulness of existing models that were developed to address the patient throughput time issue has been established, a close examination reveals that these models cannot sufficiently address the issue of patient throughput time. The issue of patient throughput time is affected by several causative factors, including waiting time, length of stay (LoS), and decision-making [9], [22], but existing models have failed to sufficiently handle these causative factors [9] because these models do not sufficiently consider all causative factors that affect the issue of throughput time in ED [18]. Thus, patient throughput time must be improved by minimizing patients' waiting time and LoS and considering decision-making factors [23].

Waiting time refers to the total time that a patient waited before being served in ED; overcrowding in ED increases patient waiting time [24], [25]. LoS is related to the total time that a patient spent in ED, and it starts from the time when the patient entered ED (arrival time) to the time the patient physically left ED (departure time) [1]. The relationship of patient waiting time and LoS with patient throughput time is directly incremental. An increase in patient waiting time and LoS leads to an increase in patient throughput time in ED, which induces the issue of throughput time [26]. Management decision-making in any domain is challenging. However, decision-making in EDs is particularly sensitive because of its impact on the quality of care given, the risk of mortality, and the number of patients that leave ED without being treated [8]. The decision-making factor is related to the process and decisions implemented by ED top management to ensure high-efficiency ED services in terms of patient throughput time and cost [27]. However, despite the crucial impact of the decision-making factor on the issue of patient throughput time in ED, existing models do not sufficiently consider the decision-making factor in relation to patient throughput time and cost [21]. The decisions made by the top management are related to certain key aspects that are

associated with redesigning the operational flow of ED and hiring staff (i.e., number of nurses and doctors) [8]. Making incorrect or improper decisions on the reported key aspects negatively affects patient throughput time [28]. For instance, decision-making on hiring or implementing an ineffective operational patient flow with a small number of ED staff can increase the throughput time of patients due to the inability to treat patients within a short time [18]. Meanwhile, cost refers to the budget cost of the LoS of patients in ED, and it can be measured based on the treatments given to patients; it reflects the cost of implementing the scenarios of patient flow and is related to increasing the capacity of physicians, nurses, staff, and equipment [2], [3], [29], [7]. Making incorrect or improper decisions regarding the operation flow that patients should take during their stay in ED adversely affects the total budget cost by increasing the treatment cost [2].

To address the issue of patient throughput time in ED and the decision-making factor for enhancing ED performance in terms of reducing patient throughput time while being cost effective, this research aims to develop a new simulation of patient flow for ED model called SIM-PFED. The model aims to reduce patient throughput time in ED by examining the reported causative factors of the throughput time issue. The contribution of this work can be summarized as follows:

- Newly proposed operational patient flow. The proposed operational patient flow incorporates a new low-level description of the operational patient flow in ED. This new operational flow varies from conventional models in terms of the use of ED triage and acuity scale, which are used to define the emergency severity index (ESI). It also differs in the way it deals with the specified ESI patient for improving patient throughput time in ED.
- A new simulation-based decision-making model for patient flow called 'SIM-PFED' is proposed. The proposed model provides a new process for patient flow in ED based on the newly proposed operational patient flow. It combines discrete event simulation DES and ABS, thereby applying a multi-attribute decision-making (MADM) technique. This is known as the technique for order preference by similarity to the ideal solution (TOPSIS). The DES is a popular and frequently used technique by researchers to model patient emergency waiting time. In contrast, ABS is one of the most convenient techniques for simulating agent behavior. Hence, the integration of ABS and DES models is the newest and most powerful approach that has been introduced [15]. Additionally, the proposed model uses TOPSIS to select the best scenarios for reducing throughput time in ED.
- The empirical assessment of the proposed SIM-PFED in terms of reducing patient throughput time is based on actual ED datasets from four hospitals, namely, Shahid Rajaei Hospital (SRH) [1], Santa Casa de São Paulo Hospital [2], hospital in North Dublin, Ireland [3], Urgent Care Center(UCC) [20]. These datasets are

considered to be under the context of the proposed model (simulation of patient flow in ED).

The rest of this paper is structured into six main sections, as follows. Section II illustrates the related works. Section III discusses the proposed SIM-PFED model in detail with respect to its proposed steps. Section IV elaborates on the evaluation of the proposed SIM-PFED model. Section V discusses the results evaluation and performance analysis of the proposed SIM-PFED model. Section VI discusses the basis for the suggested SIM-PFED and the experiments trends detected during the comparison and experimental analysis, and Section VI concludes this study with discussing the future sets.

II. RELATED WORK

The healthcare sector of every country has a sensitive setting and plays an important role in national politics. Any deviation from the optimal health service places additional pressure on healthcare professionals [9]. The main concern regarding healthcare services is the issue of overcrowding in ED, which has been thoroughly studied [30], [31]. In developed nations, overcrowding demands urgent attention as rapidly aging societies intensify the use of ED [32], [33], which exerts a significant effect on patient safety and could reduce the chances of survival of critical patients in certain situations due to the long waiting time and LoS. Long waiting time and LoS lead to long patient throughput time. Consequently, long patient throughput time negatively affects the entire national healthcare system and its potential to provide minimum service in any country [31], [34]. Urgent care centers have been identified as one of the remedies for reducing the impact of long patient throughput time in hospital ED. Patient throughput time in ED is associated with increased LoS, waiting time, and cost and incorrect or improper decision-making for patients in ED. Patient dissatisfaction often increases with increased patient throughput time, which is considered a serious issue in ED [7].

Simulation modeling in the healthcare context covers ED healthcare management. Although ED simulation models have been extensively developed for various contexts, only a few studies have concentrated on operational patient flow with respect to patient throughput time in ED [35]–[37]. Abo-Hamad and Arisha [3] proposed a DES model to improve patient flow in ED [9], [18]. They found that unblocking ED outflows through in-patient bed management is more effective than simply increasing the physical capacity or workforce of ED. However, this model encounters a major challenge related to the increase in patients' waiting time, does not use new decision-support tools, and focuses on ED operation and cost.

Yousefi and Ferreira [2] proposed an ABS model to improve the performance of ED. The total waiting time and number of patients decreased by 12.7% and 14.4%, respectively. The limitation of this model is that it insufficiently addresses patient throughput time in terms of decision-making and cost factors. Fitzgerald, *et al.* [23]

proposed an integrated DES and queueing theory model to support decision-making for a fast-tracked ED process. The proposed model informs hospital decision-makers about the effect of fast tracking or similar program implementation on patient waiting times and acuity-based demand for nursing services. Despite the effectiveness of this model in supporting decision-making for ED fast tracking, the model does not consider the decision-making in terms of patient throughput time and cost, leading to the issue of long patient throughput time in ED [38]. Sbayou, *et al.* [39] proposed the integration of business process model and notation (BPMN) and ABM to manage resources in ED and deliver high-quality services for addressing the congestion problem and long waiting time. The evaluation results of the model revealed its effectiveness; the model reduces the cost of ED and waiting time by 5%. However, the model does not efficiently address patient throughput time in terms of LoS and staff satisfaction to increase ED performance [40].

Huang *et al.* [28] proposed a recent model in which chart review is used to measure LoS for trauma patients in ED. The results of the model revealed the efficiency of the model with respect to supporting direct communication with trauma service by the ED provider and reservation of two temporary beds, resulting in reduced LoS for trauma patients [40]. However, this model does not consider the patient in different acuity case scales and does not address the decision-making factor, resulting in the inability to reduce waiting time and increased patient throughput time in ED [41]. Hajjarsaraei *et al.* [1] proposed a DES model integrated with system dynamics (ISS) to reduce patient waiting time, LoS, and number of patients who leave without being seen (LWBS). The ISS model assesses the optimization of the fast track strategy [42] and the impact of sensitive policy parameters on the safety performance of ED. Similarly, Yousefi *et al.* [22] proposed an ABM to simulate the LWBS behavior of patients in a public hospital ED. The design of the ABM model included increasing the number of triage nurses, fast-tracked treatment, increasing the waiting room capacity, and reducing the treatment time. The ABM model succeeded in reducing the rate of LWBS by applying fast-track treatment. Despite the usefulness of ISS and ABM models, these models do not efficiently address patient throughput time [1]. The ISS model does not examine the effect of decision-making factors on LoS, waiting time, number of deaths, number of wrongly discharged patients, and total number of discharged patients [1]. Meanwhile, the ABM model does not consider the decision-making of the patient in terms of throughput time and the cost factor in ED [1].

On the basis of the limitations of existing models, the current work presents a new model called SIM-PFED that can reduce patient throughput time by addressing the causative factors of the throughput time issue with respect to waiting time, LoS, and decision-making. SIM-PFED can identify the scenario that has the least patient throughput time from all scenarios to be implemented in ED. The following section

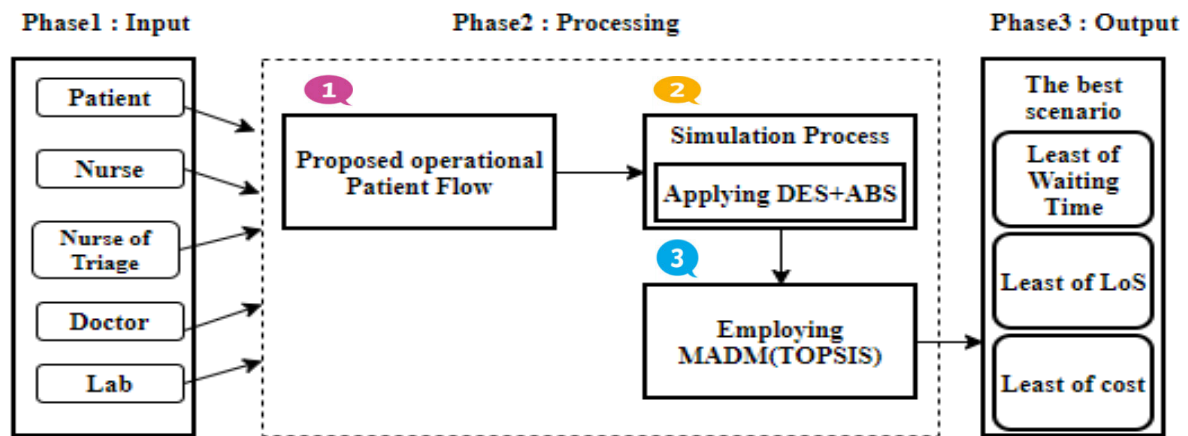


FIGURE 1. Process of the proposed SIM-PFED model.

provides a detailed explanation of the proposed model and its performance.

III. PROPOSED SIM-PFED MODEL

Figure 1 presents the process of the proposed SIM-PFED model. The SIM-PFED process comprises three main phases, namely, input, processing, and output. Unlike the ED simulation models, our proposed model introduces certain number of contributions in the processing phase. These contributions can be summarized as follow:

- We present a newly proposed operational patient flow. The proposed operational patient flow incorporates a new low-level description of the individual operational flow in ED. The significant difference between our model and conventional model is that our model utilizes ED triage and acuity level to define the emergency severity index (ESI). Likewise, this model differs in the way it copes with the specified ESI patient to enhance patient throughput time in ED.
- Simulation Process: Unlike most of the existing models, we adopt the combination of ABS and DES techniques for simulating the newly proposed operational patient flow. The ABS technique is utilized with the aim of simulating the behavior of agents. Meanwhile, the DES is used in the proposed SIM-PFED to simulate the process of the proposed operational patient flow. This is because DES is considered as a common technique to simulate the sequential process of components.
- Considering decision-making factor on the issue of patient throughput time in ED: we have employed the TOPSIS technique to address the decision-making factor of patient throughput time. Specifically, it will help to specify the best scenario to be implemented in ED to ensure minimal throughput time at a reduced cost. The application of the TOPSIS is conducted based on the simulation results. These simulation results include the average patient waiting time, cost, and the

LoS for each scenario implemented using our newly proposed operational patient flow.

A detailed description of each phase of our proposed model is presented in the following subsections.

A. INPUT PHASE

This phase aims to provide a precise explanation of the associated agents and their input details that are needed to implement SIM-PFED. We include the standard agents to be involved in the ED operational Patient Flow of ED department. These agents are nurse, doctor, and laboratory (referred to as “lab” hereafter) [43]. The input details of the patient should include personal information (ID, name, age, and phone number), arrival type, arrival time, waiting time, LoS, service time, and cost. Table 1 presents the agents involved in SIM-PFED and their input details. The input details of nurses include ID, section name of the department, and years of experience. The total number of hired nurses in ED should also be specified. For doctors, ID, the total number of doctors, and the section name of the department should be specified. Patient samples should be collected with regard to the lab agent, and the number of beds should be determined for the bed agent. A detailed explanation of processing these input data is presented in the following section.

B. PROCESSING PHASE

The collected data in the input phase are used as an input to implement the processing phase. The implementation flow of the processing phase is executed based on three steps: proposed operational flow, simulation process, and MADM method. The following subsection presents the implementation details of each step.

1) PROPOSED OPERATIONAL PATIENT FLOW

The operational flow refers to the procedure flow that a patient should follow starting from his/her the arrival to

TABLE 1. Input details.

Agent	Input data	Description
Patient	Personal information	Refers to the information of the patient with respect to patient ID, name, age, and phone number
	Arrival type	Refers to the type of patient arrival (i.e., walk-in or ambulance arrival)
	Arrival time	Refers to the time of patient arrival in ED
	Waiting time	Refers to the total waiting time of the patient in the case of not being served
	Service time	Refers to the total waiting time of the patient in the case of being served
	LoS	Refers to the total time of the patient's stay in ED starting from arrival to departure from ED; LoS is the summation of the waiting time and service time of the patient
	Cost	Refers to the total cost to be paid by the patient; it includes the budget cost of LoS for the patient in ED, which can be measured based on the treatments provided for the patient, and the cost of implementing the scenarios of patient flow
Nurse	ID-nurse	Refers to nurse ID
	Total number	Refers to the total number of nurses in ED
	Section name of the department	Refers to the name of the section where the nurse works in ED
	Years of experience	Refers to the number of years of experience
Doctor	ID-doctor	Refers to doctor ID
	Total number	Refers to the total number of doctors in ED
	Section name of the department	Refers to the name of the section where the doctor works in ED
Lab	Patient samples	Refers to samples taken from the patient to be tested
	Result	Refers to the result of testing a sample from the patient

TABLE 2. Emergency severity index that depends on patient status description.

Emergency Severity Index	Purpose	Description
ESI 1	Revival	Patient who needs critical urgency
ESI 2	Emergent	Patient who needs high urgency
ESI 3	Urgent	Patient who needs urgency
ESI 4	Less Urgent	Patient who needs less urgent attention
ESI 5	Not urgent	Patient who does not need urgent attention

his/her departure from ED. Figure 2 shows the proposed operational patient flow in ED of the SIM-PFED model. The proposed operational patient flow introduces a new low-level detail of operational patient flow in ED that is different from the flow in existing models with respect to the use of emergency department triage and acuity scale for identifying the emergency severity index (ESI) and the manner of dealing with the specified ESI patient. The proposed operational patient flow is discussed in terms of the order of patient arrival in ED as follows: register, triage, and diagnose. With regard to patient arrival, a patient can arrive in ED through two possible arrival types: walk-in or ambulance arrival. In the case of walk-in arrival, patients need to register at the ED registration desk upon arrival, and the registration staff collects the required personal information (patient ID, name, age, and phone number).

Then, the patients are directed to the triage room, where an ESI is assigned to each patient accurately. Unlike most of the existing models, in the SIM-PFED model, the worldwide Canadian emergency department triage and acuity scale (Table 2) is used in the identification of patient ESI; it replaces

the Manchester triage system used in most existing ED models. The worldwide Canadian emergency department triage and acuity scale is considered the standard ESI to be followed in ED. This scale consists of five levels, with 1 being the most critical and 5 being the least critical. When the arrival type of a patient is via ambulance arrival, the process of registration and triage have to be completed in the ambulance car. The triage process determines the order and priority under which patients must be treated.

Figure 3 depicts the pseudocode of the triage process of the proposed operational patient flow in ED. The triage result allows to transfer the patient for the specific area of treatment by using the object of select output in the simulation model. Registration and triage services are implemented on a first-come-first-served basis for all patients, and diagnosis and treatment are implemented according to the ESI scale. Unlike existing models that require patients of all ESI (including patients under critical urgent status) to be located in the waiting room after finishing triage service, in the proposed SIM-PFED model, the patient is not required to wait. The patient is served immediately according to the

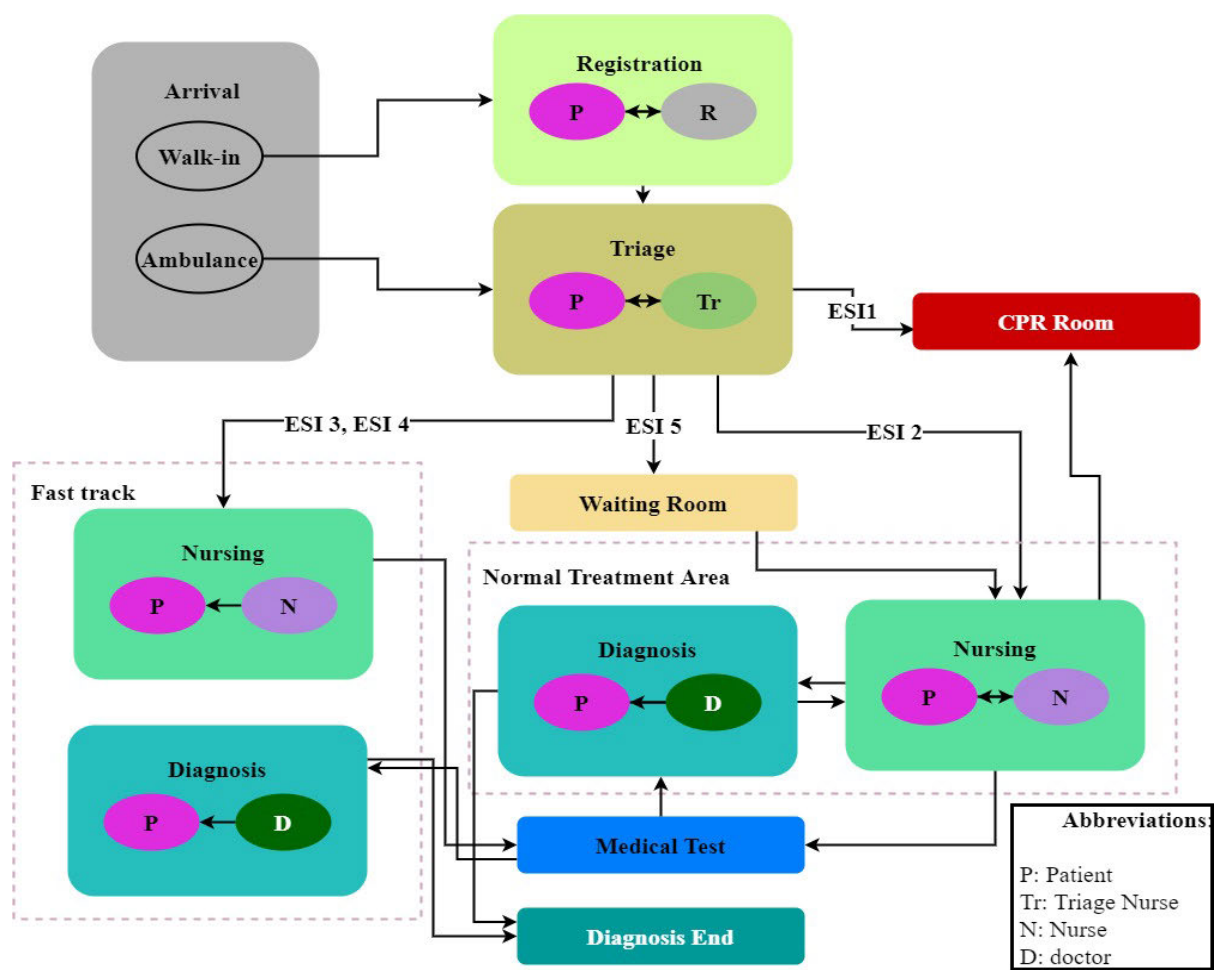


FIGURE 2. Proposed operational patient flow of the SIM-PFED model.

Triage Process Pseudo Code of the Newly Proposed Operational Patient Flow	
Input: Patient's ESI	
Output: Patient Flow in ED	
Starts	
1	Do
2	If Patient's ESI = ESI 1
3	Go-to-CPR room
4	Else If Patient's ESI = ESI 2
5	Go-to-normal treatment area
6	Else If (Patient's ESI = ESI 3 Patient's ESI = ESI 4)
7	Go- to-fast track
8	Else If Patient's ESI = ESI 5
9	Go-to-waiting room
10	While (no patient exists in the triage room).
11	End

FIGURE 3. Triage process pseudo code of the proposed operational patient flow.

obtained patient ESI. A patient with ESI = 1 has a critically urgent status; thus, the patient is directly transferred to the Cardiopulmonary Resuscitation (CRP) room to be checked by the doctors of the CRP department. Meanwhile, a patient

with ESI = 2 is categorized as having a highly urgent status; hence, the patient is led directly to the normal treatment area. Patients with ESI = 3 and 4 are assigned with the status of urgent and less urgent, respectively; they are directed to the

fast-track treatment area, where they are served immediately by a doctor and nurse without spending much time in the waiting room. Meanwhile, a patient with $ESI = 5$ is assigned with a not urgent status. Unlike in existing models, the patient with $ESI = 5$ is not sent to a polyclinic that is not under the ED department. The patient is located in the waiting room for obtaining treatment in the ED department to ensure that the patient will be served with less time consumption compared with the situation in the polyclinic, where the patient's time is wasted due to the long busy scheduling. Occasionally, the doctor transfers the patient to the lab for a medical test to complete a diagnosis. Therefore, the treatment and diagnosis of patients involve four cases

2) SIMULATION PROCESS

The proposed operational patient flow is simulated in this phase. Unlike in existing models, the simulation of SIM-PFED's operational patient flow is conducted using ABS and DES techniques in the Anylogic platform. The ABS technique is used to simulate the behavior of agents because ABS is the only available simulation model that can simulate agents' behavior, as discussed in [44], [45]. Meanwhile, DES is a common technique that can simulate the sequential process of components [46]. Thus, DES is employed in the proposed SIM-PFED to simulate the process of the proposed operational patient flow.

The combination of the two techniques is executed in Anylogic simulation software, which have capability combination of simulation techniques (DES and ABS) [43], [47], [48]. Compared with other simulation platforms, such as Netlog, Anylogic provides a user-friendly integrated-development environment with an efficient simulation engine that allows modelers to create and simulate high-validity models of complex systems in a straightforward manner [44], [46], [49]. Anylogic modeling is also the most accurate procedure to determine the probability of a difficult behavior; rather than relying on total randomization, it considers historical data and current behavior types to produce a single outcome for understanding the process thoroughly [15], [50].

Additionally, Figure 4 presents the ABS simulation design of patient flow in Anylogic. The simulated ABS and DES designs are based on the proposed operational patient flow to reflect the defined steps of the proposed operational patient flow, as described in Section III, B.1. The rate of patient arrival by walk-in is set to 0.14 per minute, and the rate of patient arrival by ambulance is set to 0.05 per minute, in line with prior studies [51]. A detailed explanation of the simulation model documentation is presented in Appendix A.

The output of the simulation process of the proposed operation flow specifies the waiting time, LoS, and cost for each simulation scenario that will be defined in the experimental studies.

TOPSIS is adopted in the next step of the process phase to assist in decision-making and in specifying and selecting the best scenario in terms of reducing patient throughput time and cost.

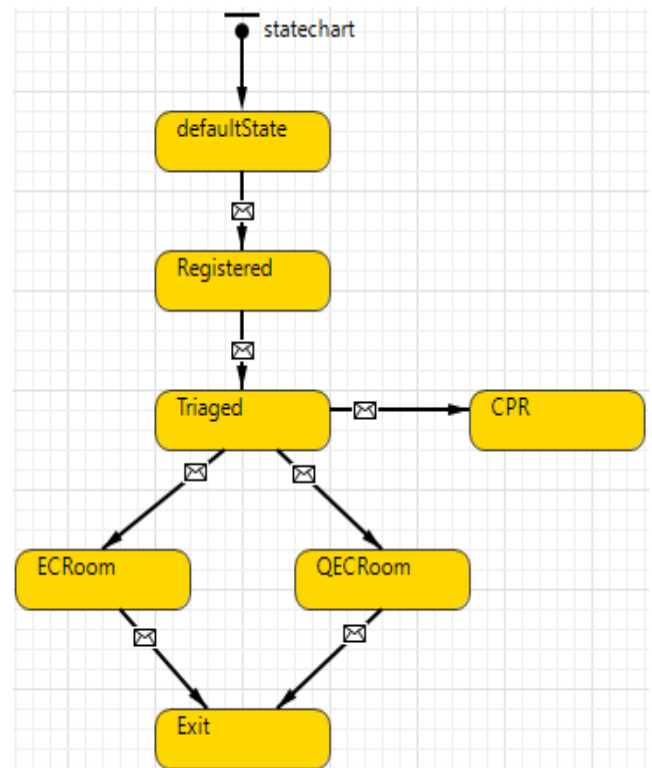


FIGURE 4. ABS simulation design of patient flow of the SIM-PFED model in Anylogic.

3) EMPLOYING THE MADM METHOD: TOPSIS

One of the prevalent MADM methods that [52], [53] proposed is TOPSIS. It emphasizes that the most suitable preference must be closer to the perfect resolution and at the same time must be very far from the so called negative ideal solution [54], [55]. The ranking of all the scenarios is done, leaving the most appropriate of the scenarios which is then placed at the top of the arranged list. A very relevant technique that can be used to rank and select alternatives that are determined externally with reference to specific features is TOPSIS [56]–[60].

The presentation of TOPSIS was initially done by Yoon and Hwang [52]. Simplicity and promptness are its features. The most appropriate substitutions are displayed within a very brief period through a simplified computational process when likened to other methods, such as the analytic hierarchy process (AHP). It has a simplified output which is not difficult to understand. The implementation of TOPSIS is done in a number of steps that do not change irrespective of the different size and quantity of attributes [56], [61]. Its level of performance is almost like that of simple additive weighting and it is more enhanced than AHP [62].

The simplicity of TOPSIS necessitates inputs that are seriously regulated by decision-makers, thereby making the output to be easily understood [62], [63]. For this reason, TOPSIS is employed for the specification of efficient scenarios created in the process of the simulation phase so as to categorize them. The evaluation of the different scenarios was

TABLE 3. Decision matrix V.

Scenarios	Attributes				
	at_1	at_2	at_i	at_{n-1}	at_n
	W_i	W_i	W_i	W_i	W_i
s_1	v_{11}	v_{12}	v_{1i}	v_{1n-1}	v_{1n}
s_2	v_{21}	v_{22}	v_{2i}	v_{2n-1}	v_{2n}
\vdots	\vdots	\vdots	\vdots	\vdots	\vdots
s_j	v_{j1}	v_{j2}	v_{ji}	v_{jn-1}	v_{jn}
\vdots	\vdots	\vdots	\vdots	\vdots	\vdots
s_{m-1}	v_{m-11}	v_{m-12}	v_{m-1i}	v_{m-1n-1}	v_{m-1n}
s_m	v_{m1}	v_{m2}	v_{mi}	v_{mn-1}	v_{mn}

done by considering the waiting time, LoS, and cost features. The exact reason for adopting TOPSIS is to identify and categorize the topmost scenario having the smallest waiting time, LoS, and cost. It is believed that the most suitable preference of TOPSIS must be closer to the perfect resolution and at the same time must be very far from the so called negative ideal solution [64]. The TOPSIS technique is performed using the standard seven steps, which we have implemented as follows:

Step 1: Construct the Decision matrix V

TOPSIS make a conversion of the problem into a decision matrix V with m scenarios (rows) and n attributes (columns). Table 3 depicts the constructed decision matrix V , the information of which is explained as follows

- S is a set that represents the scenarios where $S = \{S_j | j = 1, \dots, m\}$ where m is the total number of scenarios.
 - at is a set that represents the attributes (waiting time, LoS, and cost) where $at = \{at_i | i = 1, \dots, n\}$, where n denotes the number of attributes.
 - V is a set of values where $V = \{v_{ji} | j = 1, \dots, m; i = 1, \dots, n\}$, where v_{ji} is the value of the j^{th} scenario with respect to the i^{th} attribute.
 - W represents a set of weights where $W = \{W_i | i = 1, \dots, n\}$, where W_i is the weight of the i^{th} attribute.
- Decision matrix V that contains m scenarios combined with n attributes is shown in Table 3.

Step 2: Construct the normalized decision matrix

The decision matrix is then formed by normalizing the achieved decision matrix from Step 1. This task is conducted to transform the several attribute proportions into non-dimensional attributes to enable for a comparison across the given attributes.

The normalized normalization which involves the division of the values by the summed square root of each squared scenario in a column is a way of carrying out normalization. Thus, the value u_{ji} of normalized decision matrix U can be computed using Equation 1.

$$u_{ji} = \frac{v_{ji}}{\sqrt{\sum_{j=1}^m v_{ji}^2}}, j = 1, \dots, m \dots \text{and}, i = 1, \dots, n \quad (1)$$

where,

u_{ji} is the normalized score of the scenario; and

v_{ji} is the value of the j^{th} scenario relating to the i^{th} attribute, as explained in preceding decision matrix in Table 4.

The results of the application of the method of distributive normalization Equation on matrix V is presented matrix U , which is shown in Table 4.

Step 3: Construct the weighted normalized decision matrix

The weighted normalized decision matrix Z achieved by the application of Equation 2 is shown in Table 5. The weight values of the waiting time, LoS, and cost were set to 0.35, 0.3, and 0.1, respectively, in line with prior studies [7].

$$z_{ii} = u_{ii}^* w_i \quad (2)$$

where,

z_{ii} is the obtained weighted normalized score of the scenario;

u_{ii} is the normalized score of the scenario obtained from Step 1; and

w_i is the weight of the specified SIM-PFED attributes.

Step 4: Determine the positive and negative ideal solutions

The positive and negative scores of the scenarios are measured based on each attribute of normalized decision matrix Z . In this work, all SIM-PFED attributes (waiting time, LoS, and cost) are negative attributes. Thus, positive-ideal solutions (A^*) is a compound of the minimum weighted normalized values of any scenario for each SIM-PFED attribute. While, negative-ideal solutions (A') is a compound of the maximum weighted normalized values of any scenario for each SIM-PFED attribute. The positive and negative ideal solutions can be defined as follows:

Positive-ideal solution:

$$A^* = \{z_1^*, z_2^*, \dots, z_n^*\}, \text{ where } z^* = \{(\min_i (z_{ii}) \text{ if } i \in I1)\}$$

Negative-ideal solution:

$$A' = \{z_1', z_2', \dots, z_n'\}, \text{ where } z' = \{(\max_i (z_{ii}) \text{ if } i \in I2)\}$$

where,

A^* is set of the positive-ideal solutions;

A' is set of the negative-ideal solutions;

TABLE 4. Normalized decision matrix U.

Scenarios	Attributes				
	at_1	at_2	at_i	at_{n-1}	at_n
	Wl	Wl	Wl	Wl	Wl
s_1	u_{11}	u_{12}	u_{1i}	$u_{1(n-1)}$	u_{1n}
s_2	u_{21}	u_{22}	u_{2i}	$u_{2(n-1)}$	u_{2n}
\vdots	\vdots	\vdots	\vdots	\vdots	\vdots
s_j	u_{j1}	u_{j2}	u_{ji}	$u_{j(n-1)}$	u_{jn}
\vdots	\vdots	\vdots	\vdots	\vdots	\vdots
s_{m-1}	$u_{(m-1)1}$	$u_{(m-1)2}$	$u_{(m-1)i}$	$u_{(m-1)(n-1)}$	$u_{(n-1)n}$
s_m	u_{m1}	u_{m2}	u_{mi}	$u_{m(n-1)}$	u_{mn}

TABLE 5. Weighted normalized decision matrix Z.

Scenarios	Attributes				
	at_1	at_2	at_i	at_{n-1}	at_n
	Wl	Wl	Wl	Wl	Wl
s_1	z_{11}	z_{12}	z_{1i}	$z_{1(n-1)}$	z_{1n}
s_2	z_{21}	z_{22}	z_{2i}	$z_{2(n-1)}$	z_{2n}
\vdots	\vdots	\vdots	\vdots	\vdots	\vdots
s_j	z_{j1}	z_{j2}	z_{ji}	$z_{j(n-1)}$	z_{jn}
\vdots	\vdots	\vdots	\vdots	\vdots	\vdots
s_{m-1}	$z_{(m-1)1}$	$z_{(m-1)2}$	$z_{(m-1)i}$	$z_{(m-1)(n-1)}$	$z_{(n-1)n}$
s_m	z_{m1}	z_{m2}	z_{mi}	$z_{m(n-1)}$	z_{mn}

L_1 represents a set of positive attributes (the more, the better); and

L_2 represents a set of negative attributes (the fewer, the better).

Step 5: Calculate the separation measure

The distance of each option (scenario) to the ideal and negative-ideal solutions for all scenarios can be computed using Euclidean distance measurement. The distance of each scenario from the ideal solution can be computed with Equation 3. Similarly, the distance of each scenario from the negative-ideal one is given by Equation 4.

$$Y_j^* = \left[\sum_{i=1}^n (z_{ij} - z_j^*)^2 \right]^{1/2}, j = 1, \dots, m \quad (3)$$

$$Y_j' = \left[\sum_{i=1}^n (z_{ji} - z_j')^2 \right]^{1/2}, j = 1, \dots, m \quad (4)$$

where,

Y^* and Y' represent the distance of each scenario from the ideal solution and negative-ideal, respectively.

Step 6: Calculate the relative closeness to the ideal solution

For each scenario, the degree of closeness with respect to ideal solution A^* can be calculated with Equation 5.

$$At_j^* = \frac{Y_j'}{(Y_j^* + Y_j')} \quad 0 < At_j^* < 1, \quad j = 1, 2, \dots, m \quad (5)$$

where,

At_j^* is the relative closeness value (SEV) of the j^{th} scenario, which is between 0 and 1.

The relative closeness value (At_j^*) is a number between 0 and 1, with 0 being the worst possible scenario and 1 being the best scenario. Relative closeness is related to the efficiency value of implementing the scenario (SEV) in ED for securing improved performance in terms of cost and patient throughput time.

Step 7: Rank the scenarios

The set of scenarios is ranked according to the descending order of their obtained (SEV_j). The highest SEV value refers the scenario with the highest efficiency (the best one) to be implemented in ED, and it can help the top management of the hospital improve ED operations and throughput time performance.

TABLE 6. Overview of the experimentation's design.

Goal	Analysing the models for operational patient flow process in ED: SIM-PFED, Safety Simulation Model [1], ABS Model [2], Interactive Simulation-based Decision Support (IS-BDSF) [3] and Urgent Care Center(UCC) [20] with the aim of assessing the waiting time and LoS results.
Independent variables	SIM-PFED and existing ED simulation models: Safety Simulation Model, ABS Model, (IS-BDSF) and SEDO-UCC.
Context	Four real benchmark datasets: <ul style="list-style-type: none"> • Shahid Rajaei Hospital (SRH-ED): including 7 scenarios for ED; • Acute Physiology Chronic Health Evaluation II (APACHE II) dataset: including 6 ED scenarios. • North Dublin, Ireland emergency department (NDI-ED) dataset: including 6 ED scenarios; and • Simulation ED Overcrowding-Urgent Care Center (SEDO-UCC) dataset: including 3 ED scenarios
Dependent variables	Patient Throughput in terms of the Waiting time and LoS.

IV. EXPERIMENTAL STUDIES

Accurate explanation regarding the experiments' definition and design with reference to the guidelines on reporting and documentation of experiments that [65] proposed is done in this section. The summary of experimental design and the major elements in the experiments is shown in Table 6. The major elements are discussed as follows:

A. EXPERIMENT DEFINITION

The intention of the experiments was to evaluate how effective SIM-PFED is in comparison with other models such as Safety Simulation Model [1], ABS Model [2], Interactive Simulation-based Decision Support model IS-BDSF [3], and Simulation ED Overcrowding-Urgent Care Center(SEDO-UCC)[20]. The ability of the ED simulation model to take charge of the throughput time issue through the reduction of patient flow in time ED shows that it is very effective [1], [17]–[19]. This therefore necessitates the evaluation of the ED simulation model in order to properly measure the waiting time and LoS. The experimental research questions are as follows:

- Research Question 1 (RQ1): IS the SIM-PFED less waiting time than Safety Simulation Model, ABS Model, IS-BDSF and UCC?
- Research Question 2 (RQ2): Are the LoS results produced by SIM-PFED better than the LoS results produced by Safety Simulation Model, ABS Model, IS-BDSF and SEDO-UCC models?

B. HYPOTHESIS FORMULATION

Corresponding to the specified research questions, the following null hypotheses are suggested:

- $H_{10_{waitingtime}}$ The waiting time of the SIM-PFED and a specific model (Safety Simulation Model, ABS Model, IS-BDSF and SEDO-UCC) are the same.

- $H_{10_{LoS}}$: The LoS of the SIM-PFED and a specific model (Safety Simulation Model, ABS Model, ISBDSF and UCC) are the same.

If there is a decline of the null hypothesis to a reasonable extent, then there will be a formulation of another hypotheses as follows:

- $H_{1_{waitingtime}}$: The time of the SIM-PFED and a particular model (Safety Simulation Model, ABS Model, IS-BDSF and SEDO-UCC) are not the same.
- $H_{2_{LoS}}$: The LoS of the SIM-PFED and a particular model (Safety Simulation Model, ABS Model, IS-BDSF and SEDO-UCC) are not the same.

C. VARIABLES AND MEASURES

The experimental independent variables are SIM-PFED while the other models are as follows: Safety Simulation Model [1], ABS Model [2], IS-BDSF [3], and UCC [20]. In order to properly minimise ED patient throughput time, as intended by this study, the aforementioned models were deemed appropriate to SIM-PFED. The reason is that an evaluation of those models was done by making use of dataset as well as the equivalent waiting time and LoS technique of measurement for performance evaluation in the current study. Based on the researcher's level of awareness, the models that are specified here for the purpose of comparison are the commonly used models having the ability of achieving the best results through the use of the selected datasets.

There was a consideration of two additional dependent variables in the experiments: waiting time and LoS. The additional variables were regularly used in order to evaluate how effective the ED patient throughput time is. The reason is that the application of an ED operational patient flow in reality is supposed to be able to improve patients' throughput time in the ED department. This can be achieved through the reduction of patients' waiting time so that ED performance can be

TABLE 7. Details of each conducted experiment.

Number of Experiment conducted (CS)	Name of the Dataset	Reference	Number of Scenarios	Number of Simulation Experiments
CS1	Emergency Department of SRH (SRH-ED)	[14]	6	6
CS2	Santa Casa de São Paulo Hospital (APACHE II)	[15]	6	6
CS3	North Dublin in Ireland Emergency Department (NDI-ED)	[16]	7	7
CS4	Urgent Care Center (UCC)	[20]	3	3

improved with a view to obtaining patients' satisfaction as quality treatment is being given and at the same time patients' throughput time is being reduced in ED [21], [22]. The total time spent by a patient while waiting for health services in the ED patient flow process is the waiting time consumption. Related to the total time spent by the patient in the ED is the LoS factor which is the patient's first time of arrival at ED (arrival time) to the time that the patient physically departs from the ED (departure time). Regarding the waiting time and LoS of the dependent variables, the measurement of SIM-PFED was done for the verification of how it can reduce the waiting time and LoS by making reference to other designated methods (i.e. Safety Simulation Model [1], ABS Model [2], IS-BDSF [3] and SEDO-UCC [20]).

D. OBJECTS

To conduct the experimentations, four real benchmark datasets from the ED of the Shahid Rajaei Hospital (SRH) benchmark dataset were used (SRH-ED) [1], Acute Physiology Chronic Health Evaluation II (APACHE II) [2], North Dublin, Ireland emergency department (NDI-ED) [3], and Urgent Care Center (UCC) [20]. Regarding SRH-ED, the gathering of data from the health centre was between March and April 2017 [1]. The collected data was from the SRH-ED emergency department which is able to treat at least 40,000 patients per year [14]. SRH-ED comprised six ED scenarios and the APACHE II full detail is accessible in [1].

The collection of the Acute Physiology Chronic Health Evaluation II (APACHE II) benchmark dataset was from the Santa Casa de São Paulo Hospital's ED department [2]. The described data spanned through the working ED duration, which was between 1998 and June 1999. SRH-ED was made up of six ED scenarios and the detailed APACHE II is accessible in [2]. The confirmation of the North Dublin Ireland emergency department (NDI-ED) benchmark dataset was done in North Dublin, Ireland national emergency departments in 2006 [3]. There have been various reports nationwide highlighting the serious need for emergency care (with 1.2 million patients attending EDs). A report of the seven implemented NDI-ED scenarios in ED can be seen fully accessed in [3].

Ultimately, the release of UCC [20] dataset was done by an international modelling competition. The purpose of the

dataset was to identify the quality of the healthcare providers and be able to measure the number of techniques and the required examination rooms.

There were three well established UCC ED scenarios as described in [20]. As stated in the existing body of knowledge [1], [15], [16], [20], all the datasets were in perfect state and were current datasets in the ED domain. The datasets were being employed to evaluate current ED models, such as the safety simulation model, ABS model, and interactive simulation-based decision support model (IS-BDSF), and SEDO-UCC [20]. For this reason, the datasets are very appropriate for the evaluation of the suggested model, and the results can be compared with those of existing ED models.

E. EXPERIMENT EXECUTION

As shown in Table 7 the detailed information of each conducted case study in terms of the used dataset, simulation scenarios of the dataset used, and number of simulation experiments are presented. Each scenario is constructed by specifying the numbers of nurses in the triage department, nurses in the treatment department, doctors, and labs. These scenarios are considered an essential input in evaluating the proposed SIM-PFED to achieve a fair evaluation with other alternative models that use the same datasets with the defined scenarios. The experiment on the proposed SIM-PFED was carried out in line with the phases of the suggested model (input, process, and output) which is explained in Section III. The use of Anylogic simulation software in designing the SIM-PFED simulation was intended to implement the input and process phases so that it would be in line with the simulation aimed at, regarding the suggested operational patient flow in ED of SIM-PFED.

In relation to the process phase, Figure 6 presents a sample of the conducted simulation experiment in DES simulated logical design form in support of the marked-out scenarios in accordance to the suggested operational patient flow in ED of SIM-PFED.

A presentation of the comprehensive information about each experiment that was carried out is in Table 8. Experiment 1 (CS1) was aimed at making evaluation of the SIM-PFED's performance and then compare it with that of Safety Simulation Model [1]. Therefore, in order to confirm that the

Emergency Department

Stat 3D 2D Logic

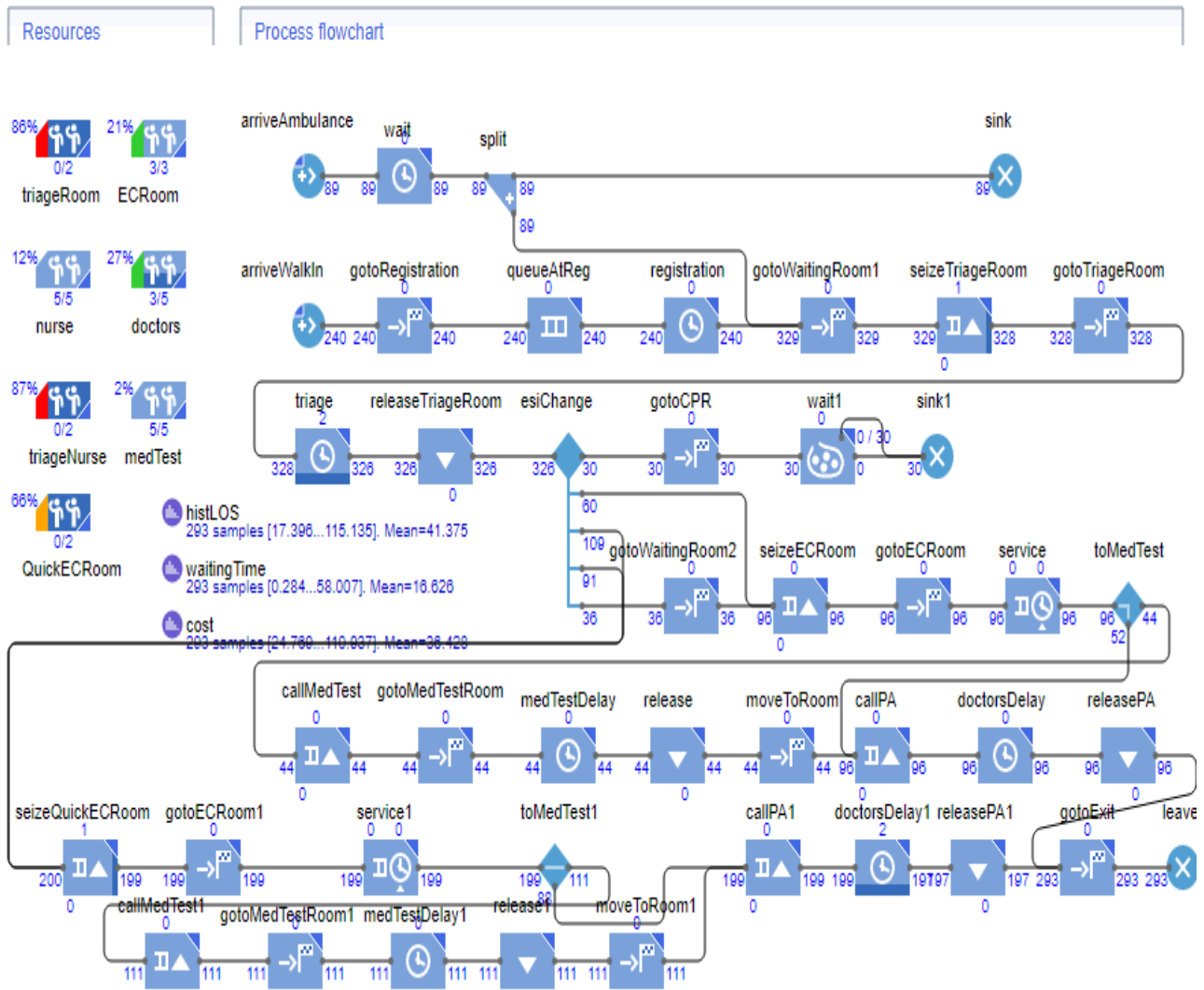


FIGURE 5. Sample of the conducted simulation experiment in DES simulated logical design form on the basis of the proposed operational patient flow.

comparison was reasonable, the necessary procedure required in [1] was carried out on CS1. The employed SRH-ED dataset comprised similar six scenarios utilized in the evaluation results of the Safety Simulation Model that were reported in [1]. The purpose of experiment 2 (CS2) was to evaluate the SIM-PFED's performance and then make a comparison of it with the ABS model's performance. Therefore, to achieve a fair assessment, the experimental procedure in [2] was strictly followed so that the result will be a reasonable comparison of the CS2 assessment with the already published result of the ABS model. In view of this, the designated six ED scenarios of APACHE II dataset were employed.

On the other hand, the carrying out of Experiment 3 (CS3) was aimed at evaluating SIM-PFED's performance so as to

make a comparison of its waiting time and LoS results with IS-BDSF model. Hence, in order to confirm that the comparison was a reasonable one, the CS3 was done in accordance with the experimental procedure in [3], thus employing the similar six scenarios of APACHE II as those in CS3 for SIM-PFED.

Finally, the carrying out of experiment 4 (CS4) was done. The purpose was to make an assessment of the waiting time and LoS effectiveness of SIM-PFED and then make a comparison with that of IS-BDSF. The experiment on CS4 was done by strictly following the experimental procedure in [20] to confirm that the comparison corroborates the reported results of the SEDU-UCC. This was achieved through the use of similarly established three

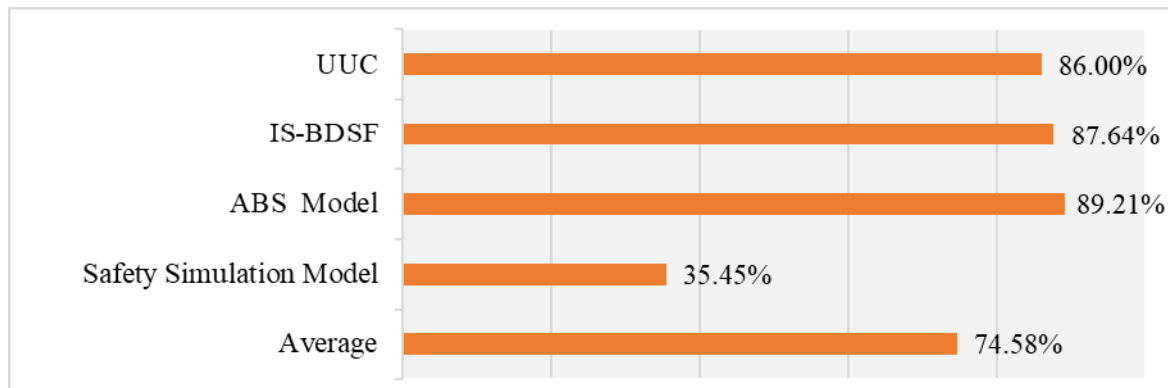


FIGURE 6. Overall improvement percentage in terms of waiting time.

TABLE 8. Details of the scenarios used in the conducted experiments.

Experiment Number (CS)	Scenario Number (SN)	Nurses in Triage Department	Number of Nurses in Treatment Department	Number of Doctors	Number of Labs
CS1	SN1	4	5	4	4
	SN2	6	6	6	3
	SN3	6	4	4	3
	SN4	7	6	6	3
	SN5	4	5	6	2
	SN6	7	6	7	3
CS2	SN1	3	2	2	2
	SN2	3	2	2	2
	SN3	2	2	3	1
	SN4	3	2	1	3
	SN5	2	1	1	2
	SN6	2	2	1	1
CS3	SN1	3	4	4	1
	SN2	4	6	6	2
	SN3	2	4	4	2
	SN4	3	6	6	3
	SN5	3	4	3	2
	SN6	4	5	6	3
	SN7	4	6	5	3
CS4	SN1	4	2	4	2
	SN2	2	2	3	2
	SN3	2	1	3	1

scenarios of the NDI-ED dataset that were utilised in CS3 for SIM-PFED.

The simulation results of each conducted experiment include average patient waiting time, cost and LoS for each scenario of each conducted case study are presented. The results of SIM-PFED for waiting time and LoS will be presented in the experimental results section. These obtained simulation results are then used as an input for TOPSIS, which is executed to determine the best scenario that can decrease patient throughput time in ED and help the top management of the hospital improve ED operational performance. The details of implementing TOPSIS have been described in Section III.B.3. Table 9 shows the ranked list

of scenarios for each conducted case study (CS1, CS2, CS3, and CS4). It includes the scenario name, scenario rank, and the obtained SEV for each scenario, which ranges 0 to 1 after normalizing the TOPSIS steps. The highest SEV of the scenario rank in the SIM-PFED results indicates the scenario with the highest efficiency (the best one) to be considered for implementation by ED decision-makers in real hospitals and clinics; this scenario ensures minimal throughput time and high cost effectiveness for ED patients.

As illustrated in Table 9, SN6, SN1, SN3, and SN2 are the utmost proficient (the best) scenarios to be executed in ED for CS1, CS2, CS3, and CS4, respectively. In CS1, the SEV of SN6 is 1 (supreme competence), which possess the maximum

TABLE 9. The ranked list of scenarios for each conducted case study.

Experiment Number	Rank	Scenario Number	SEV
CS1	1	SN6	1
	2	SN5	0.522330624
	3	SN2	0.483037395
	4	SN4	0.428417156
	5	SN1	0.141994146
	6	SN3	0
CS2	1	SN1	0.98498
	2	SN6	0.822078
	3	SN4	0.816179
	4	SN5	0.46386
	5	SN3	0.210281
	6	SN2	0
CS3	1	SN3	0.999611328
	2	SN6	0.928394728
	3	SN2	0.856578893
	4	SN5	0.811676302
	5	SN4	0.792458751
	6	SN7	0.488195376
	7	SN1	0
CS4	1	SN2	1
	2	SN1	0.52
	3	SN3	0.50

SEV among all scenarios. Hence, the five others are labelled to be unproductive and which requires a substitution. In reference to CS2, SN1 is the superlative scenario with an SEV worth of 0.98 (extreme productivity) when set in comparison with the five other scenarios that are labelled unproductive and not endorsed for execution. In CS3, SN3 is acknowledged as the superlative scenario with an SEV of 0.997779, which is the extreme SPV value amongst the scenarios of CS3; the other scenarios are labelled unproductive. In CS4, the SEV of SN2 is 1 (supreme proficiency), the high ranked SEV of all scenarios of CS4.

V. EXPERIMENTAL RESULTS

This section contains the summary and analysis of the findings of the experiment carried out to address the research questions identified in Section IV

The statistical analysis using SPSS was carried out to examine the identified hypotheses. A two-tailed one-sample t-test was adopted to examine the identified hypotheses. This has been identified as the most recommended significance stage by researchers and scientists [12], [53], and 5% (0.05) statistical significance level (P) was set for hypothesis testing. The conditions of choosing of 5% (0.05) significance level are represented in Table 10.

A. RQ1: IS THE SIM-PFED LESS WAITING TIME THAN SAFETY SIMULATION MODEL, ABS MODEL, IS-BDSF AND SEDO-UCC?

Table 11 shows a comparative analysis of SIM-PFED and the four alternative models (Safety Simulation Model, ABS Model, IS-BDSF and SEDO-UCC). This was performed based on the waiting time (per minute) for the experiment that was carried out. As inferred from Table 11, SIM-PFED has better overall time performance in relation to the waiting time. Specifically, SIM-PFED consumes fewer waiting time for the scenario carried out in each experiment (CS1, CS2, CS3, and CS4) compared to other models.

In addition, Table 12 shows the t-test statistical outcomes of the SIM-PFED when compared with each specific alternative model based on the experimental outcomes of the waiting time as depicted in Table 11. It is inferred in Table 12 that the attained P standards of the specific models and SIM-PFED are not up to the 0.05 significance level. Therefore, the first null hypothesis ($H_{10\text{waitingtime}}$) is prohibited at a significance level of 0.05, and the waiting time efficiency of SIM-PFED is significantly improved than that of the Safety Simulation Model, ABS Model, IS-BDSF and SEDO-UCC.

Furthermore, Figure 6 indicates the improvement percentage in regard to the waiting time of the proposed

TABLE 10. Selection criteria.

P-value Criteria	Result
$p \geq 0.05$	Accept null hypothesis
$p < 0.05$	Reject null hypothesis

TABLE 11. Waiting time results (per minutes) of the SIM-PFED, safety simulation model, ABS Model, IS-BDSF and SEDO-UCC.

Experiment Number	Model Name	Waiting time						
		SN1	SN2	SN3	SN4	SN5	SN6	SN7
CS1	SIM-PFED	5.87	4	6.56	3.55	3.59	1.19	-
	Safety Simulation Model	9.27	5.27	8.68	5.92	6.97	1.95	-
CS2	SIM-PFED	2.3	19.96	16.38	5.61	11.94	5.61	-
	ABS Model	126	95.4	84	74.4	151.2	79.8	-
CS3	SIM-PFED	41.29	11.19	6.32	13.51	13.01	8.49	24.34
	IS-BDSF	204.1	185.9	98.7	141.3	110.8	105.2	99.3
CS4	SIM-PFED	12	8	16	-	-	-	-
	SEDO-UCC	80	60	105	-	-	-	-

TABLE 12. T-tests results for waiting time.

Model Name	Mean	Std. Deviation	P-value
Safety Simulation Model	6.3433	2.6478	0.003
SIM-PFED	4.127	1.909	0.002
ABS Model	101.800	30.393	0.000
SIM-PFED	10.300	6.942	0.015
SEDO-UCC	135.043	43.725	0.000
SIM-PFED	16.879	12.194	0.011
IS-BDSF	81.67	22.546	0.024
SIM-PFED	12.00	4.000	0.035

SIM-PFED in relation to that of the current models that were chosen (Safety Simulation Model, ABS Model, IS-BDSF and SEDO-UCC). The improvement percentage is regulated based on the waiting time and of each scenario in each model in Table 11.

Additionally, Equations 6 was used to determine the upgrading percentage with respect to the waiting time. This equation is basic and it is a well-known equation for evaluating the upgrading percentage of performance testing for models [54], [66]–[70].

$$PWIM_j = \frac{WSIM_i - WSEM_{ij}}{WSEM_{ij}} \times 100 \quad (6)$$

where,

$PWIM_j$ is the percentage upgrading of waiting time for the SIM-PFED model against the j^{th} existing model.

$WSIM_i$ is the waiting time for the i^{th} scenario of the SIM-PFED model; and $WSEM_{ij}$ is the waiting time for the i^{th} scenario of the j^{th} current model.

In the illustration in Figure 6, the waiting time efficiency of SIM-PFED is 35.45%, 89.21%, 87.64% and 86.00% higher than the efficiency recorded for Safety Simulation Model, ABS Model, IS-BDSF and SEDO-UCC, respectively. In addition, the overall average waiting time performance of SIM-PFED compared to the four models show that the performance of SIM-PFED largely improves than that of the Safety Simulation Model, ABS Model, IS-BDSF and SEDO-UCC in regard to the waiting time at a percentage of 74.58%.

B. RQ2: ARE THE LoS RESULTS PRODUCED BY SIM-PFED BETTER THAN THE LoS RESULTS PRODUCED BY SAFETY SIMULATION MODEL, ABS MODEL, IS-BDSF AND SEDO-UCC MODELS?

As presented in Table 13, the LoS experimental outcomes of the SIM-PFED is compared with each specific model (the Safety Simulation Model, ABS Model, IS-BDSF and SEDO-UCC) for the experiments that were conducted. The experimental outcomes reveal the superiority of the SIM-PFED over the other four alternative models,

TABLE 13. LoS results (per minutes) of the SIM-PFED, safety simulation model, ABS Model, IS-BDSF and SEDO-UCC.

Experiment Number	Model Name	LoS						
		SN1	SN2	SN3	SN4	SN5	SN6	SN7
CS1	SIM-PFED	30.27	27.39	32.19	28.55	29.11	23.71	-
	Safety Simulation Model	114.38	111.01	113.13	111.3	110.16	107.28	-
CS2	SIM-PFED	28.14	46.02	40.92	30.31	35.75	27.69	-
	ABS Model	269.4	228	211.2	204.6	299.4	208.8	-
CS3	SIM-PFED	67.05	36.2	30.24	38.19	36.56	33.7	48.43
	IS-BDSF	588	564	450	510	450	450	444
CS4	SIM-PFED	30	25	30	-	-	-	-
	SEDO-UCC	250	180	250	-	-	-	-

TABLE 14. T-tests results for LoS.

Model Name	Mean	Std. Deviation	P-value
Safety Simulation Model	111.210	2.463	0.000
SIM-PFED	28.537	2.874	0.000
ABS Model	236.900	38.820	0.000
SIM-PFED	34.805	7.474	0.000
SEDO-UCC	226.667	40.415	0.003
SIM-PFED	28.333	2.887	0.010
IS-BDSF	493.714	60.964	0.000
SIM-PFED	41.481	12.596	0.000

in achieving improved LoS outcomes. This is evident through the decreasing LoS for each scenario of experiment carried out.

Furthermore, the t-test was adopted to examine the second null hypothesis (H_{2LoS}).

Table 14 shows the statistical outcomes of the t-test centred on the LoS outcomes of the experiments carried out in Table 13. The outcomes of the t-test in Table 14 suggests that the second hypothesis (H_{2LoS}) ought to be prohibited at a 0.05 significance level. This is because the obtained P-values are not up to a 0.05 significance level. Also, the results reveal that on the average, SIM-PFED performs better at decreasing the LoS compared to the Safety Simulation Model, ABS Model, IS-BDSF and SEDO-UCC.

Meanwhile Figure 7 reveals the improvement percentage of LoS achieved by SIM-PFED, in comparison to the conventional models that were selected (Safety Simulation Model, ABS Model, IS-BDSF and SEDO-UCC). The enhancement in upgrading percentage of the LoS and each scenario in

the models is presented in Table 12. The LoS enhancement percentage is calculated based on the LoS outcomes of the experiments that were carried out with the use of the identical method used for quantifying the upgrading percentage, based on the waiting time. Based on the illustration in Figure 7, the LoS effectiveness SIM-PFED is 74.4%, 85%, 91.6% and 87.4% higher than Safety Simulation Model, ABS Model, IS-BDSF and SEDO-UCC, respectively. In addition, the general average LoS performance values indicate that the value for SIM-PFED is largely improved compared to the other four models based on the waiting time, at a percentage of 85.6%.

VI. DISCUSSION

Explanation regarding the basis for the suggested SIM-PFED and the probable occurrence that that could convey the trends accomplished in the experiments' analysis is clearly clarified.

The statistical analyses clearly show that the SIM-PFED model is more beneficial in the handling of the patient throughput time than the other four models.

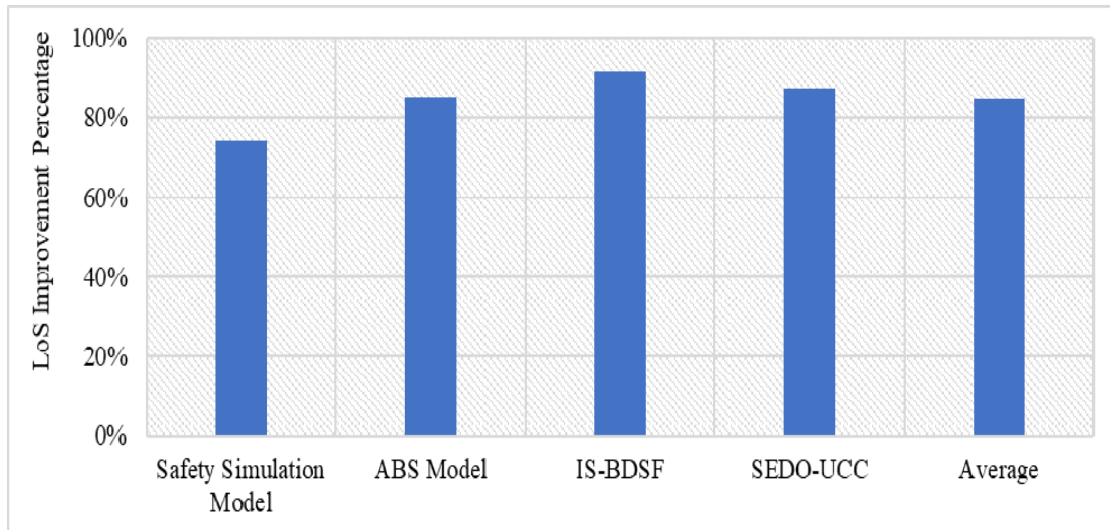


FIGURE 7. LoS overall improvement percentage.

TABLE 15. Comparative analysis of SIM-PFED and existing models.

Model	Waiting time	LoS	Decision-making	Cost	Defined scenarios' ranked list
Safety Simulation Model [14]	✓	✓	✗	✗	✗
ABS Model [15]	✓	✓	Partial	✓	✗
IS-BDSF [16]	Partial	Partial	✗	✗	✗
SEDO-UCC [20]	Partial	Partial	✗	✓	✗
SIM-PFED	✓	✓	✓	✓	✓

The SIM-PFED's ability to bring about reduction in the patient throughput time in ED, in relation to waiting time and LoS, is so distinct from the other four models. SIM-PFED is able to create a ranked list of scenarios with little involvement of experts through the implementation of the recently suggested operational patient flow, ABS, DES, and TOPSIS.

A substantial quantity of patient throughput time in relation to waiting time and LoS is consumed by the specified models. The reason is that the adopted operational patient flows leading to an increase in the patient throughput time does not have what it takes to handle decision-making and the cost factors that reduce patient throughput time in ED. By adopting SIM-PFED, the major problem of the other current models regarding the participation of top manager in the selection of the most appropriate scenario to be carried out in ED so as to ensure that there is reduction in patient throughput time and cost is tackled. The utilization of TOPSIS is intended to ascertain the scenario with the maximum efficiency which is created through a ranked list of scenarios.

Table 15 presents a comparative analysis of the proposed SIM-PFED model and the specific existing models on the basis of the key measurements of the throughput time issue with respect to catering to the key causative factors of this

issue in ED as follows: reducing or catering to waiting time, LoS, cost, and addressing decision-making for identifying the most efficient scenario to be implemented in ED by producing a ranked list of scenarios. The comparative analysis is revealed that the SIM-PFED model has better ability to deal with the major factors causing the patient throughput time problem while the other current models are deficient. They are unable to handle the various factors causing long patient throughput time in ED, which brought about the throughput time problem. The major assessment regarding the throughput time problem reveals that SIM-PFED is greater in strength than the other models, thus making it to be more beneficial to the actual ED practices than other models.

VII. CONCLUSION AND FUTURE SETS

The key contributions of this research are related to the development and evaluation of the SIM-PEED model. SIM-PEED was designed with the capability to address patient throughput time challenges with respect to causative factors, namely, waiting time, LoS, and decision-making. SIM-PFED introduces a new patient flow in ED to decrease patient throughput time on the basis of the proposed operational patient flow, the combination of ABS and DES by Anylogic simulation software, and the application of TOPSIS.

The proposed operational patient flow was used to determine the flow that each patient has to follow in ED with aim of reducing patient waiting time and LoS. Existing simulation methods use a single simulation technique, which creates difficulties in simulating complex systems, such as ED. Unlike these approaches, the proposed SIM-PFED adopts the combination of ABS and DES to simulate the proposed operational patient flow, including the behavior and flow of patients in ED, and calculate patient waiting time, LoS, and cost. Thereafter, TOPSIS is applied to help hospital decision-makers identify the best scenario (in terms of reducing patient throughput time and cost) to be implemented in ED. The cost of treatment depends on LoS but is not fully determined by it; three types of cost are considered: cost of stay per day, cost of medical procedures, and cost of all requirements in the hospital (including staff and all facilities needed) [71]. The effectiveness of the proposed SIM-PFED was also assessed to determine the capability of the proposed model in reducing patient throughput time. The findings show that SIM-PFED can decrease the patient throughput time in ED and help hospital decision-makers identify the best scenario to be implemented in ED.

During the experiments and thorough literature exploration in this study, several potential developments in the proposed SIM-PFED were identified to expand this work. Further research can be conducted to improve the performance of ED with respect to catering to the staff utilization factor. SIM-PFED establishes a clear view of the daily operation flow for patients in ED and provides decision-makers with insights into the performance of patient flow with respect to throughput time in ED. The integration of TOPSIS and simulation operation flow significantly contributes to the decision-making process by specifically revealing the best scenario to be implemented in ED for securing enhanced performance in terms of two attributes: cost and patient throughput time. However, the performance of the proposed model in terms of decision-making can be enhanced by adding other attributes that can affect decision-making, such as staff utilization. Staff utilization refers to the experience, knowledge, and hiring cost of staff. Inadequate involvement of staff utilization in ED increases throughput time. Inadequate staff involvement also increases the likelihood of making improper decisions for patients or incorrect diagnoses, which lead to an improper treatment manner and low cost effectiveness with respect to time consumption [72].

In the SIM-PFED, the multi-attribute decision making method TOPSIS has been applied to obtain the optimal alternative. Further research can dig deeper into improving the performance of selecting optimal alternative (scenario) by applying an aggregation operator in multiple attribute decision making, such as Pythagorean fuzzy interaction power, and Bonferroni means aggregation operators [73].

Further research can be conducted with various project datasets to expand the proposed SIM-PFED. In this study, SIM-PFED was applied to three datasets of real hospitals to assess the model's performance. However, due to limited

resources and other limitations in accessing other datasets that can be used in ED simulation, the proposed SIM-PFED could not be applied to other projects datasets. Additionally, there is a limitation to the performance compared with other existing models. Within ED operational patient flow, there are various techniques to be compared with. Nevertheless, we were unable to equate our model with all these models due to several reasons that are beyond our control, such as the ambiguity and complexity associated with simulation implementation, and the unavailability of the source code of these models for public use. To minimize this limitation, we compared the performance of the proposed SIM-PFED model with those models considered to be the most relevant to SIM-PFED, as these selected models were evaluated using SRH-EDA, PACHE II and NDI-ED datasets with the same size of scenarios of a dataset measured data as the present study. To the best of our awareness, the above-mentioned models and benchmarks for comparison are the best results reported so far using the selected datasets for the related ED simulation models. Hence, further research could be performed with different project datasets to extend the scope of the proposed SIM-PFED. The SIM-PFED configuration can also be implemented in real hospitals and clinics that have different departments and compared with others existing models.

APPENDIX A

SIMULATION MODEL DOCUMENTATION

A. AIM OF MODEL

This research presents a hybrid simulation model of DES and ABS with MADM (TOSIS) simulation model of patient flow to improve ED performance, to reduce the patient throughput time in ED.

1) MODEL OUTPUT

There are three key performance indicators for this research:

- 1- Average of LoS
- 2- Average of waiting time
- 3- Average of cost

B. LOGIC

1) BASE MODEL LOGIC DES LOGIC MODEL

The logic of SIM-PEFD: First, patients arrive at the ED. Then, patients are triaged and an ESI is accurately assigned to each patient. The operational patient flow of SIM-PEFD model is based on the worldwide Canadian triage system in ED.

2) ABS LOGIC

The model consists of the agents, resources, and ED real system which interacts with the resources based on the scenario. The ABS model is defined to use a statechart representing a general safe plan of patient behavior inside ED. The transitions among the ED entities for those transitions are visualized by the statechart in **Figure 4**.

3) SCENARIO LOGIC

This research focus is on patients who are in the process of treatment in ED. Several scenarios are considered. When dif-

ferent number of resources are added, each scenario exhibits different patient waiting time, LoS, and cost of operational patient flow

4) COMPONENT

a: DES ENTITIES

The main entities of the SIM-PEFD model are patients that arrive within the ED through the community. Each of them will be assigned attributes like a triage classification which leads to the flow of patient to the special path related to his triage level, based on Table 2.

List of activities

- Registration: Patient registered
- Triage: Canadian emergency by nurses in triage section
- CPR: The assessment the patient who have ESI 1
- Normal treatment Area: The assessment the patient who have ESI 2 and ESI 5
- Fast track: The assessment the patient who have ESI 3 and ESI 4
- Medical test: The lab process
- Diagnosis: Assessment the doctor and nurse

List of resources

Nurses in triage department, number of nurses in treatment department, number of doctors, and number of labs.

List of queues

- Patients arrive walk in or in an ambulance.
- Registration: First come first serve
- Triage: By the priority in Table 2
- CPR: Urgent serve
- Normal treatment Area: First come first serve 2
- Fast track: First come first serve
- Medical test: First come first serve
- Diagnosis End: Exit point

b: ABS

- Statechart: Entry point default State
- Transition: Registered with message type object
- Transition: Triage with message type object
- Transition: CPR with message type object
- Transition: ECRoom with message type object
- Transition: QECRoom with message type object
- Transition: Exit with message type object

C. DATA

1) DATA SOURCES

Table 16 shown the list equations of the model accounting section III.A provides the details of the elements of data sources.

Input parameters for DES model summarized in the Table 17.

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TABLE 16. List equations of the model accounting.

Inflows	Outflows
ED patient arrival	LoS: $\text{histLoS.add}(\text{time}() - \text{agent.timeAdmitted})$;
Arrival rate/time scale	Waitingtime: $\text{histwaitingTime.add}(\text{agent.waitingTime})$;
Agent.startWaitingTime = time();	Cost: $\text{istcost.add}(\text{agent.workTime} / 60 * \text{costPerHour})$;
agent.timeAdmitted = time();	ED discharge rate Patients In ED* $(1 - \text{agent.timeAdmitted}) / (\text{Patient time in ED} * \text{Time scale})$
Agent.waitingTime+= time() agent.startWaitingTime;	
Patient in triage to ED (Patient in triage* $(1 - \text{gent.timeAdmitted}) / (\text{Triage time} * \text{Time Scale})$)	
Algebraic equation method	

TABLE 17. DES model input parameter.

DES input parameter	Activity	Distribution	Min	Most Likely	Max
Processing time (min)	Registration	Triangle distribution	0.5	1	1.5
	Triage	Triangle distribution	5	8	15
	Waiting	Triangle distribution	15	20	30
	Treatment	Triangle distribution	5	-	10
Lab	Blood test	Triangle distribution	1	-	2

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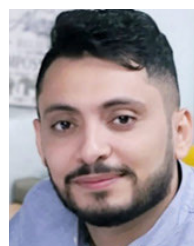
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