IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received June 7, 2021, accepted July 1, 2021, date of publication July 12, 2021, date of current version July 22, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3096263

Solving the Emergency Care Patient Pathway by a New Integrated Simulation-Optimisation Approach

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The work of Wahid Ghazi Allihaibi was supported by Umm Al-Qura University for his Ph.D. research.

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Royal Brisbane and Women's Hospital Human Research Ethics Committee (RBWH HREC) under Ref. HREC/16/QRBW/622 PHA approval. Ref. RD006759.

ABSTRACT One of the most critical objectives in the healthcare system is maximising patient flows in the emergency care patient pathway. Patient emergency flow analysis indicates that the timetabling of a patient's movement from one activity to another through the Emergency Department (ED) is critical for treating patients. The ED deals with the patient's arrival, triage, physician assessment, imaging and laboratory studies, treatment planning, nursing procedures, and decisions to admit or discharge the patient. Any delayed activities in patient flow reduce the service level of healthcare. To address these challenges, this paper develops a stochastic ED Simulation-Optimisation approach by considering stochastic variables, such as patient interarrival times and treatment times, using statistical distributions. This type of distribution depends on two main elements: day shifts and patient categories. A hybrid evolutionary algorithm is integrated with the simulation to find a satisfactory solution for this stochastic optimisation problem in real time. Computational experiments show that the proposed approach can serve more patients in specific time windows or provide the same quality of the service with the use of fewer medical resources.

INDEX TERMS Construction heuristic, emergency department, healthcare optimisation, integrated approach, simulation.

I. INTRODUCTION

The Emergency Department (ED) plays a vital role in the community as it provides appropriate and timely acute care 24/7 for the public, in addition to a health system response in the event of a disaster or public health emergency. Patients are referred to the ED for many reasons, such as complex cases, liability concerns, and diagnostic testing. The number and growth rate of emergency visits have increased rapidly in the last two decades [1]. This increase causes an imbalance between patients (demand side) and medical resources (supply side). Consequently, the medical resources capacity cannot accommodate excessive patient loads, and therefore patient waiting times are longer. The crowding in the ED causes longer waiting times and reduces patient privacy. Moreover, a crowded ED increased delays, decreased satisfaction, increased mortality, and reduced an institution's ability to accept more referred patients [1], [2]. In 2014-2015, it was reported that "approximately 7.4 million people visited an ED in Australia; 73% of patients spent 4 hours or less in the ED; 29.73% of patients were admitted to hospital from the ED, and 47% of them were admitted within 4 hours" [3]. Importantly, about 2% of the scheduled ED visitors left the ED before their assessments, typically because of long waiting times. According to [4], reducing the ED processing time by one hour can add $9,000 to the revenue by reducing the number of patients who leave without being seen. In this context, busy healthcare systems are creating new challenges

The associate editor coordinating the review of this manuscript and approving it for publication was Jenny Mahoney.

for the healthcare industry, which is keen to adopt better healthcare management systems and more cutting-edge analytical solutions [1].

Over the last decade, there have been many academic studies on simulation and optimisation models for healthcare management [5]; however, examples of real-world implementation are rarely found in the literature. In the real world, healthcare managers must maximise the utilisation of their available resources while being constrained by a specific budget and a specified level of care. Due to humanistic and governmental obligations, these healthcare systems must provide high-quality care and service while, achieving the highest number of patients in a given time period or minimising the total weighted waiting time [5]. This paper aims to develop a new integrated Simulation-Optimisation approach to solve a stochastic ED system for real-world implementation in the Royal Brisbane and Women's Hospital (RBWH), Brisbane, Australia.

According to the literature, many researchers developed mathematical programming models of the ED optimisation problem under a limited budget to increase capacity (i.e. serving more patients in a specific time) and efficiency (i.e. the same quality of the service or higher using fewer resources) [6]–[8]. A multi-objective model was developed to minimise the number of doctors, nurses, and lab technicians and patient service time by maximising patient flow [6]. The number of beds and arrival rates have a potential impact on the patient flow and system efficiency, and there is a strong relationship between the demand for resources of the ED and the inpatient hospital [7]. The developed model included many decision variables, and the proposed solution techniques calculated the values of these variables, such as the patient's arrival time, patient's departure time, and patient service time. The main objective of the ED optimisation model is to reduce the total waiting time with a limited number of resources, such as doctors, beds, and nurses. The problem of the planning of emergency admissions was addressed [8] using integer programming to minimise the utilisation of the additional beds while maximising the revenue where the number of available beds is known. Mixed integer linear programming was used in healthcare optimisation to minimise the number of waiting patients in [9], where IBM ILOG-CPLEX Solver was used to solve the proposed model. Other operations research techniques, such as simulation techniques [10], [11] and decision support systems [12], were used to solve the ED optimisation problem to improve the efficiency of the ED system. Scheduling approaches were also developed by many researchers in the assignment and sequencing of patients and medical staff [13] to reduce the number of patients waiting due to the arrival of patients in the ED. Due to the complexity, heuristic techniques were proposed to minimise the waiting time of patients depending on scheduling the allocation of beds. These heuristic rules include triage first in first out, waiting time ratio, shortest processing time, earliest due date, and triage shortest processing time. The scheduling theory and utilisation of the hospital resources have a significant impact on improving the patient flow and producing efficient capacity [14]. Many operations and activities are studied in the patient flow, such as consultation, X-ray, and blood test. Static and dynamic scheduling approaches are compared according to the analysis results of patient flow and utilisation of resources. Performance evaluation process algebra is applied to model the patient flow and analyse the performance of the hospital system. This model provides an accurate prediction of the treatment time for upcoming patients to reduce the long waiting time and increase the efficient utilisation of resources. An efficient and scalable system was introduced to predict the ED patient volume in hospitals by using Google Trends search data [15]. A software was developed to allocate resource and staff in hospital to improving patient flow and reducing ED congestion. Some researchers developed the stochastic scheduling problem to optimise the emergency patient flow considering beds in the ED system as parallel machines. A novel blocking patient flow (BPF) scheduling heuristic algorithm was developed to schedule patients dynamically in the ED [16]. The total patient waiting time was improved by more than 8 % by using a BPF heuristic algorithm comparing to two straightforward scheduling rules, namely, first-come first-served (FCFS) and shortest processing time (SPT). Although mathematically formulating the ED optimisation problem provides considerable benefits to the healthcare system, it is challenging as the arrival and treatment times are stochastic and there are limitations in predicting the need for emergent care. A stochastic mixed integer programming model was proposed by [17] to minimise the total expected patient waiting times, where the sample average approximation approach was used as a solution technique. This approach considered three queues of patients, two assessment queues before and after having ancillary examinations by physicians and a queue supervised by nurses for the treatment. A stochastic mixed-integer programming model was proposed to optimise the medical staff and beds in ED by decreasing the average total patient waiting time [18]. The average total patient waiting time was improved by up to 23.24%. Moreover, some researchers focused on minimising the total patient tardiness or waiting time through the timelines of the system [19], [20]. Fuzzy logic and an evolutionary algorithm were proposed to solve a stochastic optimisation problem with multiple objectives, such as minimising the total patient waiting time and the makespan [21]. The meta-modelling optimisation approach was suggested to investigate and optimise the effective resources in the ED by reducing the total average waiting time for patients in the ED [22]. By considering the budget, a patient's wait time was improved by 49.6%, and the cost of resource usage was reduced by 51%. Recently, integrated Simulation-Optimisation approaches were investigated to improve the overall performance for both the patients and healthcare resources [23], [24]. A metaheuristic approach was tested to minimise - personnel allocated to an emergency department according to patient flow and staff scheduling limitations [25]. Furthermore, a simulation model with an optimisation method was proposed to represent the ED and then optimise the human allocation resources (e.g. medical and para-medical) in the hospital where average waiting time and average inpatient stay were reduced by 12 minutes and 21 minutes respectively [26]. A simulation-optimisation approach was presented to optimise resource allocation between emergency departments, pharmacies, laboratories, and radiology departments under budget and resource constraints [27]. Radial basis function, data envelopment analysis, the design of experiments and artificial neural network were combined in this new approach. By using the new resource level, the patients' waiting time for bed, the mean waiting time in triage queue and the mean waiting time in the drugstore were decreased by 32%, 16% and 64% respectively. Genetic Algorithms (GA) were developed to optimise the patient flow in the ED by minimising the associated expenditure [28]. Discrete event simulation and queuing theory were used to build an ED-Simulation model where each patient was served in sequenced operations by multiple service providers, such as nurses and doctors. The developed model considered patient waiting time and associated costs to measure the ED performance. The allocation of service providers was considered through several operations to improve the ED performance. Most researchers focused on the ED simulation applications during normal conditions, while few papers published on the ED simulation applications during disaster conditions [29]. The discrete event simulation (DES) has been widely employed in modelling healthcare systems [30] and investigating emergency departments [31]. The patient flow through the ED was improved by integrating the ED with other units such as the short stay unit (SSU) and inpatient units (IU) [32]. In this paper, the impact of the SSU and IU in reducing the ED congestion was investigated using the ED-Simulation model, in which statistical tests were proposed to establish the patient arrival times and service times.

In a real-world ED system, however, different categories of patients may require multiple types of services. All patients in the same category undergo an identical sequence of activities, while patients from different categories can undergo common activities. For example, the triage unit is a common area for all walk-in patients or ambulance patients before they are taken to the examination room. The cost of the provided service or activity for each patient depends on the service providers (e.g. number of doctors, lab technicians, nurses), the resources needed (e.g. number of wards), and the total patient demand for the hospital. By considering these realistic constraints and requirements, this study developed an integrated Simulation-Optimisation approach to solve the utilisation of several resources in the system and provide a measure of performance for the selection by a healthcare manager. The contribution and innovation of this study are highlighted below:

- Develop an integrated Simulation-Optimisation approach for a real-world stochastic ED system.
- Integrate the adapted GA with a novel constructive heuristic to solve this stochastic ED problem.
- Solve a multi-objective ED scheduling problem to minimise the total waiting time and the makespan while maximising the utilisation of the existing resources.
- Deal with the uncertainties by defining stochastic variables such as patient interarrival times and treatment times in the ED system.
- Solve large-scale problems for real-world implementation to improve ED efficiency.

The rest of this paper is structured as follows. In Section 2, we present a mathematical model for an ED system. In Section 3, we introduce a new Discrete Event Simulation model for an ED system. In Section 4, we propose an integrated Simulation-Optimisation approach by integrating the GA into the simulation process. Computational results and insightful analysis are reported in Section 5. Finally, the significance and benefits of this research are presented in the last section.

II. ED MATHEMATICAL MODEL

The stochastic optimisation mixed integer programming (SOMIP) approach is applied to formulate the ED optimisation problem as an ED-SOMIP model [33], [34]. In this model, the objective function is constructed to solve the patient total waiting time under limited resources [20]. In the proposed mathematical model, many stochastic elements from the stochastic distribution are included to solve ED-SOMIP model such as patient's interarrival time per shift, patient's treatment time for each patient category, and the ratios of five categories of patients according to the Australasian Triage Scale (ATS), where interarrival and treatment times are defined by different stochastic distributions according to the real-world data collected from the RBWH. The fundamental job shop scheduling techniques are applied to develop the proposed model [35]. As the ED optimisation problem is an NP-hard problem, the exact algorithms such as branch-&-bound or dynamic programming to solve the ED-SOMIP problem is time-consuming and unacceptable in practice. As, a result, we proposed in this paper a hybrid Simulation-Optimisation method that can provide good solutions in a reasonable CPU time in real-world applications.

A. PARAMETERS

P	Number of patients
i	Index of a patient; $i = 1, 2, \ldots, P$
K	Number of operations
k	Index of an operation; $k = 1, 2, 3$, for Triage, Doctor and Nurse, respectively.
D	Number of staff
$d_{i,k}$	Index of staff resource required for patient i in each operation$k$; $d \in \{1, 2, \ldots, D\}$
$g_{i,k}$	Processing time distribution of patient i for operation k (is distributed as treatment time).
r_i	Arrival time of patient i ($r_i - r_{i-1}$ is distributed as interarrival time)

PW_i	ED pathway for patient i ($PW_i = 1$ Resuscitation pathway; $PW_i = 2$ Acute pathway; $PW_i = 3$ Fast track pathway)
B	Upper bound on the number of beds in the ED
b_i	Type of bed required for patient$i$, $b \in \{1, \ldots, B\}$
e_k	Resource required by operation$k$; ($e_k = 1$ Triage staff; $e_k = 2$ Doctor; $e_k = 3$ Nurse)
b^T	Number of T type beds (b^1 = Resuscitation beds; b^2 = Acute beds; b^3 = Fast track beds)
d^γ	Number of γ type staffs (d^1 = Triage staff; d^2 = Doctors; d^3 = Nurses)
M	An arbitrary large positive number

B. DECISION VARIABLES

$s_{i,k}$ Starting time of operation k for patient i

$$y_{i,k,b} = \begin{cases} 1, & \text{if patient } i \text{ requires bed } b \text{ to implement operation } k \\ 0, & \text{otherwise} \end{cases}$$

$$z_{i,k,d} = \begin{cases} 1, & \text{if patient } i \text{ schedules for staff } d \text{ during operation } k \\ 0, & \text{otherwise} \end{cases}$$

$$t_{i,i',k} = \begin{cases} 1, & \text{if patient } i \text{ precedes patient } i' \text{ for operation } k \\ 0, & \text{otherwise} \end{cases}$$

$$q_{i,k,i',k'} = \begin{cases} 1, & \text{if patient } i \text{ operation } k \text{ before patient } i' \text{ operation } k' \\ 0, & \text{otherwise} \end{cases}$$

C. OBJECTIVE FUNCTION

The main objective function is minimising the total waiting time f_W, where total waiting time includes the initial waiting time of patients before admitting to ED and the waiting time of patients between operations in ED. The objective function computes the waiting time starting with operation two because the first operation is the Triage process, not in treatment time. So, the waiting time for the first operation "Triage process" does not include the total waiting time (objective function).

$$Min\, f_W = \sum_{i=1}^{P} \left(s_{i,2} - r_i\right) + \sum_{i=1}^{P}\sum_{k=2}^{K-1} \left(s_{i,k+1} - \left(s_{i,k} + g_{i,k}\right)\right) \quad (1)$$

D. CONSTRAINTS

Constraint (2) ensures that the ready time of each patient precedes the first operation in ED where ready time less than or equal the starting time of the first operation in the ED.

$$r_i \leq s_{i,1} \quad i = 1, \ldots, P \quad (2)$$

Constraint (3) ensures that operation k precedes operation $k+1$

$$\left(s_{i,k} + g_{i,k}\right) \leq s_{i,k+1} \quad i = 1, \ldots, P;\ k = 1, \ldots, K \quad (3)$$

Constraints (4), (5) and (6) ensure that assign each patient to the correct type of bed based on patient's ED pathway from triage process.

$$\text{If } PW_i = 1 \quad \text{Then } \sum_{b\in\alpha}^{B} y_{i,k,b} = 0 \quad \text{where } \alpha = \left\{b | b \in B, b > b^1\right\} \quad i = 1, \ldots, P;\ k = 1, \ldots, K \quad (4)$$

$$\text{Else If } PW_i = 2 \quad \text{Then } \sum_{b\in\alpha}^{B} y_{i,k,b} = 0 \quad \text{where } \alpha = \left\{b | b \in B, b > b^2\right\} \quad i = 1, \ldots, P;\ k = 1, \ldots, K \quad (5)$$

$$\text{Else If } PW_i = 3 \quad \text{Then } \sum_{b\in\alpha}^{B} y_{i,k,b} = 0 \quad \text{where } \alpha = \left\{b | b \in B, b > b^3\right\} \quad i = 1, \ldots, P;\ k = 1, \ldots, K \quad (6)$$

Constraints (7), (8) and (9) ensure that each process should be completed by the right staff resource.

$$\text{If } e_k = 1 \quad \text{Then } \sum_{d\in\delta}^{D} z_{i,k,d} = 0 \quad \text{where } \delta = \left\{d | d \in D, d > d^1\right\} \quad i = 1, \ldots, P;\ k = 1, \ldots, K \quad (7)$$

$$\text{Else If } e_k = 2 \quad \text{Then } \sum_{d\in\delta}^{D} z_{i,k,d} = 0 \quad \text{where } \delta = \left\{d | d \in D, d > d^2\right\} \quad i = 1, \ldots, P; k = 1, \ldots, K \quad (8)$$

$$\text{Else If } e_k = 3 \quad \text{Then } \sum_{d\in\delta}^{D} z_{i,k,d} = 0 \quad \text{where } \delta = \left\{d | d \in D, d > d^3\right\} \quad i = 1, \ldots, P; k = 1, \ldots, K \quad (9)$$

Constraint (10) ensures that both staff resources and beds are used simultaneously.

$$\text{If } \sum_{d=1}^{D} z_{i,k,d} = 1 \quad \text{Then } \sum_{b=1}^{B} y_{i,k,b} = 1 \quad i = 1, \ldots, P;\ k = 1, \ldots, K \quad (10)$$

Constraints (11), (12) and (13) address the sequence of different patients, i and i' on same operation k.

$$s_{i,k} \geq s_{i',k} + g_{i',k} - M * \left(1 - t_{i',i,k}\right) \quad (11)$$

$$s_{i',k} \geq s_{i,k} + g_{i,k} - M * \left(1 - t_{i,i',k}\right) \quad (12)$$

$$t_{i',i,k} + t_{i,i',k} = 1 \quad (13)$$

Constraint (14) ensures that bed b is only occupied by one patient i at a given time.

$$\sum_{i=1}^{P} y_{i,k,b} \leq 1 \quad k = 1, \ldots, K;\ b = 1, \ldots, B \quad (14)$$

Constraint (15) ensures that patient i only occupies one bed b in ED.

$$\sum_{b=1}^{B} y_{i,k,b} \leq 1 \quad i=1, \ \ldots, P; \ k=1,\ldots,K \tag{15}$$

Constraint (16) makes sure the patient i is scheduled exactly once to one staff d for each operation$k$

$$\sum_{k=1}^{K}\sum_{d=1}^{D} z_{i,k,d} = 1 \quad i=1,\ldots,P \tag{16}$$

Constraint (17) ensures that patient i is assigned to operation k using only one staff d

$$\sum_{i=1}^{P} z_{i,k,d} \leq 1 \quad k=1,\ldots,K; \ d=1,\ldots,D \tag{17}$$

Constraints (18) and (19) to ensure that the patient is scheduled correctly on different beds and staff (operations)

$$s_{i',k'} \geq s_{i,k} + \left(y_{i,k,b} * g_{i,k}\right) - M * \left(1 - q_{i,k,i',k'}\right)$$
$$i=1,\ldots,P; \quad k=1,\ldots,K; \ i'=1,\ldots,P;$$
$$k'=1,\ldots,K; \quad b=1,\ldots,B \tag{18}$$

$$s_{i',k'} \geq s_{i,k} + \left(z_{i,k,d} * g_{i,k}\right) - M * \left(1 - q_{i,k,i',k'}\right)$$
$$i=1,\ldots,P; \quad k=1,\ldots,K; \ i'=1,\ldots,P;$$
$$k'=1,\ldots,K; \quad d=1,\ldots,D \tag{19}$$

III. ED SIMULATION MODEL

The proposed ED system includes the main processes and activities, such as the patient's arrival, triage, physician assessment, imaging and laboratory studies, treatment

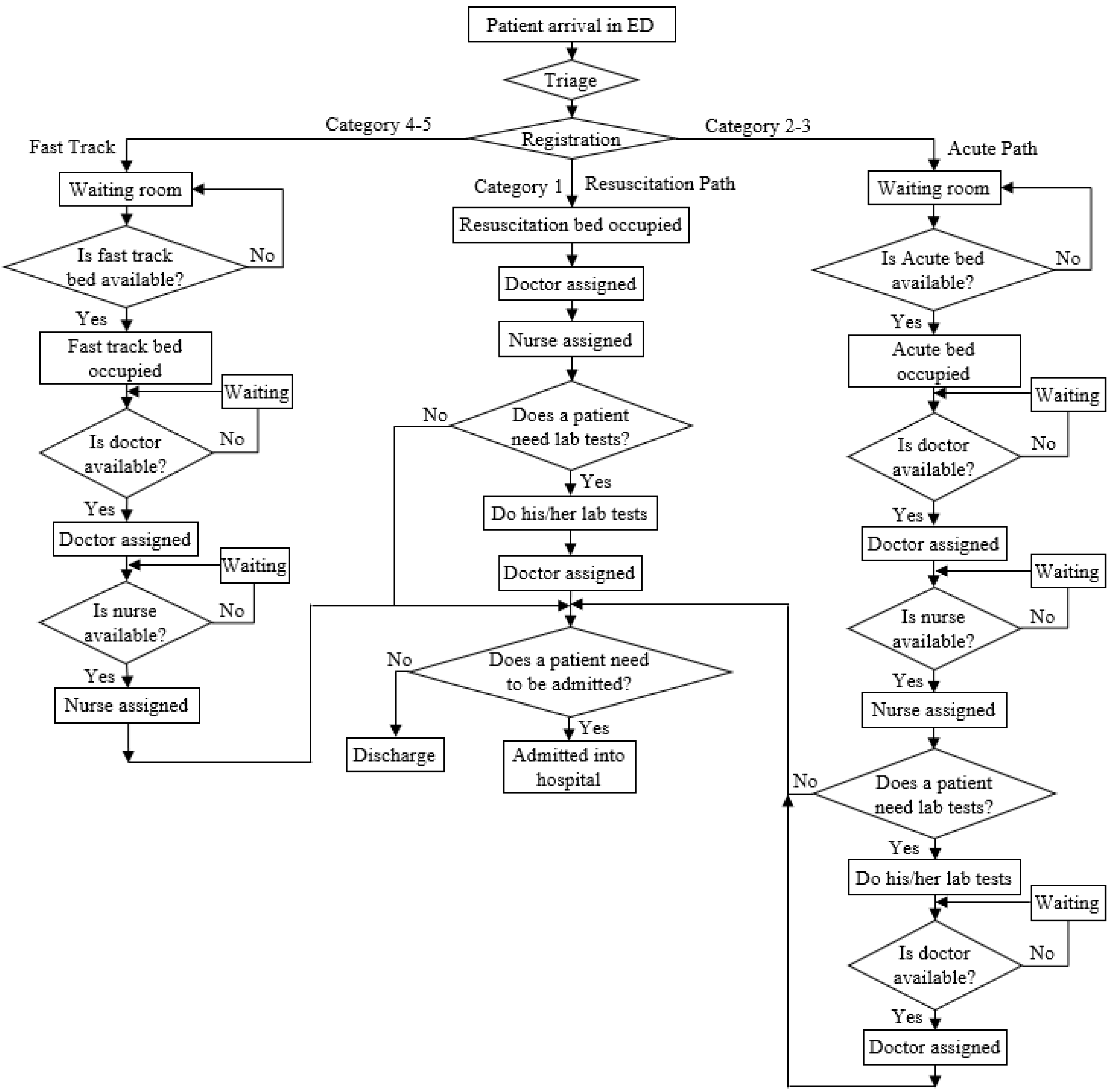

FIGURE 1. A new DES model for a real ED system.

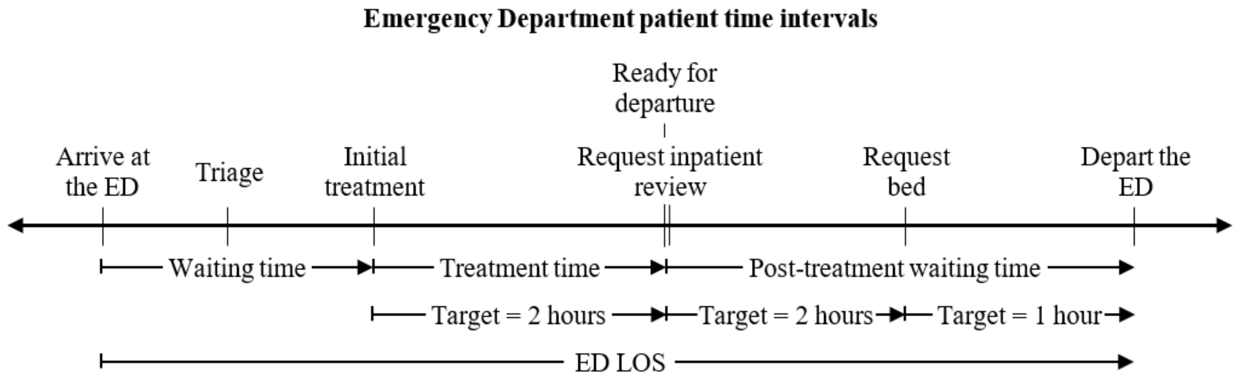

FIGURE 2. Time points of the patient stay in the ED.

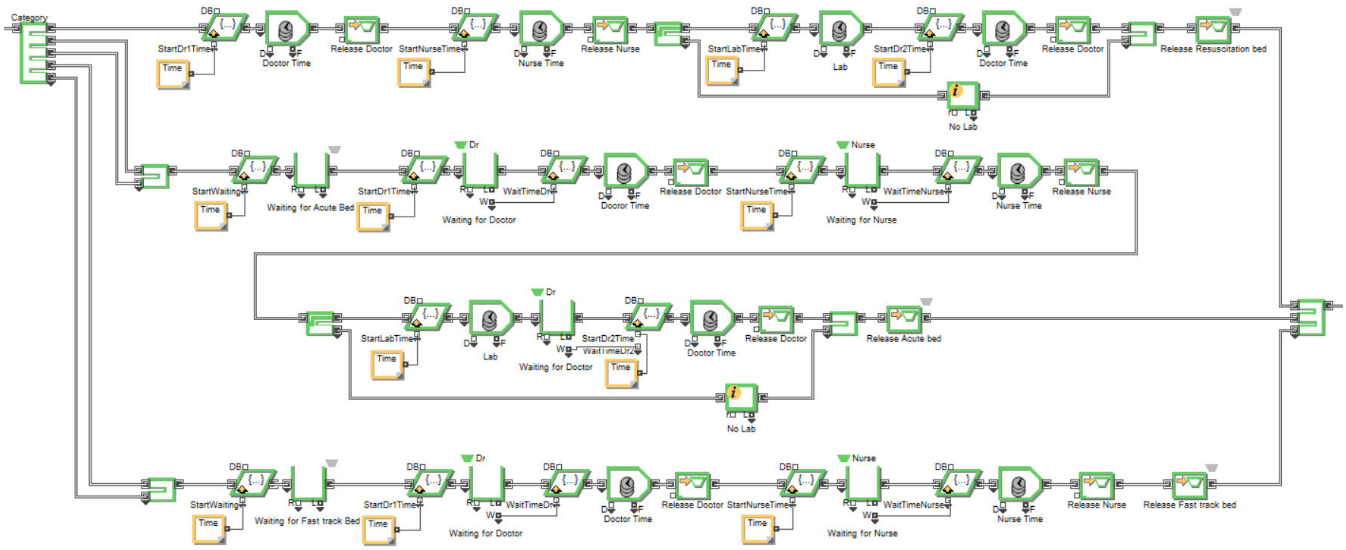

FIGURE 3. ExtendSim model of the ED processes.

planning, nursing procedures, decision to discharge or admit, and access to inpatient beds. These activities occur in order, and any delays in the operations of the patient flow in the ED can have an impact on patient throughput and may cause bottlenecking [36]. In the current research, the ED operations are formulated as a DES model. The DES model is a useful technique that assists the healthcare decision-makers to reconfigure the existing system to improve service performance and reduce operating costs. In the proposed Simulation model, we build the model based on the five distributed categories of patients according to the ATS. The patient interarrival times and treatment times are established using the real data collected from the RBWH, where various disease groups are distributed to the different ATS categories with specific ratios. Furthermore, interarrival times, and treatment times are stochastic for each patient. Statistical distributions are constructed depending on the type of each patient and whether this distribution is appropriate.

Figure 1 shows that the patients are categorised into five ATS categories which are assigned to three types of beds, where each category is assigned to a specific type of bed. Patients in Category 1 are assigned to resuscitation beds, in Categories 2-3 are assigned to acute beds, and in Categories 4-5 are assigned to fast track beds. The patient's service priority depends on the patient type and the availability of medical resources, such as beds, doctors, and nurses. Patients are discharged from the ED or admitted into hospital to receive more treatment. Category 1 has the highest priority to be served without waiting time, while in Categories 2-5 the waiting room is used if there is no bed or doctor available.

Figure 2 describes the patient length of stay in the ED (LOS_{ED}), where the LOS_{ED} of each patient includes three main stages: waiting time, treatment time, and post-treatment waiting time, in other words LOS_{ED} = ED departure time – ED arrival time. The waiting time includes the period between the patient's arrival time and the initial treatment time, including the spent time in triage. Treatment time is the second stage targeted to 2 hours and starts with the initial treatment and continues to the ready for departure time. Finally, the post-treatment waiting time is 3 hours, which includes 2 hours for waiting for a specialist consultation and 1 hour for waiting for a bed. This stage starts with the inpatient review and continues to the departure from the ED, including a bed request. Treatment time includes the waiting time before assigning a doctor and nurse. Figure 3 analyses the ED processes in detail for each ATS category, where the processes in the ED are detailed using ExtendSim software. The proposed ED-DES model has been developed and executed in the ExtendSim environment, using PC processor Intel(R) Core(TM) i7-7700 CPU @ 3.60GHz and RAM 16.0 GB, based on multiple objectives and several realistic constraints. The proposed objectives aim to minimise the patient's total waiting time, minimise the patient's length of stay, and improve the utilisation of resources. The constraints are developed according to real-life case studies that include the upper and lower bounds of patient arrival times, patient treatment times, personnel (doctors and nurses), and daily shifts.

IV. AN INTEGRATED SIMULATION-OPTIMISATION APPROACH

In this section, an integrated Simulation-Optimisation approach is developed to improve the solution's accuracy. The proposed approach consists of three main steps: 1) produce the ED's stochastic variables, such as patient interarrival and treatment times, using statistical distributions. Patient interarrival times are classified into three shifts: day, evening, and night, while treatment times are distributed statistically according to five patient categories and each disease group is distributed to the different ATS categories by specific ratios; 2) obtain the solution of the ED-DES model using ExtendSim software; 3) integrate a novel blocking patient flow (BPF) heuristic algorithm and the adapted GA as a hybrid heuristic into the simulation process using the stochastic variables produced in Step 1 and the result of the ED-DES model obtained in Step 2.

Figure 4 presents the main framework of the proposed stochastic Simulation-Optimisation approach, of which a new hybrid optimisation method is applied after using statistical distribution to produce stochastic variables in the simulation. The improvement rate of the produced solution is calculated depending on the selected criteria, such as patient waiting time. The acceptance of the produced solution depends on the calculations of the data for each hospital as a base model. If the improvement rate is acceptable, then apply the developed optimisation method; otherwise, continue to obtain more improvements and learning regarding the parameters of the simulation process. The stochastic variables in Step 1, such as patient interarrival per shift and treatment time per patient category, are produced. For instance, the treatment time for Category 1 is Erlang distribution.

The initial solution of the ED-DES model in Step 2 is selected and evaluated using the proposed objective functions. The first step in the proposed hybrid GA is to consider a patient's scheduling representation or solution structure. The chromosome representation (patient's scheduling) in this paper represents each job in the schedule as a gene in a chromosome, in which each chromosome consists of $(P+B-1)$ genes, where P is the number of patients and B is the number of beds. Furthermore, the chromosome $(B-1)$ consists of "*" asterisks, which are used to separate the genes. Therefore, to differentiate one bed from another on the chromosome, an asterisk is used. In this way, the entire set of patients can be encoded on a single string in bed order.

A novel BPF heuristic algorithm is developed and embedded in the adapted GA approach below:

1. Categorise all arrival patients into five categories; $C = 1:5$.
2. Categorise beds into three types; $T = 1:3$.
3. Set number of patients in each category $= P_C$.
4. Set number of beds in each type $= B_T$.
5. Set number of beds B; $B = B_1 + B_2 + B_3$.
6. Set number of patients P; $P = P_1 + P_2 + P_3 + P_4 + P_5$.
7. Construct a list of available beds $(ABL)_T$ of each Type T.
8. Select bed b_T; $b_T \in \{1_T, 2_T, 3_T \ldots, B_T\}$.
9. Select patient p_C; $p_C \in \{1_C, 2_C, 3_C \ldots, P_C\}$.
10. Generate patients' sequence solutions.
    - 10.1 Assign patients randomly to each gene of a chromosome to which none of them is assigned.
    - 10.2 Assign patients from 1 to P to the rest of the unfilled genes of the chromosome.
    - 10.3 Generate number of genes, asterisks "*", of each chromosome $= B - 1$.
    - 10.4 Generate number of chromosomes.
        - 10.4.1 Choose two patient sequences or chromosomes, patient sequence 1 (PS1) and patient sequence 2 (PS2), from the population.
        - 10.4.2 Copy the genes from PS1 corresponding to the same positions in the new prospective patient sequence.
        - 10.4.3 Remove the genes from PS2 copied from PS1 to avoid any duplication in the new sequences.
        - 10.4.4 Complete the rest of the empty locations of the genes in the new sequence with unremoved genes that remain in PS2.
11. Apply the BPF algorithm.
    - 11.1 If $C = 1$, then
        - 11.1.1 Assign patient to the available bed where $T = 1$.
        - 11.1.2 Update $(ABL)_1$.
    - 11.2 Construct patient waiting list $(PWL)_C$, where $C = 2:5$.
    - 11.3 If $(PWL)_C > 0$, then
        - 11.3.1 If $C = 2:3$, then
            - 11.3.1.1 Apply the first-in first-out (FIFO) heuristic to $(PWL)_2 \cup (PWL)_3$.
            - 11.3.1.2 If $(ABL)_2 > 0$, then
                - 11.3.1.2.1 Assign patient to the available bed where $T = 2$.

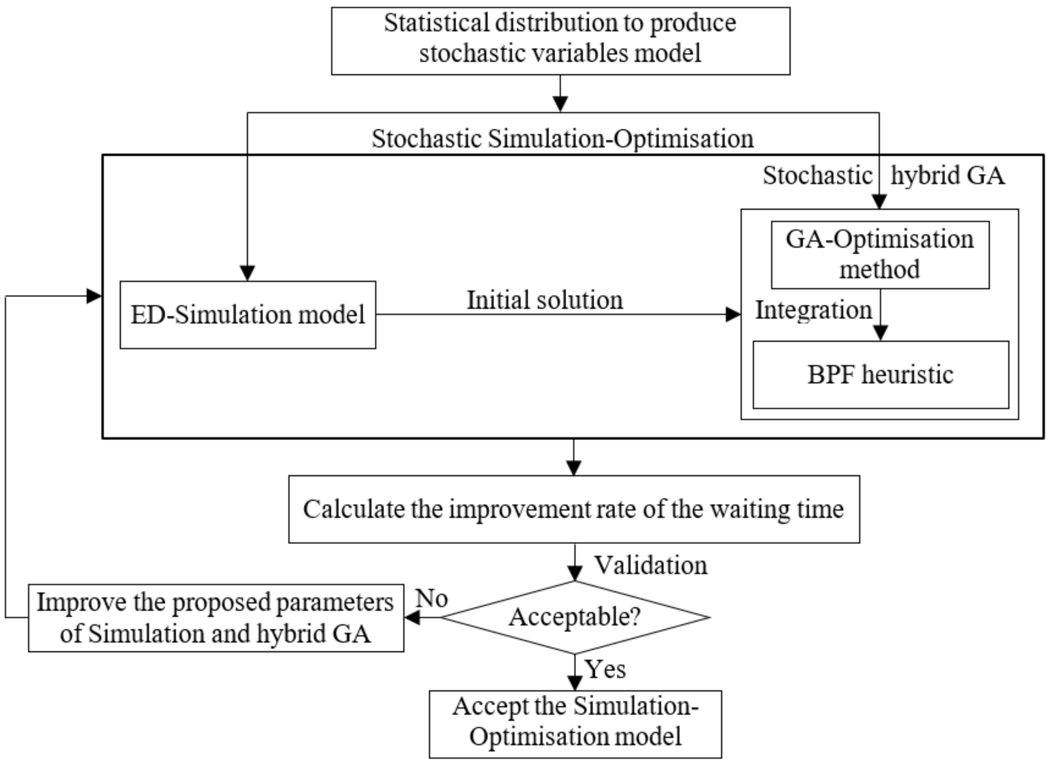

FIGURE 4. Framework of the stochastic Simulation-Optimisation model.

11.3.1.2.2 Update $(PWL)_2 \cup (PWL)_3$.
11.3.1.2.3 Update $(ABL)_2$.
11.3.1.3 Else
11.3.1.3.1 $(PWL)_2 \cup (PWL)_3 + 1$.
11.3.1.3.2 Update $(PWL)_2 \cup (PWL)_3$.
11.3.1.3.3 Go to step 11.3.

11.3.2 If $C = 4 : 5$, then

11.3.2.1 Apply the FIFS heuristic to $(PWL)_4 \cup (PWL)_5$.
11.3.2.2 If $(ABL)_3 > 0$, then
11.3.2.2.1 Assign patient to the available bed where $T = 3$.
11.3.2.2.2 Update $(PWL)_4 \cup (PWL)_5$.
11.3.2.2.3 Update$(ABL)_3$.
11.3.2.3 Else
11.3.2.3.1 $(PWL)_4 \cup (PWL)_5 + 1$.
11.3.2.3.2 Update$(PWL)_4 \cup (PWL)_5$.
11.3.2.3.3 Go to step 11.3.

12. Calculate the objective function value.
13. If the satisfied solution is obtained, maximum number of iterations or specificity solution has been reached, then stop.
14. Apply a crossover for any two solutions (sequences).
15. Apply a small mutation for each solution using the swap method and then go to Step 11.

The BPF heuristic integrates with GA by eliminating infeasible solutions that do not satisfy the blocking conditions and help to select the suitable candidates from the population for accelerating the GA operations. The integration between BPF and GA algorithms is explained in detail in Figure 5, where a numerical example is given to clarify the GA operations such as crossover and mutation. Figure 5 shows the initial population that includes three beds and eighteen patients that have been assigned to produce two initial schedules (chromosomes) as follow:

Initial Schedule 1: $\{P_1, P_2, P_3 * P_4, P_5, P_6, P_7 * P_8, P_9\}$, where $\{P_1, P_2, P_3\}$ is assigned to B_1, $\{P_4, P_5, P_6, P_7\}$ to B_2 and $\{P_8, P_9\}$ to B_3.

Initial Schedule 2: $\{P_{10}, P_{11}, P_{12} * P_{13}, P_{14}, P_{15}, P_{16} * P_{17}, P_{18}\}$, where $\{P_{10}, P_{11}, P_{12}\}$ is assigned to B_1, $\{P_{13}, P_{14}, P_{15}, P_{16}\}$ to B_2 and $\{P_{17}, P_{18}\}$ to B_3.

The values of some GA parameters are tuned up as follow:
Population size ($N_{pop} = 50$).
Maximum number of generations ($N_{gen} = 1000$).
Maximum number of stall generations ($N_{stall} = 100$).

The BPF algorithm is applied to the initial schedule to eliminate infeasible solutions and accept the reliable solutions. The crossover and mutation operators applied to find the better solutions are depicted in Figure 5. In this paper, a crossover probability cross is applied over the two selected parents (patient schedule 1 and patient schedule 2) to get a new offspring (offspring schedule 1 and offspring

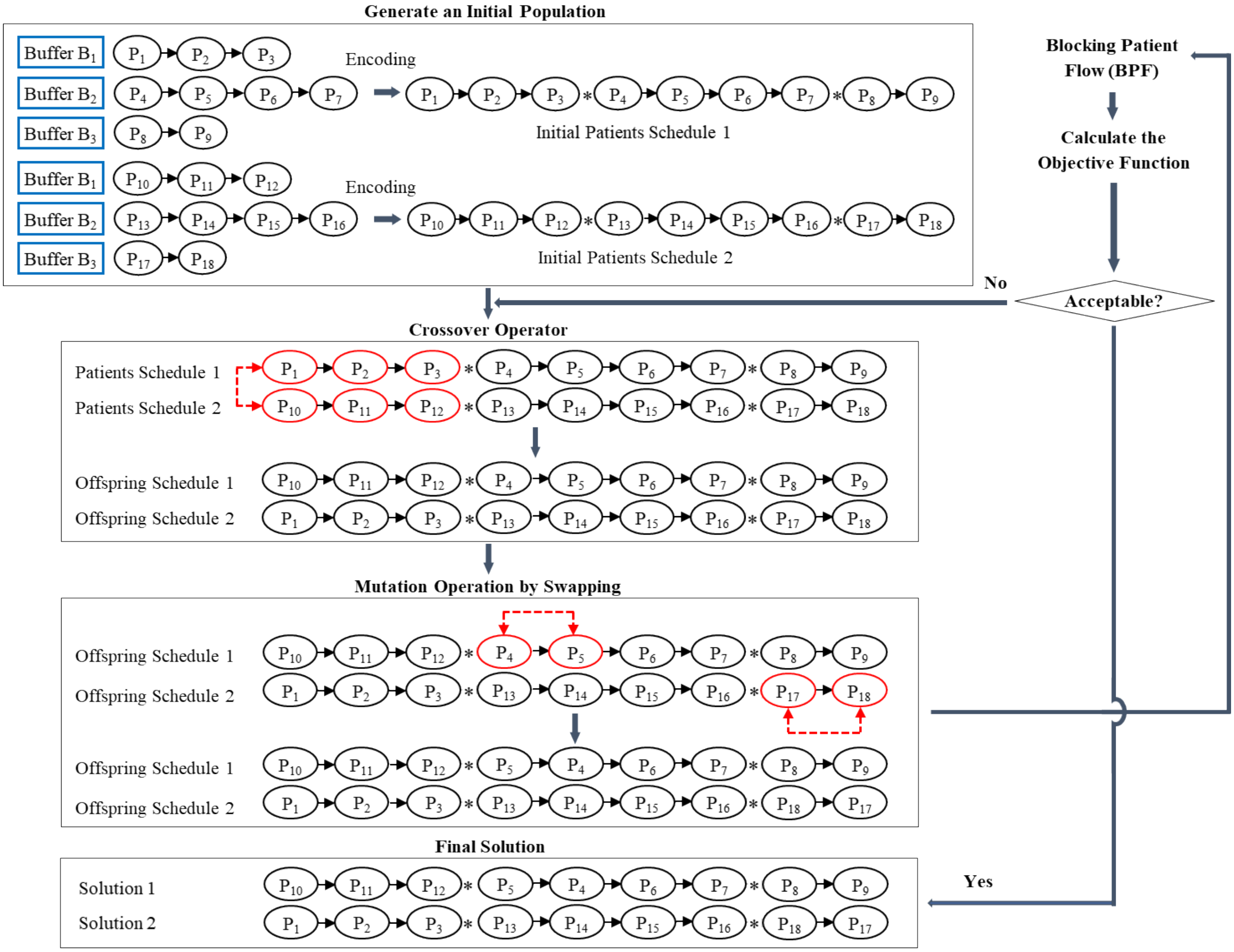

FIGURE 5. Hybrid Genetic operations with chromosome encoding (sequence of patients on beds).

schedule 2). The crossover will be done only in the same type of bed using different patients. Different patient groups will be changed in the schedules by the crossover considering the bed types. The mutation occurs with 50% probability. If it occurs, randomly select a bed type and two random indices in this bed type and swap the patient positions (i.e. a "bit flip" operation). The selection is randomly select two parents' queues indices m, n from the first half of the population with uniform probability, where $n \neq m$ and $1 \leq n \leq \frac{N_{pop}}{2}$, $1 \leq m \leq \frac{N_{pop}}{2}$. Moreover, randomly select parents' queues for one-bed type and generate offspring patient schedules. The mutation occurs, randomly select parents' queues for one-bed type and two random patients' schedule in this parents' queues for one-bed type and swap the patient positions (i.e. a "bit flip" operation). The maximum number of iterations (1000) has been used as a stop criteria.

V. COMPUTATIONAL EXPERIMENTS

The data was collected from the RBWH based on a real-world project. The patients used in the proposed model are classified into five categories, and three shifts are used in a day (day, evening, and night). As a stochastic element, the interarrival time of each patient in each shift follows a specific statistical distribution. ATS Categories in Australia are adopted according to the Australian College of Emergency Medicine [37], as shown in Table 1 below. Each disease group is distributed to the different ATS categories by specific ratios, as displayed in Table 2.

TABLE 1. Patient categories and recommended response times.

Australasian Triage Scale Category	Recommended Response Time
Category 1	Immediate
Category 2	10 minutes
Category 3	30 minutes
Category 4	60 minutes
Category 5	120 minutes

According to the RBWH data, the triage percentage for each ATS Category is classified in Figure 6 Most of the patients are concentrated in Category 3 and Category 4 with 42% and 33% respectively, and then Category 2 and

TABLE 2. Percentage of ATS categories for each type of disease.

Disease group number	Disease group name	Category 1	Category 2	Category 3	Category 4	Category 5
1	CARDIOVASCULAR	0.02	0.42	0.41	0.14	0.01
2	DERMATOLOGY	0	0.02	0.31	0.47	0.2
3	ENDOCRINE	0.05	0.18	0.59	0.16	0.02
4	ENT & MOUTH	0	0.03	0.37	0.46	0.14
5	ENVIRONMENTAL CONDITIONS	0.01	0.24	0.34	0.31	0.1
6	GASTROINTESTINAL	0	0.05	0.62	0.31	0.02
7	HAEMATOLOGY	0	0.16	0.58	0.24	0.02
8	IATROGENIC CONDITIONS	0	0.04	0.43	0.33	0.2
9	IMMUNOLOGICAL	0	0.25	0.62	0.13	0
10	INFECTIOUS	0	0.06	0.42	0.41	0.11
11	METABOLIC DISORDERS	0	0.13	0.5	0.33	0.04
12	MISCELLANEOUS CONDITIONS	0	0.04	0.24	0.27	0.45
13	NEOPLASIA	0.02	0.09	0.61	0.24	0.04
14	NEUROLOGICAL	0.03	0.14	0.57	0.24	0.02
15	OBSTETRIC & GYNAE	0	0.04	0.66	0.28	0.02
16	OPHTHALMOLOGY	0	0.11	0.43	0.36	0.1
17	ORTHOPAEDIC CONDITIONS	0	0.03	0.26	0.52	0.19
18	PAEDIATRIC CONDITIONS	0.01	0.06	0.64	0.26	0.03
19	PSYCHIATRIC	0	0.29	0.38	0.2	0.13
20	RENAL	0	0.06	0.72	0.21	0.01
21	RESPIRATORY	0.02	0.19	0.58	0.19	0.02
22	SYMPTOM CODES - NO DIAGNOSIS	0	0.06	0.62	0.3	0.02
23	TOXICOLOGY	0.01	0.15	0.3	0.26	0.28
24	TRAUMA	0.01	0.11	0.31	0.46	0.11
25	UROLOGY	0	0.07	0.54	0.35	0.04
26	Unknown Diagnostic	0	0.02	0.28	0.39	0.31

Category 5 with 13% and 11% respectively, while the lowest number is assigned to Category 1 with 1%.

In this model, stochastic variables, such as the patient interarrival time per shift and treatment time per patient category, are defined using statistical distributions. Table 3 shows how two candidate probability distributions fit the random variables in real time. The green parts show the distribution which better fit the data. Day interarrival time follows Person Type 6, evening interarrival time follows Weibull distribution; and finally, night interarrival time uses Gamma distribution. Moreover, the treatment times for five categories of patients are distributed using Erlang, LogLogistic, Weibull, Exponential, and Weibull distributions.

Table 4 shows the percentage of patients' arrival hourly for three shifts: day shift from 9 am to 7 pm, evening shift from 7 pm to 12 am, and night shift from 12 am to 9 am. It can be seen in Table 4 that most of the patients arrived during the day shift.

Table 5 presents a comparative study using Simulation only and using the integrated Simulation-Optimisation approach. The Simulation approach applies many sequencing rules such as first come first served (FCFS), and shortest processing time (SPT) for a comparison. Five categories of patients are tested to evaluate the waiting time performance. In this experiment, 18,345 patients were treated in the ED during a three-month time window, where 12,397 patients

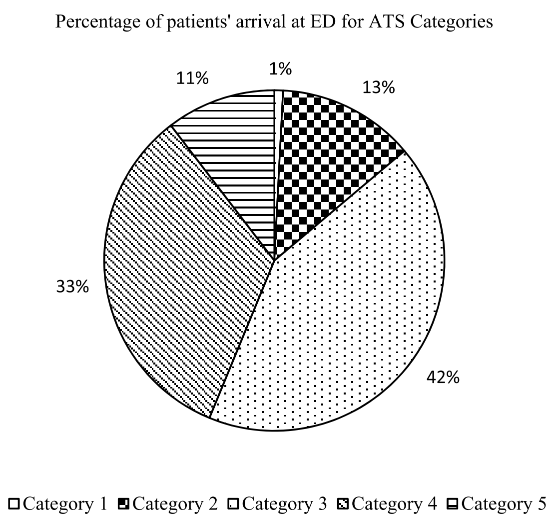

FIGURE 6. Percentage of patients' arrivals for ATS categories.

TABLE 3. Probability distributions to fit the real data.

	Day interarrival time	
Candidate distributions	**Pearson 6**	**Erlang**
Maximum likelihood estimates	beta = 3544.07 p = 1.35028 q = 3.96294	m = 1 beta = 1539.71
Goodness of fit (Kolmogorov-Smirnov)	Stat 7.13e-002 p-value 0.605	Stat 7.22e-002 p-value 0.588
	Evening interarrival time	
Candidate distributions	**Exponential**	**Weibull**
Maximum likelihood estimates	beta = 145.906	alpha = 1.04513 beta = 148.56
Goodness of fit (Kolmogorov-Smirnov)	Stat 2.47e-002 p-value 0.11	Stat 2.4e-002 p-value 0.129
	Night interarrival time	
Candidate distributions	**Gamma**	**Weibull**
Maximum likelihood estimates	alpha = 1.29077 beta = 365.506	alpha = 1.15287 beta = 496.706
Goodness of fit (Kolmogorov-Smirnov)	Stat 5.02e-002 p-value 0.303	Stat 5.29e-002 p-value 0.253
	Treatment time for category 1	
Candidate distributions	**Erlang**	**Exponential**
Maximum likelihood estimates	m = 1 beta = 134.172	beta = 135.451
Goodness of fit (Kolmogorov-Smirnov)	Stat 2.15e-002 p-value 0.156	Stat 2.32e-002 p-value 0.101
	Treatment time for category 2	
Candidate distributions	**LogLogistic**	**Pearson Type 6**
Maximum likelihood estimates	p = 2.29149 beta = 125.867	beta = 185.453 p = 2.96721 q = 4.26036
Goodness of fit (Kolmogorov-Smirnov)	Stat 6.78e-002 p-value 0.579	Stat 7.87e-002 p-value 0.387
	Treatment time for category 3	
Candidate distributions	**Weibull**	**Exponential**
Maximum likelihood estimates	alpha = 1.00503 beta = 66.7348	beta = 66.413
Goodness of fit (Kolmogorov-Smirnov)	Stat 1.76e-002 p-value 0.241	Stat 1.82e-002 p-value 0.206
	Treatment time for category 4	
Candidate distributions	**Exponential**	**Weibull**
Maximum likelihood estimates	beta = 79.5728	alpha = 1.00678 beta = 79.9256
Goodness of fit (Kolmogorov-Smirnov)	Stat 1.86e-002 p-value 0.32	Stat 2.08e-002 p-value 0.205
	Treatment time for category 5	
Candidate distributions	**Gamma**	**Weibull**
Maximum likelihood estimates	alpha = 1.40007 beta = 92.6968	alpha = 1.21178 beta = 138.537
Goodness of fit (Kolmogorov-Smirnov)	Stat 1.69e-002 p-value 0.438	Stat 2.23e-002 p-value 0.145

TABLE 4. Percentage of patients' arrival for three shifts.

Shift name	Start time	Finish time	Arrived patient number	Percentage of arrivals for each shift hourly	Percentage of total arrivals hourly
Day	9:00 am	10:00 am	1098	10.31%	5.99%
Day	10:00 am	11:00 am	1202	11.28%	6.55%
Day	11:00 am	12:00 pm	1198	11.25%	6.53%
Day	12:00 pm	1:00 pm	1074	10.08%	5.85%
Day	1:00 pm	2:00 pm	1100	10.33%	6.00%
Day	2:00 pm	3:00 pm	1083	10.17%	5.90%
Day	3:00 pm	4:00 pm	1037	9.74%	5.65%
Day	4:00 pm	5:00 pm	946	8.88%	5.16%
Day	5:00 pm	6:00 pm	956	8.97%	5.21%
Day	6:00 pm	7:00 pm	958	8.99%	5.22%
Evening	7:00 pm	8:00 pm	910	23.74%	4.96%
Evening	8:00 pm	9:00 pm	876	22.85%	4.78%
Evening	9:00 pm	10:00 pm	771	20.11%	4.20%
Evening	10:00 pm	11:00 pm	686	17.89%	3.74%
Evening	11:00 pm	12:00 am	591	15.41%	3.22%
Night	12:00 am	1:00 am	502	13.01%	2.74%
Night	1:00 am	2:00 am	422	10.94%	2.30%
Night	2:00 am	3:00 am	389	10.08%	2.12%
Night	3:00 am	4:00 am	329	8.53%	1.79%
Night	4:00 am	5:00 am	280	7.26%	1.53%
Night	5:00 am	6:00 am	281	7.28%	1.53%
Night	6:00 am	7:00 am	327	8.47%	1.78%
Night	7:00 am	8:00 am	523	13.55%	2.85%
Night	8:00 am	9:00 am	806	20.89%	4.39%

were discharged, and 5,948 patients were admitted from the ED. In Table 5, Wilcoxon rank-sum test [38] was used which is a is a nonparametric test. The null hypothesis of this test is that a metric observed from the 50 runs of the Simulation and Simulation-Optimisation approaches are shown in Figure 7 from continuous distributions with equal medians, against the alternative that they are not. In Table 5, we reject the null hypothesis of each metric which is good. So, we can conclude that the proposed approach improvement is statistically significant. The data sensitivity analysis was implemented by MATLAB software.

The Simulation and Simulation-Optimisation models are run for three months, and results are averaged from 50 runs [39]. The Simulation-Optimisation approach execution time for 50 runs was around 3 hours and 33 minutes. Verification and validation of the simulation models are critical in determining the correctness of these simulation models [40], [41]. Because of the system starting in an empty state, the model had warm-up periods that are ranged between 7-11 days. The total waiting time

TABLE 5. Comparison of results before and after using optimiser.

	Simulation Approach		Simulation-Optimisation Approach		Improvement	
Criteria	Average	Standard deviation	Average	Standard deviation	Average improvement	P-value
Resuscitation bed utilisation (%)	5.50	0.03	13.19	0.15	7.69	7.07E-18
Acute bed utilisation (%)	40.75	0.04	53.25	0.53	12.50	7.07E-18
Fast track bed utilisation (%)	88.04	0.08	98.75	0.32	10.71	7.07E-18
Category 1 waiting time performance (%)	82.32	3.23	93.48	2.08	11.16	7.07E-18
Category 2 waiting time performance (%)	93.40	0.71	95.20	0.67	1.80	6.32E-16
Category 3 waiting time performance (%)	92.44	0.61	98.05	0.39	5.60	7.07E-18
Category 4 waiting time performance (%)	73.24	2.75	90.31	1.17	17.07	7.07E-18
Category 5 waiting time performance (%)	67.63	5.56	83.80	1.46	16.17	7.07E-18
Overall waiting time performance (%)	83.13	1.74	93.27	0.67	10.14	7.07E-18
Average length of stay (min)	166.27	3.38	159.79	8.07	6.48	7.19E-06
Total waiting time of all patients (min)	692251.02	117135.44	368671.30	66638.59	323579.72	1.08E-17
Total waiting time of Category 1 patients (min)	1392.91	355.18	741.77	237.99	651.14	2.80E-14
Total waiting time of Category 2 patients (min)	73706.35	18794.67	39253.54	12594.33	34452.81	5.88E-14
Total waiting time of Category 3 patients (min)	336241.01	85739.41	179071.39	57454.28	157169.62	1.67E-13
Total waiting time of Category 4 patients (min)	231494.14	59029.60	123286.63	39555.99	108207.51	3.85E-14
Total waiting time of Category 5 patients (min)	49416.61	12600.94	26317.97	8444.01	23098.64	7.64E-14
Makespan	129563.70	12.24	129444.20	11.33	119.50	7.06E-18
Maximum queue length	51	10.84	32	6.32	19	7.37e-15

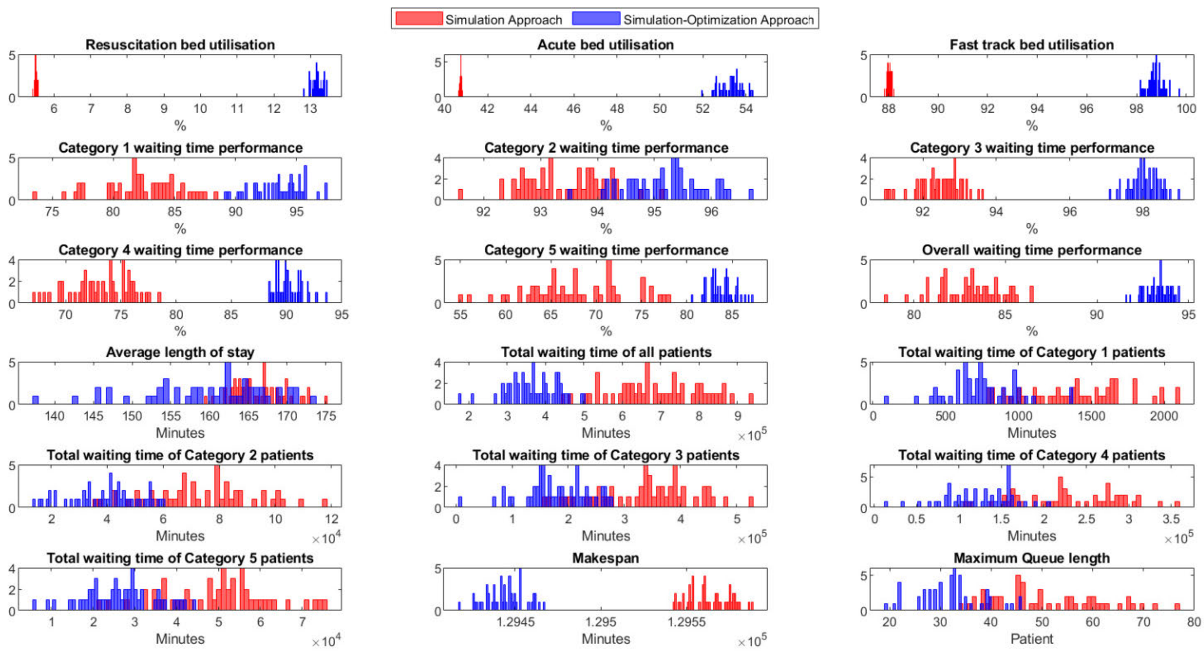

FIGURE 7. Distributions of Simulation and Simulation-Optimisation approaches.

of all patients has been determined to be 692251.02 and 368671.3 minutes for the Simulation and Simulation-Optimisation approaches respectively with improvement 15652.98 and 339232.7 minutes in comparison to the current practice (707904 minutes). The Simulation approach has not provided a big improvement rate which is less than 0.02 and

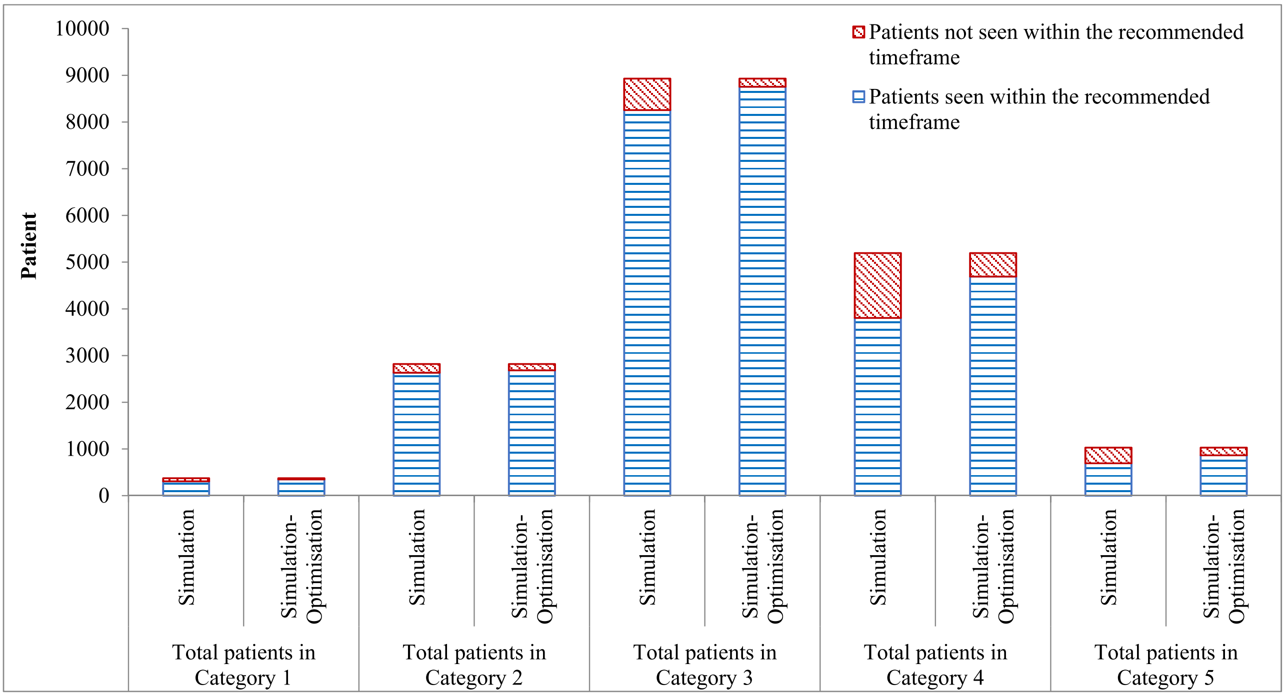

FIGURE 8. **Comparison of results by Simulation only and Simulation-Optimisation.**

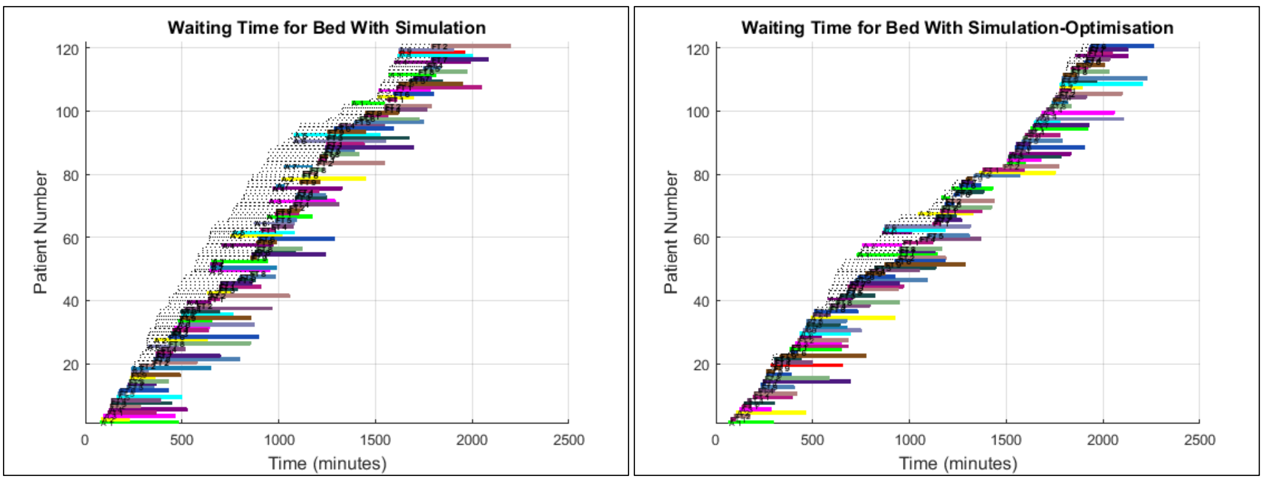

FIGURE 9. **Patients' waiting time for scheduling 120 patients using Simulation and Simulation-Optimisation approaches.**

not significant, and the solution results are very close to the practice in the three months period. In contrast, the improvement rate of the Simulation-Optimisation approach is 0.47. The average length of stay in ED has been determined to be 166.27 and 159.79 minutes for the Simulation and Simulation-Optimisation approaches respectively. Furthermore, the capacity of the resources was kept the same before and after optimisation. As shown in Table 5, waiting time performance and bed utilisation improved by using the GA optimiser, where three bed types were assessed according to their utilisation. Resuscitation bed utilisation improved by 7.69%, Acute bed utilisation improved by 12.5%, and Fast track bed utilisation improved by 10.71%. With the integration of GA, the patient waiting times reduced by approximation 11.16%, 1.8%, 5.6%, 17.07%, and 16.17% for Categories 1-5 respectively. Moreover, Table 5 shows that the total waiting time of all patients in the system improved by 5,393 hours during the three-month time window (up to 47% on efficiency improvement). Table 5 shows that the average length of stay in ED improved by 6.48 minutes during the three-month time window (up to 4% on efficiency improvement). The total waiting times for different categories improved

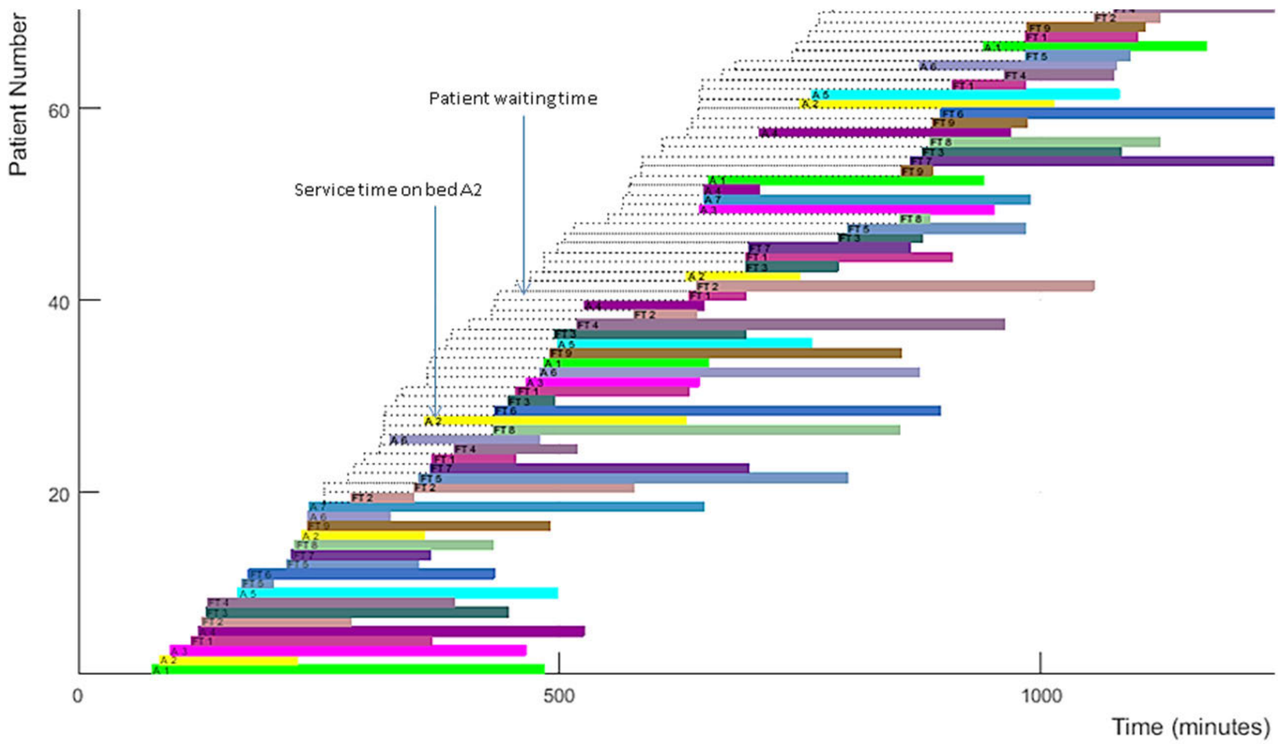

FIGURE 10. A detailed analysis of the patients' waiting times and bed types of Figure 9.a.

in minutes by 651.14, 34452.81, 157169.62, 108207.51, and 23098.64 for Categories 1-5 respectively. The most effective improvement was for Category 3. The completion times for the last operation were 129563.7 and 129444.2 for three months for the Simulation and Simulation-Optimisation approaches respectively. The averages of maximum queue length of patients in ED were 51 and 32 for three months for the Simulation and Simulation-Optimisation approaches respectively. Table 5 shows that the average of maximum queue length of patients in ED improved by 19 patients during the three-month time window (up to 37% on efficiency improvement).

Figure 8 shows that the hybrid GA improved the number of patients that were seen within the recommended timeframe, specifically for Categories 3-5.

Figure 9 compares the waiting times for scheduling 120 patients using the Simulation and Simulation-Optimisation approaches. Figure 9.a and Figure 9.b show the patient waiting time for 120 patients (vertical axis) as a sample within 2,500 minutes (horizontal axis) using the Simulation and Simulation-Optimisation approaches. The patients occupied three types of bed: resuscitation (R), acute (A), and fast track (FT) bed. Resuscitation included one bed (R1), the acute bed type included seven beds (A1,.., A7), and the fast track bed type included nine beds (FT1,.., FT9). The time that each patient spends in the system includes treatment time (coloured rectangle) for a specific bed and waiting time before starting treatment (white rectangle). The improvements in the patient waiting time are very clear, as the hybrid GA improved the patient waiting time.

Figure 10 evaluates the patient waiting times in detail considering the bed types. For instance, Patient 9 occupied bed A5 (light blue) from the 165th minute to the 497th minute with no waiting time, while Patient 35 occupied the same bed from the 497th minute to the 761st minute with a waiting time from the 382nd minute to the 497th minute.

VI. CONCLUSION

This paper presents a new integrated Simulation-Optimisation approach to improve the overall efficiency and effectiveness of the ED under a limited budget and resource capacity. A Simulation approach is developed to deal with the uncertainties by defining stochastic variables, such as patient interarrival times and treatment times, in the ED system. A construction algorithm is developed to build the initial solution that is improved by a hybrid GA. Based on the real-world data collected from the RBWH, extensive computational experiments show that the proposed approach results in an average improvement in the total waiting time performance of 10.14%. Using the proposed hybrid GA for a real-world case study, the patient queue length can be significantly reduced during a three-month time window. Furthermore, three bed types are investigated in this paper and their improvement rates are calculated and compared using the Simulation and Simulation-Optimisation approaches. The improvement rate of the utilisation for three types of bed is 10.3% on average. The completion time of the patient's last operation in the system (the makespan) improved by 119.5 minutes, implying that the availability of the resources in the system is increased during the next time window. The average of maximum queue length of patients in ED improved by 19 patients during the three-month time window. In summary, the proposed Simulation-Optimisation approach is promising for real-world implementation to improve the ED efficiency. The current research will be expanded to involve integrating the ED with other inpatient units to improve the ED's performance. The prospective mathematical model will be developed for the integrated medical units, and hybrid metaheuristic techniques will be used to solve large scale size problems.

ACKNOWLEDGMENT

The authors acknowledge Dr. John Burke and all the staff in the Emergency Department of the Royal Brisbane and Women's Hospital (RBWH), Australia.

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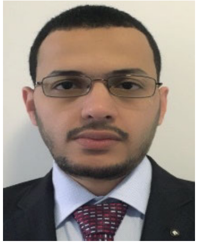

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