

Research Article

An Analytical Optimisation Framework for Airport Terminal Capacity Expansion

Sultan Alodhaibi ¹, **Robert L. Burdett**,² and **Prasad K. D. V. Yarlagadda**³

¹Department of Mathematics, College of Sciences and Arts in Al-Rass, Qassim University, Buraidah 51921, Saudi Arabia

²School of Mathematical Science, Science and Engineering Faculty, Queensland University of Technology, Brisbane, QLD 4001, Australia

³School of Mechanical Medical and Process Engineering, Science and Engineering Faculty, Queensland University of Technology, Brisbane, QLD 4001, Australia

Correspondence should be addressed to Sultan Alodhaibi; sathaieby@qu.edu.sa

Received 5 May 2020; Revised 26 June 2020; Accepted 29 July 2020; Published 5 October 2020

Guest Editor: Baogui Xin

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This article considers how to allocate additional physical resources within airport terminals. An optimization model was developed to determine where additional resources should be placed to minimise passenger waiting times. The objective function is stochastic and can only be evaluated using discrete event simulation. As this model is stochastic and nonlinear, a Simulated Annealing (SA) metaheuristic was implemented and tested. The SA algorithm repeatedly perturbs a resource allocation solution using one of two methods. The first method is creating new solution randomly in each iteration, and the second method is local search that is mimicked by any move of the current solution of x solution chosen randomly in its neighborhood. Numerical testing shows that the random approach is best, and solutions that are 12.11% better can be obtained.

1. Introduction

The high growth in passenger numbers in recent years has created considerable strains on airports. Airport terminals are expected to process the increasing passenger numbers efficiently and with minimum delay. At the same time, the required expansion of the airport capacity might be limited by the available resources (e.g., limited available land), environmental impacts, and lengthy approval processes [1]. In addition, extension of the major airport infrastructure is typically time-consuming and costly, which raises the need for the development of smart systems and methods to improve airport performance within the available infrastructure.

Airport terminals are complex systems and are inherently stochastic in nature. Passenger numbers continually change throughout the day, depending on the status of incoming or outgoing flights. It is an integrated system, and operational problems within any of its internal processes can

jeopardise the performance of other elements, creating significant bottlenecks, long passenger queues, congestion, and overall delays [2–4]. For example, disruption, congestion, and uneven passenger inflow into the terminal processing points, caused by the operation of the landside element (including the infrastructure and facilities associated with the arrival of passengers to the airport), could have a significant impact on the performance of the terminal (such as passenger boarding and take-off procedures). It involves multiple stakeholders, and each is responsible for performing particular terminal process such as check-in, security, and immigration [5].

It is conventional to subdivide airport operations into those relevant to the arrival procedures of incoming passengers and departure procedures for outgoing passengers. The arrival processes and facilities include disembarking, immigration, baggage claim, and quarantine procedures [6]. The departure processes and facilities include check-in, security screening, immigration and customs, boarding, and

take-off procedures. It is these departure flow processes that have the greatest impact on the entire operation of passenger terminals and other elements of the airport. According to Neufville and Odoni [7], the departure process requires significantly more time than the arrival process because it sometimes involves services provided to transit passengers. Due to the complex structure of airport terminals, the development of an analytical optimization framework for studying passengers flow in airports under uncertainty of future demand is a difficult task. These difficulties and challenges have led to studies of overall terminal capacity planning problems. Previous studies have generally focused on one element of the terminal or have not accounted for expandability [8]. The general aim of this paper is to propose a mathematical approach for capacity expansion planning. This model will determine where additional resources should be placed within airport terminal processes. Hence, the objective function of the proposed model is to minimise the cost of used resources and the total waiting time. A number of technical constraints exist.

The main contribution of this work is to provide a Capacity Expansion Planning Model (CEPM) for airports. Therefore, this paper has contributed to the body of knowledge by enabling two levels of planning, operational and strategic. In comparison with existing approaches, the new approach is more accurate because real waiting time can be identified and effects of uncertainty can be included. For example, Sun and Schonfeld [9] used mathematical functions, which are more approximate.

2. Related Work

This section analyses existing research conducted to address the issues of passenger flows within airports. The irregular flows occurring in airport terminal areas represent a significant management challenge, for instance, determining the number of service counters to open, and personnel allocation and reallocation issues [5–8, 10, 11]. A significant problem when studying passenger flow is capturing stochastic elements. This is because, as Guizzi et al. [12] argued, passengers behave differently inside airports according to their previous experiences. Thus, in order to assist decision-makers at the airport terminal to address sudden and unforeseen congestion conditions, extensive research has been conducted on uncertainty. Yamada et al. [13] examined links between passenger behavior and facilities and identified several sources of congestion.

Additionally, Alodhaibi et al. [14] conducted their research using a simulation framework developed in [15] to investigate how the arrival pattern of passengers affects international terminal operations. The simulation outcomes provided a better understanding of the behavior of passenger airport access, which could lead to reduced waiting time and possible congestion by increasing the number of working stations (i.e., number of check-in counters) at peak times.

Safety concerns in recent times have caused many changes to security screening procedures and this impacts passenger throughput times. Previous research can be categorized according to related topic areas, including the

significance of the security screening system in airport operations, the capacity of security screening areas, and dynamic system management [16–21]. For instance, Dorton and Liu [21] proposed the application of a DES for the security screening system coupled with a queuing. The aim is to analyze external factors influencing security screening operation efficiency and to identify the effect on throughput and cycle time.

In airport apron areas, a common optimization problem is gate assignment, which considers the minimization of passenger walking distance, from check-in to baggage claim area. Genç et al. [22] applied a heuristic to solve stochastic approaches to minimise the total duration of ungated flight. Similarly, Ding et al. [23] applied a Tabu Search metaheuristic to identify the problem when the number of aircraft exceeds the number of available gates. The two objective functions optimized were number of ungated aircraft and total walking distance. Finally, the research by Mota [24] is noteworthy as a mix of two models was applied to satisfy the different mandatory restricted policies related to airport terminal processing units, such as opening or closing check-in counters for each flight, check-in starting time, and load balance.

Capacity planning problems feature prominently in airport terminal research. For instance, Solak et al. [8] considered terminal operations to be a network system and used a multistage stochastic-integer linear programming model to determine the optimal capacity, taking into account optimal future expansion and desired LOS. The main objective was to minimise the maximum delay of each passageway and processing station by considering the variation in demand as a significant constraint. Also, Sun and Schonfeld [9] investigated uncertainties within the terminal. They found that facility performances are nonlinear functions. These functions are represented by delay level as a function of utilisation rates of capacity and demand fluctuations as indicated by uncertainties in traffic predictions. It is known that passenger departure flow is an important process for any airport facility because of the fixed departure time of flights. The same researchers [25, 26] go further by considering strategic airport facility planning under demand uncertainty and proposed a mixed-integer nonlinear program to determine when and where to adjust process capacity over a number of planning periods. Airport congestion and delay cost are approximated using some appropriate mathematical functions.

The novelty of our work lies in integrating a discrete event simulation to an optimization model for airport terminal capacity planning. Hence, undertaking such research is significant to identify a real waiting time and to know the effect of decision. Other models like Sun and Schonfeld's [9, 27], for instance, use mathematical functions, which are exact. Furthermore, in [26], the same authors used a discrete approximation technique when the model is solved where the mathematical relations in the formulation are accurate. Hence, a simulated annealing metaheuristic was applied to perform airport terminal capacity expansion and this may be the first application of such an approach to this domain.

3. Problem Description and Formulation

This section defines the variables and parameters used in our capacity expansion model. The purpose of the model is to determine where additional resources should be placed in order to reduce the waiting costs. Each resource type has different costs, and a budget for total spending has been provided.

3.1. Model Notation

(i) Indices

p, r, k, t, f : process, resource, passenger types, period, and shift.

(ii) Sets

P, R, K, T, F : processes, resources, passenger types, periods, and shifts.

(iii) Parameters

$\bar{N}_{r,p}, \bar{N}_r$: maximum number of resources of type r in process p and across all processes
 $C_{r,p}$: cost of providing a resource of type r in process p
 $V_{k,p}$: cost incurred per unit of waiting time for passengers of type k in process p
 B : total budget available for capacity expansion
 $n_{r,p}$: current number of resources of type r in process p
 $\tau_{k,p}$: expected time taken to serve passenger k in process p .

(iv) Decision variables

$N_{r,p}$: number of resources to open of type r in process p
 $W_{k,p}$: total waiting time incurred in process p for passengers of type k .

The model is as follows:

$$\text{minimize } \sum_p \sum_r C_{r,p} N_{r,p} + \sum_k \sum_p V_{k,p} W_{k,p} \quad (1)$$

[resource cost + cost of waiting],

subject to

$$N_{r,p} \leq \bar{N}_{r,p}, \quad \forall p \in P; \forall r \in R \quad \text{[upper bound]}, \quad (2)$$

$$\sum_p N_{r,p} \leq \bar{N}_r, \quad \forall r \in R \quad \text{[upper bound]}, \quad (3)$$

$$\sum_r C_{r,p} N_{r,p} \leq B, \quad \forall p \in P \quad \text{[budget constraints]}, \quad (4)$$

$$f_{r,p} \leq F_{r,p}, \quad \forall p \in P; \forall r \in R \quad \text{[shift constraints]}, \quad (5)$$

$$N_{r,p} \geq 0, \quad \forall p \in P; \forall r \in R \quad \text{[positivity]}, \quad (6)$$

$$W_{k,p} = \text{SIMULATE}(N_{r,p}, \tau_{k,p}) \quad (7)$$

[calculation of waiting time via simulation].

The objective function (1) has two components: (i) the cost of purchasing/acquiring additional resources of type r in process p and (ii) the total passenger waiting time converted to a dollar value. Constraints (2) and (3) ensure that the additional resources of type r do not exceed the maximum number of resources. Constraint (4) restricts spending to a particular budget. Constraint (5) restricts the decision variable $N_{r,p}$ to be positive. The waiting time of passengers at different processes is a stochastic auxiliary variable and depends on the number of resources assigned and the processing time, which is a random variable. It is computed using simulation in equation (7) using the simulation model from [11, 15].

3.2. Simulated Annealing. To solve the proposed model, a metaheuristic approach is advocated as constraint (7) cannot be handled using mixed-integer programming, without the application of a simulation model. Of the different metaheuristics, simulated annealing was chosen. It is an effective and computationally fast search algorithm for solving hard optimization problems by Burdett and Kozan [27–29] and is well suited to probabilistic and nonlinear optimization problems. The algorithm is iterative and comprises two nested “for” loops. The outer loop controls and alters the “temperature” parameter T . In the inner loop, a specified number of solution refinements (a.k.a. perturbations) are entertained and evaluated. Refinements are accepted when they are explicitly better; otherwise, they are accepted/rejected probabilistically according to the following function:

$$P(\Delta f) = e^{-1 * (\Delta f / T)}, \quad (8)$$

where $\Delta f = f' - f$ is the difference between the new solution f' and the current solution f . At every temperature, a selected number of perturbations are evaluated. SA requires several parameters (i.e., primary temperature, the cooling rate, the number of function evaluations at every temperature, and the final temperature). At early stages of the search, the temperature is high and many nonimproving moves are accepted. As the search progresses, the temperature is reduced and solutions are only accepted if a strict improvement occurs. With the slow reduction in temperature, worse solutions are accepted with less probability. The SA metaheuristic was implemented in C++ and the simulation model was integrated to evaluate the waiting times. Preliminary numerical testing was performed to identify an appropriate starting temperature (see Figure 1). It is evident from the graph below that the best parameter values of this problem are as follows: temperature (T) = 15000, cooling rate (α) = 0.015, and total number of iterations = 600.

3.2.1. Simulated Annealing Algorithm Description

(1) Phase 1: Create Initial Solution. SA may be initialized with a randomly created solution or via some heuristic/constructive algorithm. However, because of the resource limitation constraints, some of the generated solutions will

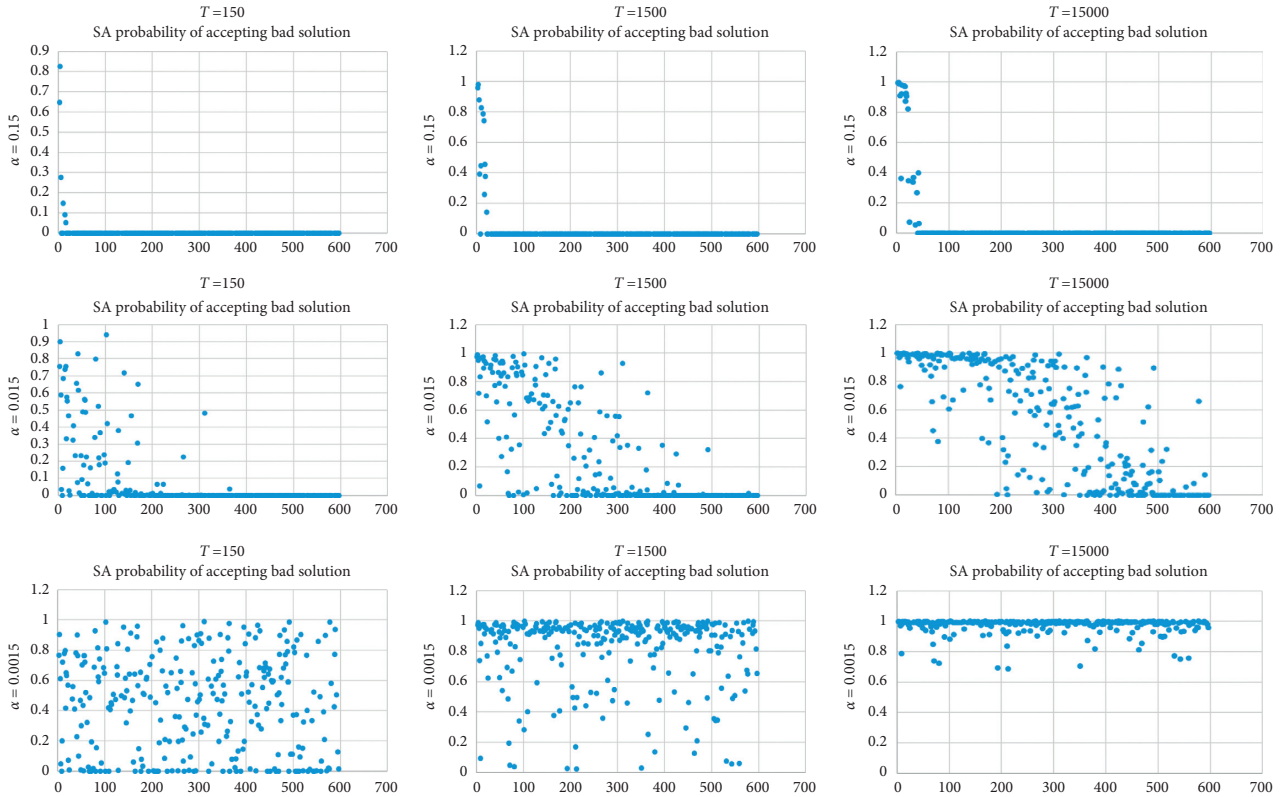


FIGURE 1: Selecting the best initial parameters.

not be feasible. The solution chromosome should simultaneously reflect two main characteristics:

- (i) Number of resources for each process, such as check-in resources (i.e., economy and business counters), security screening resources, and immigration resources (i.e., common counters and SmartGates).
- (ii) The number of assignment resources for each shift.

These solutions should be corrected via a corrective algorithm. Algorithm 1 is used to initialize a set of solutions.

(2) *Phase 2: Perturbing a Solution.* To create a new solution, it is necessary to perturb the current solution. There are many perturbation techniques that can be applied. In this article, a new solution is created by randomly changing the number of resources assigned to a randomly selected airport process. The creation of a new solution is performed by Algorithm 2.

(3) *Phase 3: Assess New Solution.* In this step, the goodness of the new solution is evaluated. Algorithm 3 demonstrates the assessment procedures. The generated solution will be simulated to measure a performance matrix, such as the average waiting time at each processing point. Also, the best cost will be selected by comparing it with the current cost.

(4) *Phase 4: Stop Criteria.* Finally, the condition of stopping the SA algorithm is based on the given maximum number of iterations. Algorithm 4 is an illustration of the main loop of the stopping criteria algorithm.

4. Numerical Testing and Analysis

In this section, the SA metaheuristic approach coupled with discrete event simulation is analyzed. In this numerical investigation, there are three types of process and five types of resources that were considered. Process type 1, the check-in process, has five separate lines, each with eight counters, two for business and six for economy. Process type 2 is security screening with five lanes. Process type 3 is immigration, which has eight common counters and 10 SmartGates. It is assumed that there are three periods during the day to which these processes are assigned to be operated. Figure 2 is a snapshot of the simulation outputs, for instance, the appropriate number of resources that need to be opened, the average waiting time that passengers spent at each process, and the cost of resources ending with the total cost.

The cost of waiting time is considered based on the given policy of acceptable queue time in a particular process. This is named the cost of inconvenience, as it exceeds given acceptable average waiting time. For example, passengers at the check-in process can be classified as business and economy, each with different queue time limits. Kazda and Caves [30] argued that the average waiting time should not be higher than 12 minutes for economy class and 3 minutes for business. The summary of input data used in this study is listed in Table 1.

Two different methods of creating new solutions were used to generate a starting solution. The first is creating a new solution randomly and the second is local search. The

```

(a) For (each Shift);
(2) For (each process  $p_1$ );
(3)   do
(4)      $N_{r_{1,1},p_1} \leftarrow U(1, r_{1,1})$ ; //Select resources of type 1 in process  $p_1$ 
(5)      $N_{r_{1,2},p_1} \leftarrow U(1, r_{1,2})$ ; //Select resources of type 2 in process  $p_1$ 
(6)      $X \leftarrow N_{r_{1,1},p_1} + N_{r_{1,2},p_1}$ ; economy and business counters;
      } while  $x \leq r_{1,1} + r_{1,2}$ ;
(7)   End
(8)  $N_{r_{2,p_2}} \leftarrow \text{Uniform}(1, \overline{N}_{r_{2,p_2}})$ ;
(9)  $N_{r_{n,p_n}} \leftarrow \text{Uniform}(1, \overline{N}_{r_{n,p_n}})$ ;
(10) End

```

ALGORITHM 1: CreateSolution.

```

(1) If (change in process  $p_1$ );
(3)   while  $x \leq$  number of available  $r_{1,1}$  and  $r_{1,2}$  do
(4)      $N_{r_{1,1},p_1} \leftarrow U(1, r_{1,1})$ ; //Select resources of type 1 in process  $p_1$ 
(5)      $N_{r_{1,2},p_1} \leftarrow U(1, r_{1,2})$ ; //Select resources of type 2 in process  $p_1$ 
(6)      $X \leftarrow N_{r_{1,1},p_1} + N_{r_{1,2},p_1}$ ;
(7)   Else If (change in  $p_2$ )
(8)      $N_{r_{2,p_2}} \leftarrow U(1, \overline{N}_{r_{2,p_2}})$ ;
(9)   Else
(10)     $N_{r_{n,p_n}} \leftarrow U(1, \overline{N}_{r_{n,p_n}})$ ;

```

ALGORITHM 2: PerturbSolution.

```

(1) Function Local Search();
(2) cost ← Simulate();
(3) If (cost < best);
(4)   Update Best solution;
(5)   best ← cost;
(6) Else
(7)   If (cost < current);
(8)     Update Current solution;
(9)     current ← cost;
(10) Else
(11)    $prob = e^{-1 * ((cost - current) / T)}$ 
(12)   If ( $U(0, 1) > prob$ )
(13)     Reject the new solution;
(14)   Else
(15)     Accept the new solution
(16)

```

ALGORITHM 3: EvaluateSolution.

```

(1) Parameter initialisation
(2) CreateSolution();
(3) Simulate();
(4) do
(5)   PerturbSolution();
(6)   EvaluateSolution();
(7)    $x \leftarrow x + 1$ ;
(8) } while ( $x < max\_iter$ )

```

ALGORITHM 4: Main loop.

random search method initializes SA with a randomly created solution, while the local search initializes SA via constructive algorithm by changing one solution chromosome and then refinement by SA. For each method, 10 runs were repeated with the same parameters. The results of the runs are presented in Tables 2 and 3. The general parameters used for both methods are as follows: temperature (T) = 15000, cooling rate (α) = 0.015, and the maximum number of runs = 1500.

The first column refers to the number of better solutions, where the average number of better solutions obtained by random search approach is 7.9 and the local search approach

is able to find 7.8 better solutions on average. The second column presents the total average waiting time spent in the airport terminal process. It is evident that local search provides lower waiting times compared with the random approach. It also has shorter run-time, with an average of 15.27 minutes compared to 21.05 minutes for the random approach. However, from the results presented in both tables, it can be clearly seen that the random search method reduces the objective function value by 12.11%. The mean μ value of the objective function obtained from the random approach is \$1998.3, whereas μ of objective function value of the local search is \$2256.

From the 10 replications of both random search and local search, solution numbers 4 and 6 from the random search and local search were selected as the best solutions for two reasons. The first reason is that the value of the objective function is closer to the mean value of all the objective values. The second reason is that the chosen simulation runs


```

Line Number      1      2      3      4      5
Class            B E B E B E B E B E
-----|-----|-----|-----|-----|
Shift (1)        1 4 1 2 2 2 2 4 2 2 Screening counters: 5 Immigration counters: 8 SmartGate: 7
Shift (2)        2 3 1 3 1 3 2 3 2 3 Screening counters: 5 Immigration counters: 6 SmartGate: 9
Shift (3)        1 4 2 2 1 1 1 4 1 2 Screening counters: 4 Immigration counters: 2 SmartGate: 3
-----|-----|-----|-----|-----|
                Average WT      WT      Resources
                (minute/Passenger)  cost      cost
check in Avarage WT (B):      1.35863      |      0      |      440
check in Avarage WT (E):      56.0925      |      70      |      840
Screening Avarage WT :      0.359279      |      0      |      210
Immigration Avarage WT :      0.0329785      |      0      |      240
Smart Gate Avarage WT :      0.597841      |      11      |      190
Total Avarage WT:      58.4412 minute/Passenger
Total Cost:      2001 $

```

FIGURE 2: Snapshot of simulated annealing results.

TABLE 1: Summary of the input data.

Domain of the airport	Values
<i>Check-in</i>	
(i) Cost for opening new check-in counter	20\$
(ii) The acceptable average waiting time for economy passengers	12 minutes
(iii) Cost for inconvenience at check-in for economy	15\$
(iv) The acceptable average waiting time for business passengers	3 minutes
(v) Cost for inconvenience at check-in for business	25\$
<i>Security screening</i>	
(i) Cost for opening new security screening desk	15\$
(ii) The acceptable average time that normal passengers should wait	5 minutes
(iii) Cost for inconvenience at security screening for normal passengers	15\$
(iv) The acceptable average time that diplomatic passengers should wait	2 minutes
(v) Cost for inconvenience at security screening for diplomatic passengers	20\$
<i>Immigration</i>	
(i) Cost for opening new immigration desk	15\$
(ii) Cost for opening new SmartGate	10\$
(iii) The acceptable average waiting time at common counter	7 minutes
(iv) Cost for inconvenience at common counters	20 \$
(v) The acceptable average waiting time at SmartGate	0.5 minute
(vi) Cost for inconvenience at SmartGate	10\$

TABLE 2: Summary of simulated annealing results using random search technique.

Run #	# of better solutions	Random search		
		Total average waiting time	Objective function value	Run-time (min)
Run 1	6	118.73	2031	21.05
Run 2	5	58.44	2001	21.16
Run 3	10	126.39	2060	23.48
Run 4	9	39.57	2038	23.43
Run 5	6	64.74	1973	20.24
Run 6	9	148.18	1874	20.55
Run 7	8	112.714	1913	17.36
Run 8	10	86.67	1997	21.55
Run 9	7	127.8	2052	17.36
Run 10	9	131.25	2044	24.36
μ	7.9	101.4484	1998.3	21.054
σ	1.7	34.725498	58.99160957	2.256671

provide the minimum total average waiting time in the airport.

Figure 3 demonstrates the best solution given by the random search for the solution run number 4. The optimal

solution for this simulation run with regard to opening additional resources for check-in is summarized in Table 4. The average waiting time is 1.91 minutes for business-class passengers and 34.5 minutes for economy-class passengers.

TABLE 3: Summary of simulated annealing results using local search technique.

Run #	# of better solutions	Local search		
		Total average waiting time	Objective function value	Run-time (min)
Run 1	7	38.88	2336	13.7
Run 2	10	92.31	2195	14.02
Run 3	9	80.49	2182	15.4
Run 4	10	94.97	2042	15.48
Run 5	8	22.25	2180	17.22
Run 6	8	28.89	2250	22.22
Run 7	8	72.6	1994	12.53
Run 8	8	85.47	2531	17.27
Run 9	4	86.45	2638	12.21
Run 10	6	45.6	2215	13.27
μ	7.8	64.82	2256.3	15.27
σ	1.72	26.45	186.49	2.88

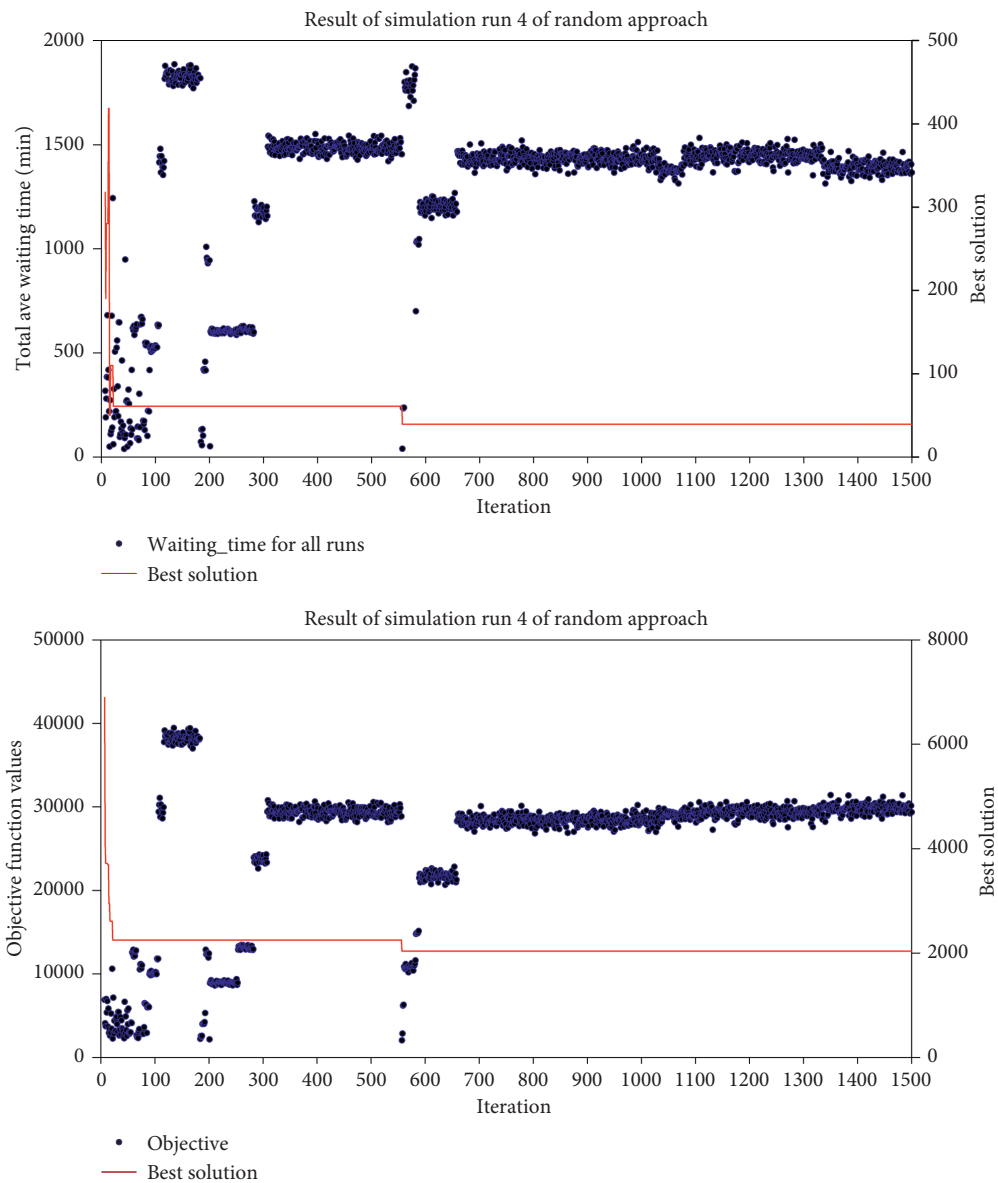


FIGURE 3: SA optimisation results using the random method of creating new solutions.

TABLE 4: Check-in additional resource results using the random technique.

	Line 1		Line 2		Line 3		Line 4		Line 5	
	Business	Economy	Business	Economy	Business	Economy	Business	Economy	Business	Economy
Shift 1	1	4	2	3	2	4	1	4	1	4
Shift 2	2	2	1	1	1	1	1	2	2	4
Shift 3	2	4	1	6	1	6	1	2	2	4

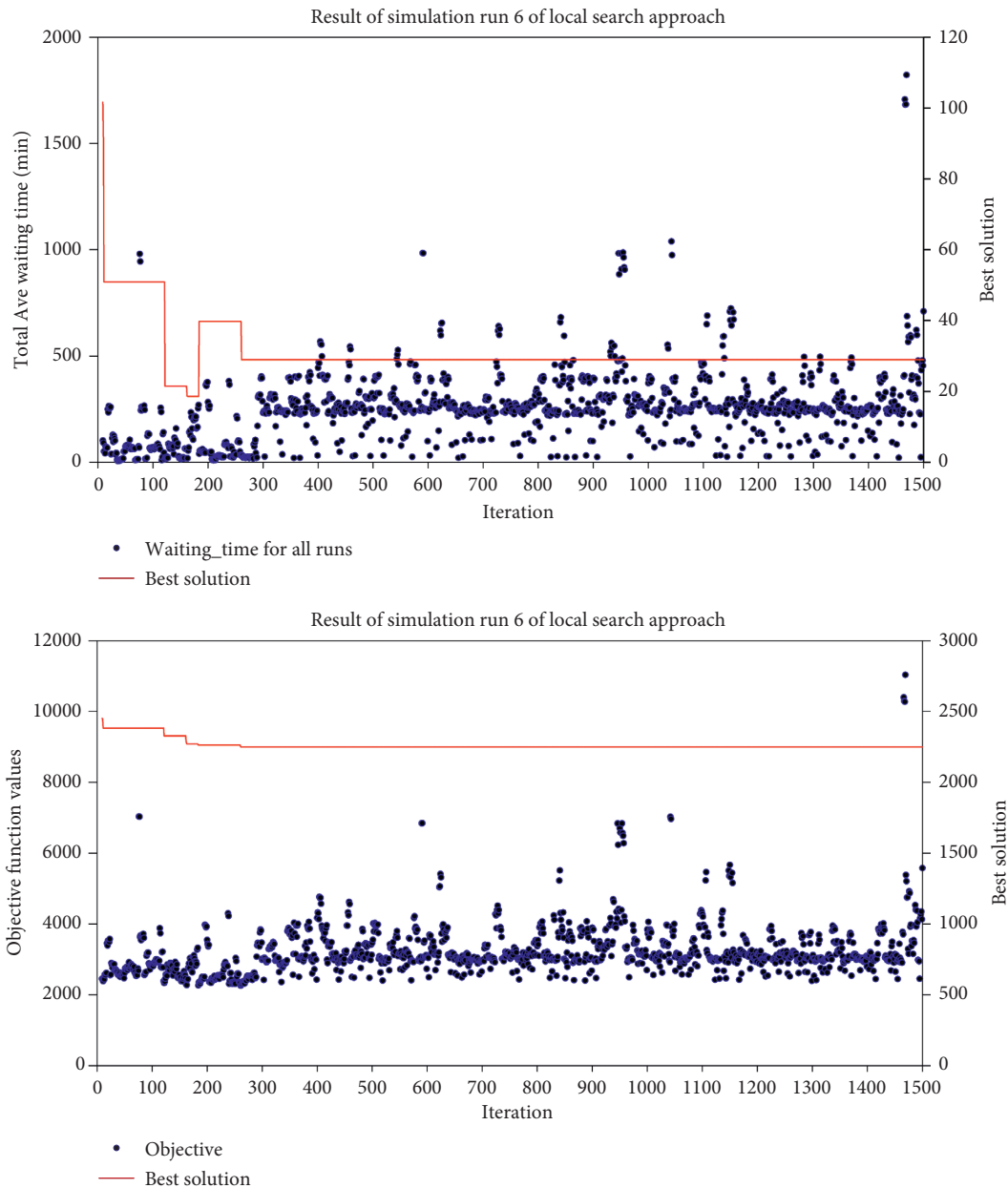


FIGURE 4: Optimisation results using the method of creating new solution using local technique.

For the security screening checkpoints, the opening resources are 5, 2, and 3 control checkpoints for shift 1, shift 2, and shift 3, respectively, having an average waiting time of 3.04 minutes. The opening common immigration process is 4, 3, and 5 counters, while for SmartGates there are 8, 9, and 7 kiosks for the three shifts, having average waiting times of 0.11 and 0.02 minutes for the common immigration desks

and SmartGate kiosk, respectively. The total cost of opening all resources is \$2038 given that the total average time spent in the queues is 39.57 minutes.

Figure 4 illustrates the optimal solution provided by the SA algorithm using local search for creating a new solution. In this simulation run, the solution is characterised from the total cost of \$2250 given that the total average waiting time

TABLE 5: Check-in additional resource results using local technique.

	Line 1		Line 2		Line 3		Line 4		Line 5	
	Business	Economy	Business	Economy	Business	Economy	Business	Economy	Business	Economy
Shift 1	1	4	2	3	3	5	2	5	1	5
Shift 2	2	7	1	2	1	3	4	3	1	4
Shift 3	2	1	2	2	2	2	4	1	2	1

spent in the system is 28.89 minutes. The optimal solution for this simulation run is opening a check-in resource based on the detailed information listed in Table 5. By adding this resource, the average waiting time at the check-in process will be 1.56 minutes for business-class passengers and 7.03 minutes for economy-class passengers, reductions of 20.17% for business-class passengers and 132.29% for economy-class passengers compared with the random search method.

For the process of security screening checkpoints, the best solution can be found when opening 4, 4, and 5 security control checkpoints for shift 1, shift 2, and shift 3, respectively. By opening these numbers of resources at the security screening process, the average waiting time is 7.92 minutes. Finally, the immigration process should open 5, 4, and 3 common immigration counters and 10, 10, and 9 SmartGates for the three shifts, in order to get the optimal solution, having the average waiting of 0.10 minutes and 0.012 minutes for the common counters and SmartGates, respectively.

5. Conclusion

This paper has discussed the development of a mathematical approach to perform capacity planning in airport terminals. The objective of the model is determining where additional resources should be opened to decrease the cost of time spent in the queues of the airport terminal. Since the proposed problem is probabilistic and nonlinear, a meta-heuristic approach is advocated. The waiting times are computed using discrete event simulation and those times are used in the objective function. Two different approaches for creating new solutions were used in this study. The first one is creating a new solution using the random technique and the other is creating a new solution by using the local search technique. The random technique decreased the objective function value by 12.11%. It also has shorter run-times, with average of 15.27 minutes compared to 21.05 minutes for the random approach.

The developed model can be more accurate because the effect of decision can be known and real time can be identified. It also can provide strategic planning, while the proposed simulation model can be used for the operational planning level. This work has contributed to the body of knowledge by enabling two levels of planning, operational and strategic.

On the other hand, the lack of access to the detailed data related to operational facilities due to the recent strict regulations with respect to security issues resulted in some difficulties in developing the modelled passengers' flows within international terminal. Because of these difficulties, this model has been simplified by, firstly, utilizing available

data collected by previous research, and, secondly, making an assumption where needed.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

Dr. Sultan Alodhaibi mainly undertook this research as a Ph.D. student and formulated and conducted the experimental design. He designed, developed, and tested the simulation models and wrote the main manuscript. Dr. Robert L. Burdett provided necessary guidance for mathematical optimisation of simulation models and interpretation of the simulation results. Professor Prasad K. D. V. Yarlagadda conceived the project and got necessary infrastructure and funding for undertaking this research. He also planned and helped in design of simulation model and related experiments and supervised and oversaw the full project from its inceptual stage to final stages of delivery. All authors reviewed and commented on the manuscript.

Acknowledgments

This research was supported by the Australian Research Council's Linkage Project "Improving Productivity and Efficiency of Australian Airports" (140100282). The authors would like to acknowledge QUT High Performance Computing (HPC) for providing the computational resources for this research.

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