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# A Passenger-Centric Model for Reducing Missed Connections at Low Cost Airports With Gates Reassignment

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**ABSTRACT** Low cost carriers usually operate from no-frills budget terminals which are designed for quick aircraft turnaround, faster passenger connections with minimal inter-gate passenger transfer times. Such operations are highly sensitive to factors such as aircraft delays, turnaround time and flight connection time and may lead to missed connections for self-connecting transfer passengers. In this paper, we propose a passenger-centric model to analyze the effect of turnaround times, minimum connection times and stochastic delays on missed connections of self-connecting passengers. We use Singapore Changi International Airport Terminal 4, which mainly caters to budget/low cost carriers, as a case study to demonstrate the impact of operational uncertainties on these passenger connections, considering an optimal gate assignment by using heuristic search for scheduled arrivals. The proposed model also incorporates reassignment of gates in the disrupted scenario to minimize spatial deviation from the optimized gate assignments. Results show that the chances of missed connections can be significantly reduced by operationally maintaining higher turnaround time and minimum connection time and by bringing down delays at the airport. Specifically, by maintaining the flight turnaround time at 50 min, minimum connection time at 60 min and by containing arrival delays within 70% of the current delay spread at Terminal 4, transfer passenger missed connections can be prevented for almost all the flights. The gate assignment method adopted in this study is generic and may help to identify the gates, which are more prone to missed connections given operational uncertainties under different flight scenarios.

**INDEX TERMS** Low cost carrier, self-connecting passengers, missed connections, flight delays, gate reassignment.

## I. INTRODUCTION

According to the International Air Transport Association's forecasts, global passenger traffic will proliferate at 3.5% compound annual growth rate, leading to a doubling in passenger numbers from today's levels to 8.2 billion by 2037 [1]. Asia Pacific region is predicted to be the biggest driver of air traffic demand with more than half of the new passenger traffic coming from this region. This eastward shift in aviation's centre of gravity is driven by a combination of continued robust economic growth, improvements in household incomes and favourable population and demographic profiles [1]. If not carefully planned for, the expected traffic growth shall not only strain the existing infrastructure, but also lower the quality of passenger service. This geographical restructuring of world air traffic therefore, can only be sustained by better utilizing infrastructure bottlenecks and moving away from flight-centric, unimodal travel options towards passenger-centric, multimodal operations at airports. This may mean designing an integrated air transportation system that is sensitive to the evolving transportation needs of technology savvy commuters, while at the same time robust to operational variability existing in the system. In this context, low cost carriers (LCC) are well positioned to facilitate

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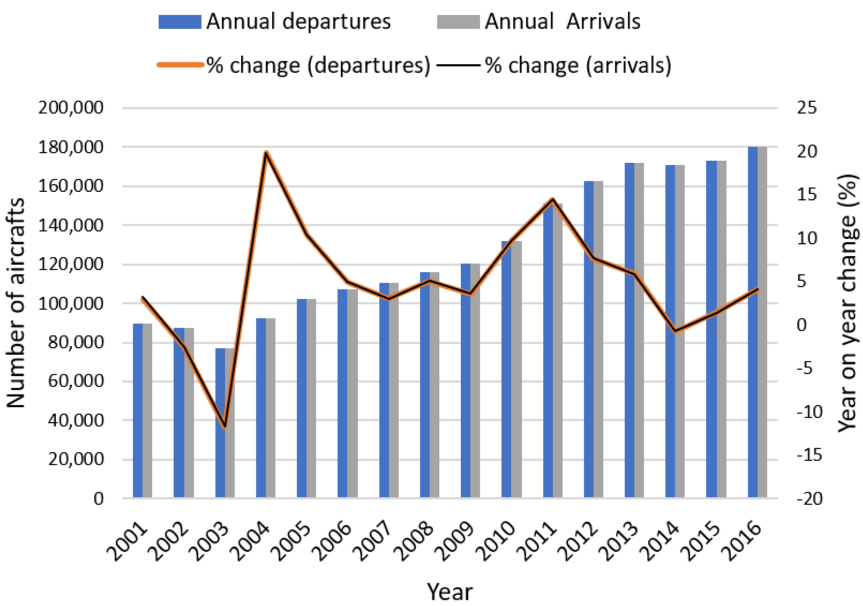



**FIGURE 1.** Aircraft departures and arrivals - year on year change at Singapore Changi Airport with spikes at 2004 and 2011 with introduction of new LCCs.

the increasing travel aspirations in the Asia Pacific region by offering an assortment of demographic travel routes at competitive costs, especially as air transport becomes more affordable.

LCCs have witnessed a steady growth over the past decade. In 2015 alone, LCCs catered to 10 percent more passengers than 2014, a growth rate that was 1.5 times the world's average passenger growth rate [2]. The trend continued in 2018 with LCCs outgrowing the world's average growth rate and widening the market share in both advanced and emerging economies. In fact, LCCs transported an estimated 1.3 billion passengers in 2018 which accounts for approximately 31 percent of the world's total scheduled passengers [3]. LCCs - with their quick and direct connections to destinations served infrequently by FSCs - may even act as catalysts towards realizing European Commission's vision for 2050: 90% of domestic travelers completing their journey, door-to-door, within 4 hours.

The growth of LCCs has given rise to phenomena like budget or LCC terminals and in some cases, entire airports like the London Stansted Airport, catering exclusively to the operational requirements of LCCs [4]. These LCC terminals are 'no frill' terminals, designed to facilitate passenger movement by reducing the passenger transit time and are configured to provide quicker turnaround times (TAT) for aircraft. Such LCC terminals/airports act as point-to-point networks wherein there is limited visibility of passenger connections [5]. Thus, complete travel itineraries of passengers at these airports are not often known in advance to the airport management staff or airlines which serve these passengers. Moreover, to remain profitable, LCCs function around a business model which calls for lower operational costs and resort to practices like shorter TATs. This leads to interesting phenomena at LCC terminals/airports, when self-connecting passengers flying on aggressive flight schedules, experience uncertainties that exist in the very nature of airport operations.

## II. BACKGROUND

### A. TERMINAL 4 AT SINGAPORE CHANGI AIRPORT

In South-East Asia, Singapore Changi airport has emerged as a major hub airport. Changi Airport has witnessed high traffic growth for the years 2004 and 2011 (refer figure 1). Specifically, the year 2004 saw an annual increase of almost 20 percent for arrivals and departures over the previous year due to the arrival of two major low-cost carriers, Tiger Air and Jet Star, which started operations in late 2003 and 2004 respectively. A similar trend was observed in 2011, in the form of an year-on-year increase of approximately 15 percent in arrivals and departures, with the introduction of Scoot Airlines in 2011.

In 2017, Singapore Changi Airport opened Terminal 4 which serves LCCs primarily. Although, Terminal 4 serves few full service carriers (FSCs) such as Cathay Pacific and Korean Air, efficient terminal design and passenger responsiveness has made Terminal 4 an ideal destination for LCCs [6]. The terminals configuration is linear which in fact, facilitates shorter TAT and lesser passenger walking distance [7]. Further airport operations are designed to cater to the transfer needs of self-connecting transfer passengers in order to tap into the burgeoning LCC market. The new terminal has 21 contact gates (refer figure 2) and can handle up to 16 million passengers per year. Terminal 4 offers services such as self-service check-in and automated bag drop among others under the concept called 'Fast and Seamless Travel'(FAST) at Changi [8]. These efficient passenger processing services benefit transfer passengers immensely who

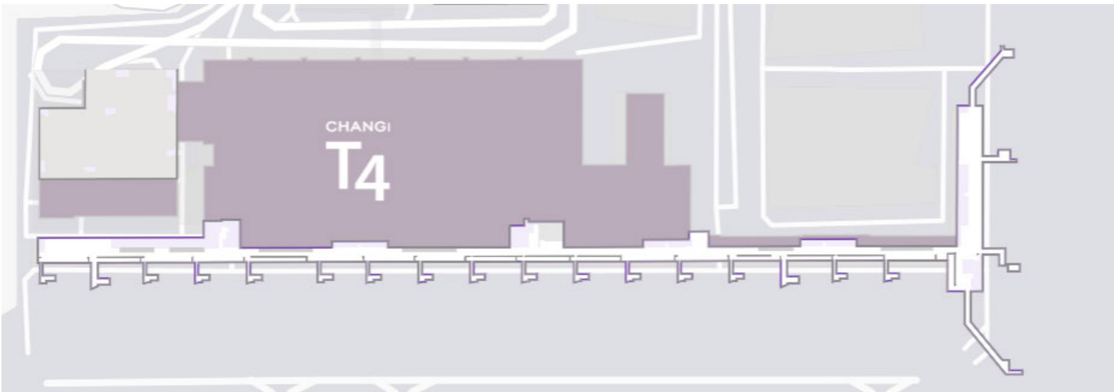
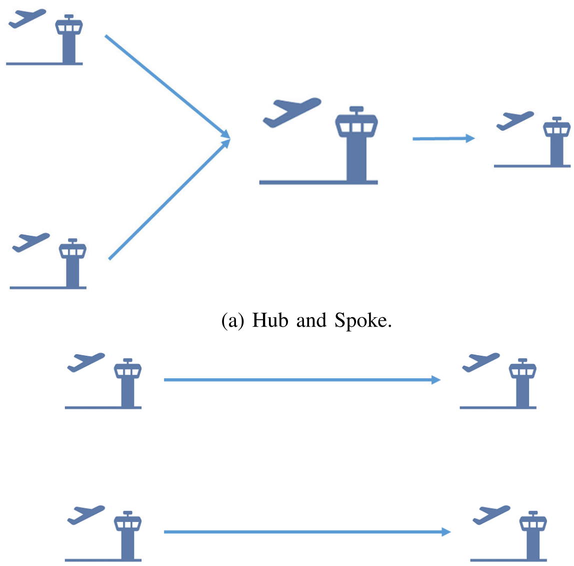



**FIGURE 2.** Layout of Terminal 4 at Singapore Changi airport.



(a) Hub and Spoke.

(b) Point-to-Point.

**FIGURE 3.** Airline networks.

may check-in, drop off their bags, clear immigration and board their flights using fully automated systems. This results in less queuing and quicker passenger transits [6].

### B. LCC OPERATIONS

LCCs are typically categorized by two key principles: point-to-point network and cost-efficient operations [9]. Although some LCCs have evolved to offer self-connecting and hubbing options to transfer passengers, most LCCs have retained their characteristic operational models to remain cost competitive [10]. LCCs function around a business model that facilitates lower operational expenses and higher productivity archived through simpler aircraft fleet and shorter TATs.

#### 1) POINT-TO-POINT NETWORK

Simplifying operations to keep costs as low as possible, LCCs operate in a point-to-point network rather than routing flights through a central hub. Deviating from the hub-and-spoke network model (refer figure 3a) where airlines from smaller airports (spokes) feed passengers into a central hub airport, the point-to-point network model (refer figure 3b) consists of individual routes connecting origin and destination pair in the airline's network. Point-to-point network saves LCCs the complexity of coordinating airline schedules for passenger transfers, as flights need not be delayed for transfer passengers. This in turn allows higher fleet utilization.

#### 2) SIMILAR AIRCRAFT FLEET AND SHORTER TAT

LCCs operate on a fleet of similar cost-efficient aircraft (Boeing 737 or Airbus 320/319), which demand lesser maintenance and lower ground handling fees at airports [11]. Moreover, shorter TATs lead to lower occupancy at airport stands/gates which leads to cost efficient slot management. Also, shorter TATs enable longer time in the air, which imply more trips between origin and destination, increasing the airline's revenue from the same set of aircraft and crew [12].

### C. SELF-CONNECTING TRANSFER PASSENGERS AND THEIR VULNERABILITY TO SCHEDULE DISRUPTIONS

Passenger centric delay analysis has been the focus of multiple research efforts in the past. Vanderboll [13] analysed the effect of implementation of the tarmac delay rules on passenger delays and showed that implementation of these rules increased the overall passenger delays by increasing the frequency of flight cancellations. Santos *et al.* [14] presented an integer linear programming approach with constraints of bay availability, taxiway capacity and runway separation. Through this model, they were able to compute the passengers experiencing delays, numbers of missed connection and the number of aircraft using airport facilities at a given time. The Nairobi-Jomo international Airport (hub airport for Kenya Airways) was used as a case study. Bratu and Barnhart [15] calculated passenger delays due to flight disruptions in an itinerary (flight cancellation or diversion) to establish relationships between passenger delays and cancellation rates, flight leg delay distributions, load factors, and flight schedule design, using passenger booking details of a single airline. This work was further extended [16] to

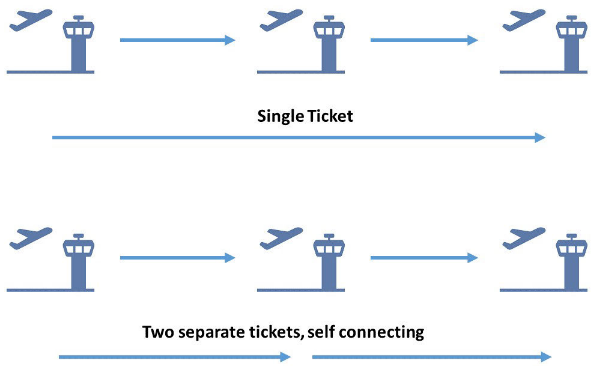



**FIGURE 4.** Transfer passengers: conventional v/s self-connecting.

evaluate passenger delays for multiple airlines and multiple airports and identifying airports wherein transfer passengers would experience longest delays, along with other results. The emergent phenomena of LCC flights, budget terminals, technologically-equipped and price sensitive self connecting passengers who customize itineraries, have not received significant attention in the literature. It is however, critical to understand the effect of flight operations on these passengers in terms of missed connections. The current research is a pilot study to evaluate the number of passengers who miss their connections due to the effect of stochastic delays, minimum connection times between connecting flights and the flight turn around time, in an environment of low cost carriers operating in budget terminals; specifically catering to the needs of such flights and passengers.

Owing to high flight density at LCC airports, inter-flight transfers by self-connecting transfer passengers have become commonplace [17]. Contrary to the conventional transfer passengers who traverse multiple flight legs on one ticket, self-connecting passengers are transfer passengers who choose to buy two or more separate tickets and transfer at intermediate airports by themselves [18], [19] (refer figure 4). This is done for greater flexibility, more connectivity options between remote locations and significant cost savings, especially by price-conscious travellers who self check-in and prefer to travel with digital boarding pass without check-in baggage. Self-connecting passengers have been steadily growing in numbers lately, a trend that is expected to continue as LCCs gain more prominence [20].

Uncertainty in airport and airline operations often manifests itself as delay which flights experience due to a host of reasons such as bad weather [21], gate or flight breakdowns [22], or runway excursions/incursions [23]. These delays, although generated at one airport, have cascading effects which propagate across the global aviation network in a sinister fashion [24], [25]. For instance, when an aircraft serving multiple flight legs experiences disruptions at an initial leg, it often carries the delay to the final leg of its journey. In the point-to-point LCC network model, any disruption may easily translate to a number of missed connections. Thus, transfer passengers who travel in LCCs are more vulnerable to miss-connections in occurrence of flight delays. Since airlines, in a point-to-point network, are not liable to passengers who miss their connecting flights, the self-connecting transfer passengers may be severely impacted due to the schedule disruptions.

## III. SCOPE AND INTENT OF STUDY

In this research we propose a passenger-centric model to analyze the missed connections due to arrival delays, tighter TAT and minimum connection time (MCT) in a gate optimized scenario (minimized transit time or transfer walking distance) at a terminal that serves low cost carriers. As a case study, we perform the analyses over Singapore Changi Airport-Terminal 4, which serves low cost carriers. Through this study, we also attempt to identify, for a given terminal, the gate(s) which are more likely to have missed connections taking into consideration assigned flights, arrival delay patterns, TAT and passenger connection time.

The remaining document is organized as follows. In section IV, we propose our research model followed by section V which explains the key factors that contribute towards missed connections. Then, the research methodology is developed in section VI with details of heuristic algorithm used for gate assignment and learning of arrival delay patterns at airport to generate disruptions for missed connection analyses. In section VII results are analyzed and discussed. We conclude in section VIII with some insights and future directions.

## IV. PROPOSED PASSENGER-CENTRIC MODEL

In figure 5 we illustrate the proposed model, for missed connection analysis, with its various sub-components and their interaction. The model consists of four key components viz. operations (variables), passenger flows (simulations), disruption patterns (historical data) and infrastructure (fixed). The first component refers to the use of information about flight arrival schedules from the Changi airport website, along with different sets of aircraft TATs to derive flight departure sequence. The second component simulates different passenger flows between aircraft using transfer passenger information along with different sets of MCTs. The third component, the arrival delay distribution is derived using commercial ADS-B data for the month of June-2016 sourced from FlightAware and thereafter, arrival delay values are drawn from the distribution to introduce stochasticity into scheduled flight operations. The fourth component, i.e. the airport infrastructure, is a fixed entity which consists of the layout of the terminal and the inter-gate distances-which transfer passengers have to traverse to make the connection (passenger walking distance) [26], [27].

Further three critical operational parameters TAT, MCT and arrival delays are varied to analyze their interactions with one another (cf. [28]). Finally all these sub-components are integrated in an optimized gate allocation scenario, to analyze their impacts upon missed connections.

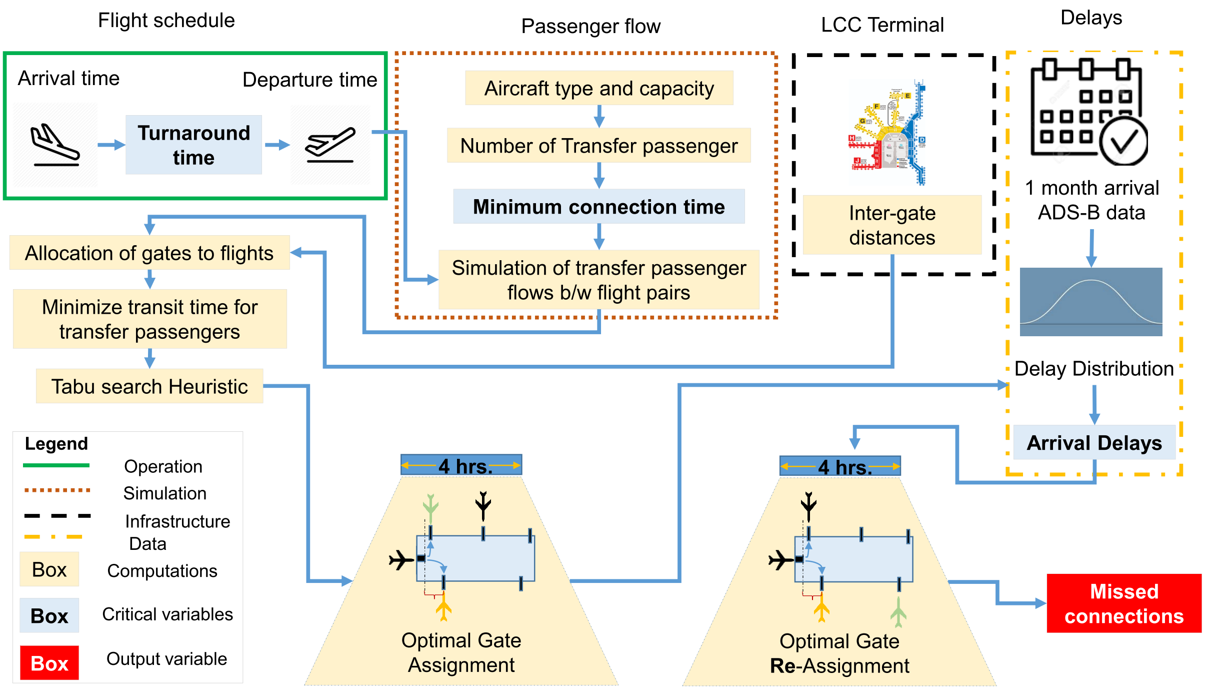



**FIGURE 5.** Proposed passenger centric model illustrating the interactions between the operations (variables), passenger flows (simulations), disruption patterns (historical data) and infrastructure (fixed) for missed connection analysis.

## V. FACTORS IMPACTING MISSED CONNECTIONS

There are several factors that impact missed connections. These are delayed operations as well as the number and distribution of associated transfer passengers. We shall discuss and model them in detail in following sub-sections.

### A. DELAYED OPERATIONS

In an airport environment, uncertainty and random events are a rule rather than an exception [29]. Flight delays can occur due to congestion, weather, enroute capacity constraints, equipment malfunction and breakdown, late aircraft/crew arrival, ground services, ground delay program, late arriving passengers etc. [30]–[32]. Among them, passenger induced delay is a major concern. In the US alone, the annual costs of delays (direct cost to airlines and passengers, lost demand, and indirect costs) in 2017 were estimated to be $26.6 billion [33].

It has also been discussed in the literature, that research on delay has remained airport-centric, lacking passenger-centric matrices to fully evaluate the system behavior [24]. Similarly, in this connected link of cause, propagation and effect of delays, the final segment has been majorly limited to economic impacts. Evaluating the passenger-centric effects of delay (i.e. missed connections) is believed to be of significant value to the existing body of research on transfer passengers and aircraft delays [24], [34].

### B. TRANSFER PASSENGERS

There are basically three kinds of passengers at any airport: Origin, Destination and Transfer passengers. Origin passengers initiate their journeys at an airport. Destination passengers who terminate their journeys at an airport. Transfer passengers both arrive and then depart in their arrival and departure flights respectively at an airport.

The third kind, transfer passengers who are served by full service airlines/legacy carriers, account for a large share of flyers at hub airports. For Singapore Changi Airport, based on the historical data we have assumed a passenger transfer rate of 40 percent. In this study, we have focused on those self-connecting transfer passengers who are required to board their connecting flights within 4 hours of their arrival at airport terminal. We assume that these are more prone to missing connections upon experiencing delays.

### C. TRANSFER PASSENGER DISTRIBUTION

A major limiting factor in the research on transfer passengers has been lack of publicly available passenger flow data at the airports [35]. It is seen that in the absence of passenger flow data, the traffic and passenger data are generated by using expert judgments and randomized inputs [36]–[38]. This is followed by obtaining an optimal allocation sequence of the aircraft to the gates to minimize average passenger transit time. It is widely understood that the quality of the solution generated depends on these underlying assumptions and inputs that are fed into the optimization algorithm. The gate allocation is, however, sensitive to different passenger flows among flights. Since this study attempts to delineate the effects of different passenger distributions on the transfer passenger transit time, we create multiple scenarios with passenger flows following specific distributions to generate stochastic passenger matrices.

### D. TAT

TAT is defined as the period for which an aircraft occupies an apron or a gate position [39], [40]. Between positioning and removal of the wheel chocks (called as block in and block out), the turnaround consist of unloading/loading of passengers and cargo, catering, cleaning and refueling of the aircraft. In keeping up with other airlines and to survive in the competition of making air travel more affordable for passengers, there is enormous pressure on airlines to bring the operational costs to minimum. One obvious way to reduce operational costs is to keep TAT as low as possible and to fly more trips with the same aircraft.

### E. MCT

In this study, MCT refers to the connection time required to travel from one gate to another by combination of walking and using the available airport transportation facilities, such as people movers and moving walkways.

## VI. METHODOLOGY

The objective of this research is to analyze the missed connections due to arrival delays, tighter TAT and minimum connection time in a gate optimized scenario (minimum transit time) at a terminal serving LCC flights. To achieve this objective, first scheduled flight and aircraft data along with airport layout information is used to develop inter-gate distance matrix and passenger flow matrices. The distance matrix, when divided with a mean travel speed, gives inter-gate transit times inside the airport terminal and the passenger flow matrix gives inter-flight movements of passengers.

Figure 6 illustrates our methodology to compute missed connections. The transit time matrix (scaled distance matrix) and the passenger flow matrix are given as inputs to a heuristic search algorithm, based on Tabu-Search method, to obtain optimum gate assignments (scheduled). After introducing delays - drawn from the distribution derived from historical disruption patterns - to the originally scheduled assignments, the effect of operational variables, TAT and MCT on missed passenger connections is analyzed in re-optimized gate scenarios. The following text details out each step of the methodological approach adopted in this study.

### A. INPUT DISTANCE MATRIX

The inter-gate distances for terminal 4 of the Singapore Changi airport were calculated using the aerodrome chart from Civil Aviation Authority of Singapore's (CAAS) Aeronautical Information Publication 2018 (amendment-2) [41] (refer figure 7a). The dimension were calculated with a magnified and scaled version of the same aerodrome chart, assuming that the passengers at the airport walk in a rectilinear pattern. Figure 7b shows the inter-gate distance matrix for terminal 4 under consideration.

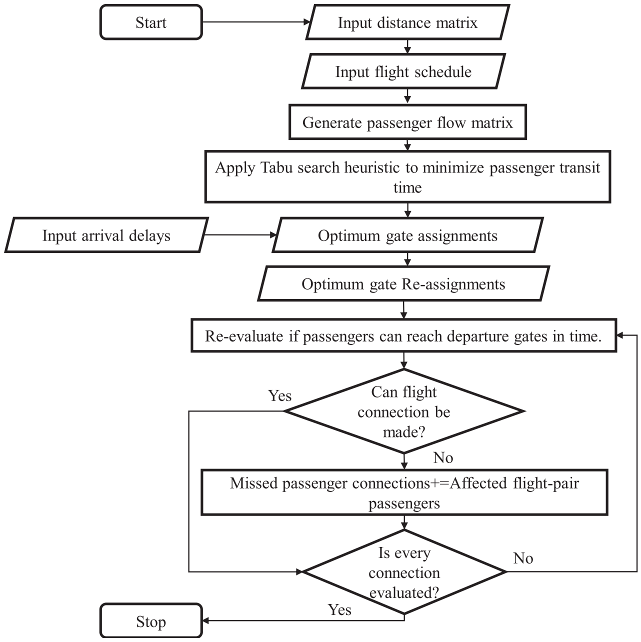
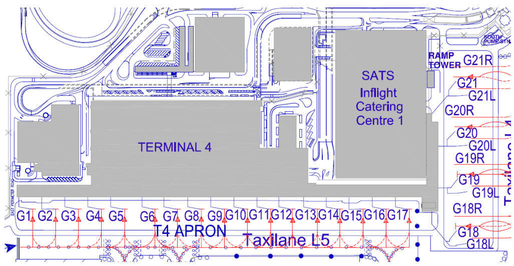



**FIGURE 6.** Flow of algorithmic logic to compute missed connections.




(a) Alignment of Terminal gates.

Arrival Gates (columns); Departure Gates (rows)

| | G1 | G2 | G3 | G4 | G5 | G6 | G7 | G8 | G9 | G10 | G11 | G12 | G13 | G14 | G15 | G16 | G17 | G18 | G19 | G20 | G21 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| G1 | 0 | 64 | 106 | 148 | 191 | 248 | 288 | 330 | 373 | 415 | 458 | 497 | 542 | 585 | 627 | 670 | 712 | 804 | 785 | 853 | 886 |
| G2 | 64 | 0 | 64 | 106 | 148 | 206 | 245 | 288 | 330 | 373 | 415 | 455 | 500 | 542 | 585 | 627 | 670 | 762 | 742 | 820 | 853 |
| G3 | 106 | 64 | 0 | 64 | 106 | 164 | 203 | 245 | 288 | 330 | 373 | 412 | 458 | 500 | 542 | 585 | 627 | 720 | 700 | 777 | 811 |
| G4 | 148 | 106 | 64 | 0 | 64 | 121 | 161 | 203 | 245 | 288 | 330 | 370 | 415 | 458 | 500 | 542 | 585 | 677 | 658 | 735 | 768 |
| G5 | 191 | 148 | 106 | 64 | 0 | 79 | 118 | 161 | 203 | 245 | 288 | 327 | 373 | 415 | 458 | 500 | 542 | 635 | 615 | 692 | 726 |
| G6 | 248 | 206 | 164 | 121 | 79 | 0 | 61 | 103 | 145 | 188 | 230 | 270 | 315 | 358 | 400 | 442 | 485 | 577 | 558 | 635 | 668 |
| G7 | 288 | 245 | 203 | 161 | 118 | 61 | 0 | 64 | 106 | 148 | 191 | 230 | 276 | 318 | 361 | 403 | 445 | 538 | 518 | 595 | 629 |
| G8 | 330 | 288 | 245 | 203 | 161 | 103 | 64 | 0 | 64 | 106 | 148 | 188 | 233 | 276 | 318 | 361 | 403 | 495 | 476 | 553 | 586 |
| G9 | 373 | 330 | 288 | 245 | 203 | 145 | 106 | 64 | 0 | 64 | 106 | 145 | 191 | 233 | 276 | 318 | 361 | 453 | 433 | 511 | 544 |
| G10 | 415 | 373 | 330 | 288 | 245 | 188 | 148 | 106 | 64 | 0 | 64 | 103 | 148 | 191 | 233 | 276 | 318 | 411 | 391 | 468 | 501 |
| G11 | 458 | 415 | 373 | 330 | 288 | 230 | 191 | 148 | 106 | 64 | 0 | 61 | 106 | 148 | 191 | 233 | 276 | 368 | 348 | 426 | 459 |
| G12 | 497 | 455 | 412 | 370 | 327 | 270 | 230 | 188 | 145 | 103 | 61 | 0 | 67 | 109 | 152 | 194 | 236 | 329 | 309 | 386 | 420 |
| G13 | 542 | 500 | 458 | 415 | 373 | 315 | 276 | 233 | 191 | 148 | 106 | 67 | 0 | 64 | 106 | 148 | 191 | 283 | 264 | 341 | 374 |
| G14 | 585 | 542 | 500 | 458 | 415 | 358 | 318 | 276 | 233 | 191 | 148 | 109 | 64 | 0 | 64 | 106 | 148 | 241 | 221 | 298 | 332 |
| G15 | 627 | 585 | 542 | 500 | 458 | 400 | 361 | 318 | 276 | 233 | 191 | 152 | 106 | 64 | 0 | 64 | 106 | 198 | 179 | 256 | 289 |
| G16 | 670 | 627 | 585 | 542 | 500 | 442 | 403 | 361 | 318 | 276 | 233 | 194 | 148 | 106 | 64 | 0 | 64 | 156 | 136 | 214 | 247 |
| G17 | 712 | 670 | 627 | 585 | 542 | 485 | 445 | 403 | 361 | 318 | 276 | 236 | 191 | 148 | 106 | 64 | 0 | 114 | 94 | 171 | 205 |
| G18 | 804 | 762 | 720 | 677 | 635 | 577 | 538 | 495 | 453 | 411 | 368 | 329 | 283 | 241 | 198 | 156 | 114 | 0 | 53 | 130 | 164 |
| G19 | 785 | 742 | 700 | 658 | 615 | 558 | 518 | 476 | 433 | 391 | 348 | 309 | 264 | 221 | 179 | 136 | 94 | 53 | 0 | 98 | 132 |
| G20 | 853 | 820 | 777 | 735 | 692 | 635 | 595 | 553 | 511 | 468 | 426 | 386 | 341 | 298 | 256 | 214 | 171 | 130 | 98 | 0 | 55 |
| G21 | 886 | 853 | 811 | 768 | 726 | 668 | 629 | 586 | 544 | 501 | 459 | 420 | 374 | 332 | 289 | 247 | 205 | 164 | 132 | 55 | 0 |

(b) Inter-Gate Distance matrix (in metres).

**FIGURE 7.** Terminal 4 at Changi International Airport, Singapore.

### B. IMPORTING FLIGHT SCHEDULE

In this study, flight arrival schedule is taken from Singapore Changi airport website for 8-Feb-2019 between 11 AM to 3 PM. The period was selected based on high density of operations, with 21 flights arriving at Terminal 4. To arrive at passenger numbers travelling in these flights, these flights are assumed to be occupied about 83% of their respective capacities, based on the average load factor for the year 2017 [42]. To derive the aircraft seating capacities, aircraft type information is taken from the website flightStats.com [43] and the aircraft seating capacity, for the given aircraft type, is obtained from seatguru.com website [44].

### C. GENERATING PASSENGER FLOW MATRIX

Based on the historic passenger movement data at Singapore Changi airport, we assumed 40 percent transfer passenger rate. Thereafter, passenger flow between different flights is modelled to follow three different distributions: (1) multinomial distribution with equal probability to move to any gate/flight, (2) multinomial distribution with probability of moving to any flight based on aircraft size serving that flight and (3) poisson distribution based on random dispatch of passengers from one flight to another.

#### 1) MULTINOMIAL DISTRIBUTION

In absence of any operational data on inter-flight passenger distribution, multinomial distribution is chosen to account for inter-flight transfers based on the characteristic property of this distribution that it allows a target number $N$ (transfer passengers from source aircraft) to break into smaller numbers $x_i$ (transfer passengers to sink aircraft) based on the acceptance probability of each sink aircraft. Thus there is never a situation when generated number of transfer passengers exceed departing aircraft capacity. Let $X_1, X_2 \ldots X_n$ be the random numbers drawn from multinomial distribution, then $X_1, X_2 \ldots X_n$ obey a probability function

$$P(X_1 = x_1, \ldots, X_n = x_n) = \frac{N!}{\prod_{i=1}^{n} x_i!} \prod_{i=1}^{n} \theta_i^{x_i} \tag{1}$$

where $x_i$ are positive integers with $\theta_i$ being their respective probabilities such that

$$\sum_{i=1}^{n} x_i = N \tag{2}$$

$$\sum_{i=1}^{n} \theta i = 1 \tag{3}$$

In other words, if $X_1, X_2 \ldots X_n$ are mutually exclusive events with $\mathrm{P}(X_1 = x_1) = \theta_1, \ldots, \mathrm{P}(X_n = x_n) = \theta_n$.

Case 1: All flights with uniform acceptance rate (refer figure 8a)

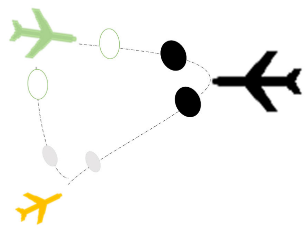
$$\theta_i = \frac{1}{n_i} \tag{4}$$

where $n_i$ refers to total number of available connecting flights for flight $i$.

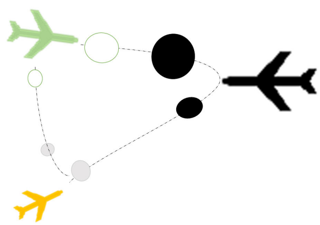
Case 2: Flights with acceptance rates proportional to their respective capacities (refer figure 8b)

$$\theta_i = \frac{C_i}{\sum_{i=1}^{n} C_i} \tag{5}$$

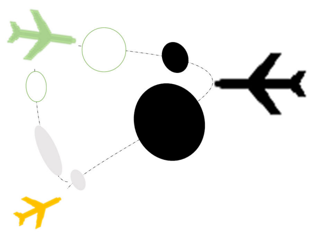
where $C_i$ refers to seating capacity of flight $i$



(a) Multinomial with equal distribution probability.



(b) Multinomial with size-based distribution probability.



(c) Poisson distribution showing random passenger dispatch

**FIGURE 8.** Inter-aircraft passenger flow modeling with ellipse size proportional to transfer passenger numbers.

#### 2) POISSON DISTRIBUTION (REFER FIGURE 8c)

The Poisson distribution gives probability of arrival passengers transferring to different available departure aircraft (connecting flights) in a given time period, given the expected number of respective transfers over the same time period. For events with an expected frequency $\lambda$ the Poisson distribution $f(k; \lambda)$ describes the probability of $k$ arrival events occurring within the observed interval $\lambda$.

$$f(k, \lambda) = \frac{\lambda^k e^{-\lambda}}{k!} \tag{6}$$

The Poisson distribution allows to model passengers transferring in bursts/groups from one aircraft to other available aircraft [45], [46]. Thus $\lambda$ is calculated by assuming all aircraft equally capable of accommodating any random number of passengers. This assumption allows to model any random number of people (tourist groups, lone travellers etc.) moving between aircraft. Poisson distribution is referred to as case III (refer figure 9 ).

The above distributions are used to model the most likely passenger flows. Figure 9 illustrates optimized walking distance for the 3 simulated passenger flows. Connection feasibility- owing to the terminal 4 geometry which requires a minimum transit time of 16 min (refer Figure 10) to move from one extreme to another [47]- between different flights

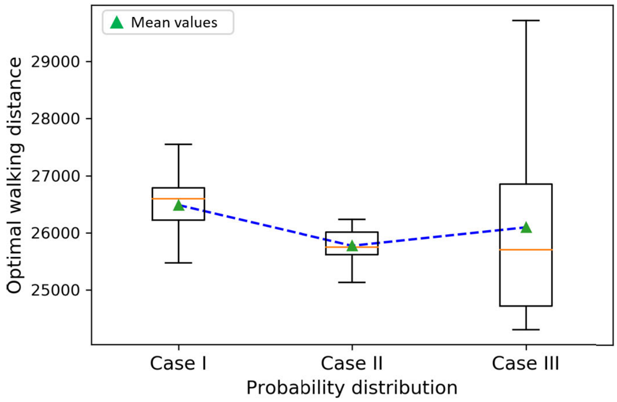



**FIGURE 9.** Effect of passenger distributions on the optimal walking distance.

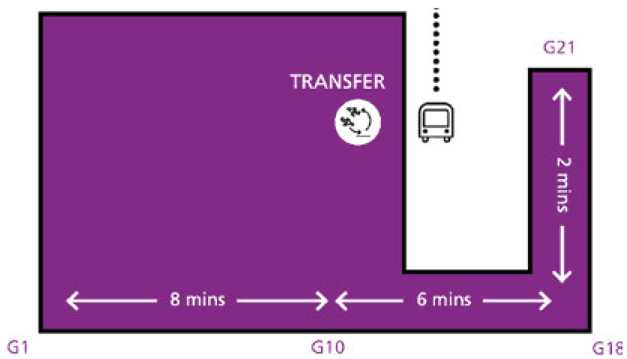



**FIGURE 10.** Transit time required to move between gates in Terminal 4.

is determined using an MCT of 30 min. Upon analyzing 30 scenarios for gate assignments, we can see the effect of passenger distributions on the optimal walking distance (refer figure 9). Poisson distribution (case III) shows the largest walking distance variation owing to the inherent randomness. It is observed while running experiments that sometimes generated scenarios are practically infeasible, as passenger traffic contribution from all the connecting flights (satisfying MCT requirement) to certain aircraft exceeds the capacity. In other words, randomly generated flows from source aircraft doesn't respect sink aircraft's capacity constraint. At the other end of passenger flow modelling paradigm, when flows are assumed to be completely uniform (case I in figure 9), walking distances show less variation. However, it is inferred that when passengers distribute according to multinomial distribution based on aircraft size (case II in figure 9), the walking distances show the least variation (refer case II in figure 9). Case II is found to replicate actual operations more reasonably as larger aircraft in reality service greater number of passengers (or else airlines may replace them with smaller ones to function viably from an economic point of view). Moreover, it is believed that in reality, passengers do not evenly distribute to connecting flights as is assumed under case I. Henceforth, all experiments will be performed on passenger flows generated using the Multinomial distribution with size-based distribution probabilities (Case II).

### D. GATE ALLOCATION TO FLIGHTS TO MINIMIZE TRANSIT TIME

Gate are assigned with an objective to minimize cumulative transit times of all the transfer passengers inside a terminal. Transit time is the distance travelled by passengers inside the terminal divided by average walking speed. The optimization model is constrained to a typical set of two constraints which forbid assigning two (or more) flights with overlapping schedules at one gate simultaneously and assigning a flight at two gates.

$$\text{Objective} : \min F = \sum_{i\in f}\sum_{j\in g}\sum_{e\in f}\sum_{k\in g} p_{i,e}\frac{d_{j,k}}{v_{avg}} x_{i,j}x_{e,k} \tag{7}$$

where,

- $d_{j,k}$ represents distance between gate $j$ and $k$
- $p_{i,e}$ represents flow of passengers from aircraft $i$ to $e$
- $v_{avg}$represents average walking speed inside airport terminal

In other words, to minimize transit time of transfer passengers from aircraft $i$ stationed at gate $j$ to aircraft $e$ stationed at gate $k$.

$$(t_i^{out} - t_e^{in})(t_e^{out} - t_i^{in}) \leq M(2 - x_{i,j} - x_{e,j})$$
$$\forall (i, e) \in f,\ i \neq e,\ \forall j \in g \tag{8}$$

where,

- $t_i^{out}$ represents scheduled departure time of aircraft $i$
- $t_i^{in}$ represents scheduled arrival time of aircraft $i$
- $M$ is a very large number

In other words, if flights $i$ and $e$ are assigned to a single gate $j$, then these can not have overlapping schedules. This can also be interpreted as, if $x_{i,j} = x_{e,j} = 1$, then $t_e^{in} > t_i^{out}$ or $t_i^{in} > t_e^{out}$ or else an arbitrary large number $M$ will constrain/prevent the assignment.

$$\sum_{j\in g} x_{i,j} = 1 \quad \forall i \in f \tag{9}$$

In other words, each arriving aircraft shall be assigned to one gate for the duration for which the aircraft is on ground.

$$x_{i,j} \in 0, 1 \quad \forall i \in f,\ \forall j \in g \tag{10}$$

The gate assignment optimization problem is NP hard, and therefore we need heuristic methods to compute solutions [48]. Since the simplex branch and bound method does not converge to a solution in reasonable time with a large number of gates and flights combinations, we adopt a heuristic search algorithm (refer Algorithm 1) for our airport data, based on Tabu search [49], [50], to obtain optimum gate assignments that minimize passenger walking distance (transit time).

### E. TABU SEARCH HEURISTIC TO SOLVE FLIGHT-TO-GATE ASSIGNMENT PROBLEM

In order to adopt Tabu search algorithm for gate assignment problem, 3 steps are performed over flight schedule, intergate distance matrix, and passenger flow data.

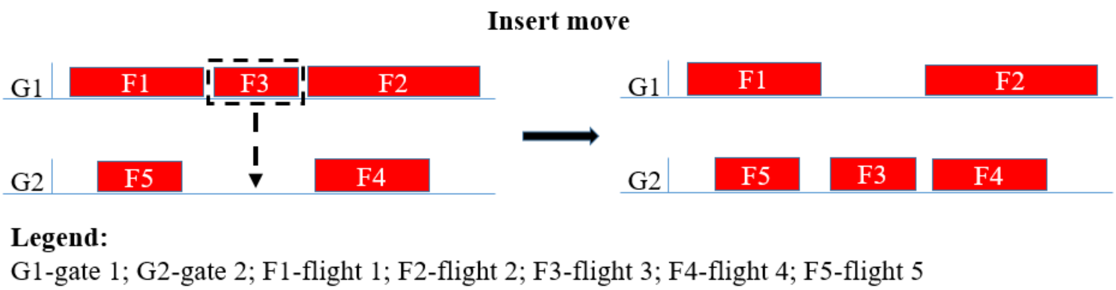



**FIGURE 11.** Solution space exploitation using Tabu search heuristic.

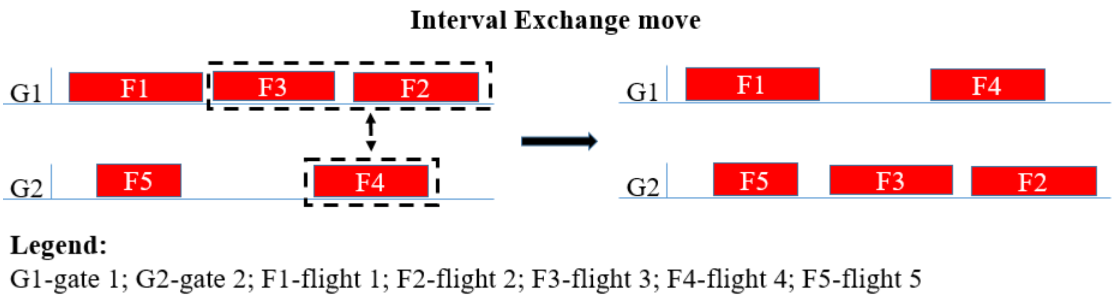



**FIGURE 12.** Solution space exploration using Tabu search heuristic.

Step 1: Trivial (first) solution - Flights are arranged in increasing order of their departure times and allocated to gates feasibly, such that idle gate times are minimized. Feasibility is ensured when two (or more) flights with overlapping ground time are not assigned to the same gate. Note, at this stage, passenger walking distance (transit time) has not been optimized. To optimize walking distance, two tabu search moves: Step 2 - insert move and Step 3 - interval exchange moves are hereafter performed as per algorithm 1.

Step 2: Insert move: Refer figure 11

1) A non-empty gate (G1) is selected.
2) A flight (F3) is randomly chosen in the selected gate(G1).
3) A candidate list of gates which can accommodate the chosen flight (F3), such that none of the other flights already allocated to the candidate gate has time overlap conflicts with F3, is determined.
4) If after inserting chosen flight (F3) in a candidate gate (G2), the solution cost reduces, the insert move is accepted. Else, other candidate gates are tried, as per algorithm 1.

Step 3: Interval exchange move: Refer figure 12

1) A list of pair of non-empty gates, that have are overlapping flights (in time), is prepared.
2) From the above list, two different gates (G1 and G2), with overlapping flights (F2 and F4) are chosen and flight duration intervals are determined.
3) Flights allocated later or earlier (F2 or F4) are appended to respective intervals until a feasible interval pair (F2 & F3; F4), which can be swapped, is determined.
4) Upon interval swap, if the solution cost reduces, the interval exchange move is accepted. Else, other candidate gates are tried, as per algorithm 1.

Further, the optimization algorithm ensures that gates are chosen such that total transit time of all transit passengers is minimized. The following hyper-parameters (as used in [50]) were employed in this study:

1) Maximum number of iterations, $iter_{max} = 300 * $ (no. of gates)-400
2) For search intensification, insert move is performed at every step. If solution cost doesn't improve over 50 insert move iterations, then interval exchange move is performed instead.
3) For search exploration, interval exchange move is performed at every 5th iteration.
4) The algorithm is terminated if solution cost doesn't improve over 10*(no. of gates) iterations, past the last best score.

In the paradigm of heuristic search, insert and interval exchange moves are akin to exploitation and exploration of the solution space respectively. Thus insert move is performed with much higher frequency when compared with interval exchange move. Moreover, insert move leads to a small local change (reduction) in walking distance value, whereas interval exchange move leads to relatively larger changes in solution.

### *F. INCORPORATING STOCHASTIC DELAYS*

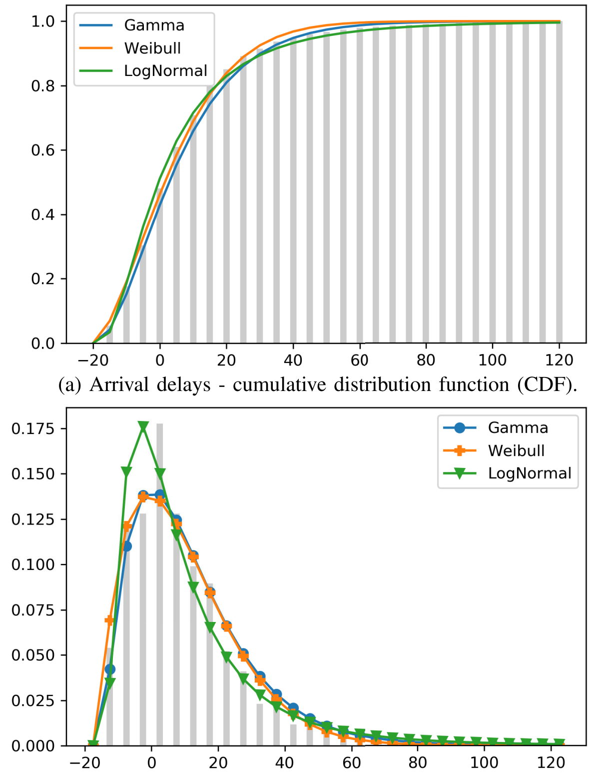
To incorporate the stochastic nature of delays, ADS-B data of aircraft movements to and from Singapore Changi airport, for the month of June 2016 is analyzed with a total of 13,812 departures and 13,403 arrivals. This data is further processed to obtain scheduled block-out time, actual block-out time, scheduled block-in time and actual block-in time. The difference of the first two entities provides departure delays and the difference of the last two entities results in

**Algorithm 1** Heuristic Search Algorithm Based on Tabu Search for Optimal Gate Assignments Minimizing Passenger Transit Time

1) Find an initial feasible gate assignment, $S_0$ following a greedy approach.
2) Set candidate gate assignment, $S_{candidate}$ to be $S_0$.
3) Find cost of the candidate gate solution, $C_{candidate}$.
4) Set the maximum number of iterations to $iter_{max}$.
5) Set the insert and interval counters to be 0.
6) Set the *tabu_memory* as an empty dictionary i.e. { }

**while** *iteration* in range(1, $iter_{max}$) **do**
  **if** (iteration is not a multiple of 5) and (insert counter is less than 50) **then**
    Find feasible insert moves
    **if** (insert move is possible) and (*tabu_memory*{*insert move*} $<$ iteration) **then**
      update the current assignment and cost to $S_{candidate}$ and $C_{candidate}$ respectively
      **if** $C_{candidate} < C_{best}$ **then**
        update the best solution $S_{best}$ and the least cost $C_{best}$
        update *tabu_memory*{*insert move*}
      **else**
        Increase insert counter by one
      **end**
    **end**
  **else**
    **if** (interval move is possible) *and* (*tabu_memory*{*interval move*} $<$ *iteration)*) **then**
      update the current assignment and cost to $S_{candidate}$ and $C_{candidate}$ respectively
      **if** $C_{candidate} < C_{best}$ **then**
        update the best solution $S_{best}$ and the least cost $C_{best}$
        update *tabu_memory*{*interval move*}
      **else**
        Increase interval counter by one
      **end**
    **end**
  **end**
  **if** solution is not improved over 10*(no. of gates) number of iterations **then**
    break
  **end**
  increase iteration count by 1
**end**
**Result:** best assignment and least cost

the arrival delays. To derive a mathematical description of the arrival delay, three commonly used distribution functions (refer figure 13a) are used to fit the measured data: Gamma (11), Weibull (12) and Log-Normal (13) distribution [39], [51], [52]. In (11)-(13), $\alpha$ is the shape and $\beta$ is the scale parameter, $\mu$ is the expected value, $\sigma$ is the standard deviation, and $\Delta x$ is the data offset (set to $\Delta x = -20$ *min*), since all functions are only defined with $x \in (0, +\infty)$.




(a) Arrival delays - cumulative distribution function (CDF).

(b) Arrival delays - probability density function (PDF).

**FIGURE 13.** **Arrival delays with fitted distributions.**

$$G(\alpha, \beta, x, \Delta x) = \frac{1}{\Gamma(\alpha)} \gamma\left(\alpha, \frac{x - \Delta x}{\beta}\right) \quad (11)$$

$$W(\alpha, \beta, x, \Delta x) = 1 - e^{\left(\frac{\Delta x - x}{\beta}\right)^{\alpha}} \quad (12)$$

$$L(\mu, \sigma, x, \Delta x) = \frac{1}{2} \operatorname{erfc}\left(-\frac{\ln (x - \Delta x) - \mu}{\sqrt{2}\sigma}\right) \quad (13)$$

To allow for an appropriate fitting, a $\chi^2$ test is applied to each distribution, but no parameter set for the functions results in an acceptance of the fitted distribution. For the Gamma distribution the best fitted parameters (lowest $\chi^2$ test value) are $\alpha = 2.26$ and $\beta = 11.7$ min, for Weibull distribution the values are $\alpha = 1.56$ min and $\beta = 27.16$ min, and for the Log-Normal distribution the values are $\mu = 2.97$ min and $\sigma = 0.75$ min.

In this context, and from a qualitative point of view, the Log-Normal distribution is able to reproduce the high peak but significantly overestimate early arrivals. Gamma and Weibull distributions are better describing the general shape of the data histogram, but are not able to reproduce the high peak in the data (refer figure 13b). Finally, the Weibull distribution is chosen for the following simulation experiments due to its better fit to the underlying dataset as qualitatively compared to other distributions.

Departure times of delayed arrivals (flights that experience positive arrival delay values), are shifted by the delay value in future. No such shift is performed on departure times of tardy arrivals (flights that experience negative arrival delay values). In other words, flights are assumed to depart at scheduled times even when they arrive early, but are considered to depart late when their arrivals are delayed (refer equations 14 and 15). This is done to model the actual LCC operations which operate on tight TAT.

$$a_{act} = a_{sch} + dl \tag{14}$$

where,

- $a_{act}$ refers to actual arrival time
- $a_{sch}$ refers to scheduled arrival time
- $dl$ refers to arrival delay (time)

$$\begin{aligned} d_{act} &= a_{sch} + dl + TAT \quad \forall dl \geq 0 \\ d_{act} &= a_{sch} + TAT \quad \forall dl < 0. \end{aligned} \tag{15}$$

where,

- $d_{act}$ refers to actual departure time
- TAT refers to turnaround time

### G. RE-ASSIGNMENT OF GATES TO MINIMIZE SPATIAL DEVIATION FROM PLANNED ASSIGNMENTS

In the presence of schedule disruptions, it is seen that at some gates occupancy times of delayed flights overlap with (originally) scheduled flights. However, owing to the '1 flight at 1 gate' constraint (refer equation 8), this situation in fact leads to conflicts. To resolve these gate conflicts, aircraft are reassigned gates with the objective to minimize spatial deviation of re-assigned gates from planned assignments. This ensures passenger inconvenience of walking additional distance is minimized, as the original allocations were optimal (minimized overall walking distance).The Gate Re-assignment model is formulated as follows:

$$\text{Objective} : \min G = \sum_{i \in f} \sum_{j \in g} p_i d_{j,a} x_{i,j} \tag{16}$$

subject to constraints 8 - 10
where,

- $p_i$ represents transfer passengers in aircraft $i$
- $d_{j,a}$ represents distance between gate $j$ and $a$, where $a$ is the originally assigned gate of flight $i$

In other words, to minimize distance between re-assigned gate $j$ and originally assigned gate $a$ to flight $i$. The objective cost function is weighted by the number of transfer passengers travelling in flight $i$, which in other words, ensure that as few passengers are re-located as possible in the disrupted scenario.

### H. REVALUATION OF FLIGHT CONNECTIONS

In the presence of positive flight delays, journeys of many passengers are impacted. Many passengers end up missing their connecting flights after their first leg of the journey gets delayed and they end up arriving late at their respective departure gates. Therefore all connections are re-evaluated for connection feasibility as per the following equation 17.

$$a_{act_i} + db_i + tr_{i,j} > d_{sch_j} \quad \forall (i,j) \in f. \tag{17}$$

where,

- $a_{act_i}$ refers to actual arrival time of flight $i$.
- $db_i$ refers to de-boarding time of passengers in flight $i$. It is assumed 10 min. Further, boarding time is not explicitly considered in connection time and, a passenger is assumed to have made a connection upon reaching the departure gate in time.
- $tr_{i,j}$ refers to transit time required by passengers to walk from arrival flight $i$ to connecting flight $j$ in the disrupted schedule.
- $d_{sch_j}$ refers to the scheduled departure time of connecting flight $j$.

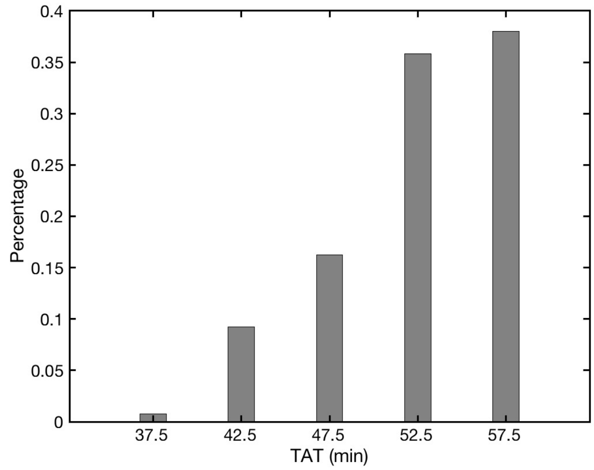



**FIGURE 14.** Turnaround time of short-haul flights at Changi airport.

### I. COMPUTING TOTAL MISSED CONNECTIONS

Passengers for whom equation 17 is violated are the ones who are deemed to have missed their connections. These passengers are then aggregated to arrive at the total head count of transfer passengers who missed their connecting flights.

### J. EXPERIMENTAL DESIGN

The experiments are designed to analyze the effects of the chosen operational parameters on the missed connections. First, the current TAT at Singapore Changi airport, which is determined using ADS-B data, shows that majority of the short layover flights (less than 1 hour) at Changi have actual TAT values within the range 50-60 minutes (refer Figure 14). Thus, an aggressive TAT estimate of 50 minutes is selected for further experiments. Moreover, the maximum terminal walking distance (between farthest gates) for terminal 4 is 16 minutes (refer Figure 10.) and therefore an MCT of 60 minutes is considered sufficient/recommended for intra-terminal connections.

To replicate real airport operations, sufficient stochasticity is introduced into the problem design by generating

**TABLE 1. Experimental design.**

| | Parameters | |
|---|---|---|
| | Variable | Fixed |
| Case I - Effect of MCT | MCT | TAT |
| | | Delay |
| Case II - Effect of TAT | TAT | MCT |
| | | Delay |
| Case III - Effect of delay | Delay | TAT |
| | | MCT |

100 scenarios for each parameter combination to evaluate missed connections in all the 3 cases.

- In CASE I, the MCT is varied from 30 to 60 min, in increments of 5 min, keeping TAT constant at 60 min. The delay values are drawn from Weibull distribution and fed into the algorithm.
- In CASE II, the TAT is varied from 30 to 60 min in increments of 5 min, keeping the MCT fixed at 60 min. The delay values are drawn from Weibull distribution and fed into the algorithm.
- In CASE III, to study the effect of delays two cases are explored (MCT = 30 min and 60 min; with TAT = 50 min) while the scale parameter $\beta$ of the Weibull distribution is varied to limit the range of stochastic delays, from 27.15 min (original $\beta$ value) to 13.57 min (50% of $\beta$ value) in steps of 10 % decrements. The variation of $\beta$ directly relates to changing the standard deviation and mean value (in terms of scaling but keeping the shape of the distribution with $\alpha = const.$) and is given by the following equations 18 and 19.

Table 1 summarizes the experimental design.

$$\sigma = \beta\sqrt{\Gamma\left(1+\frac{2}{\alpha}\right) - 2\left(\Gamma(1+\frac{1}{\alpha})^2\right)} \tag{18}$$

$$\mu = \beta\,\Gamma\left(1+\frac{1}{\alpha}\right) \tag{19}$$

## VII. RESULTS AND DISCUSSIONS

After generating multiple scenarios by taking flight arrival schedule (of 21 flights) and terminal inter-gate distance as input, transfer passengers (a total of 1336 passengers for MCT = 30 min and 1216 passengers for MCT = 60 min travelling) are optimally assigned their gates in each scenario. After incorporating the stochastic delays, gates are reassigned to resolve gate unavailability/assignment infeasibility in the disrupted scenario. Thereafter, connection feasibilty in the disrupted scenario is re-evaluated and those connections which have lesser time available than required, are deemed to miss their connecting flights and are called missed connections. The stochasticity in results obtained over multiple scenarios are captured in the form of box plots with green triangles and orange lines representing average and median values of missed connections respectively. The box, in the plots, represent quartile 1, 2 and 3 (Q1;Q2;Q3) values. The lower whisker represents the least value (of missed connections). Where IQR is the interquartile range

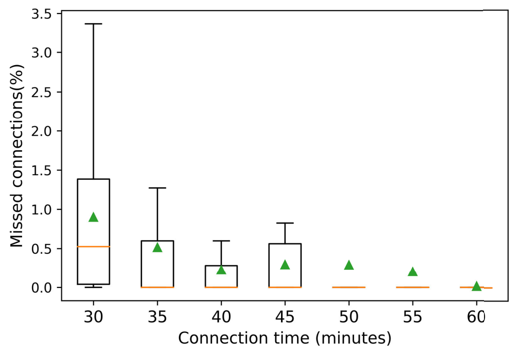



**FIGURE 15. Effect of minimum connection time on missed connections.**

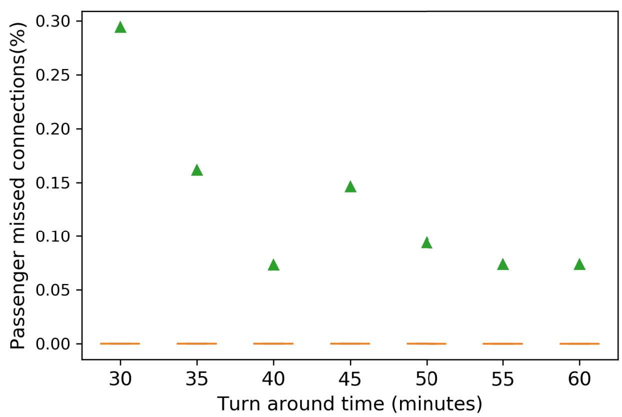



**FIGURE 16. Effect of turnaround time on missed connections.**

(Q3-Q1), the upper whisker extends to last datum less than Q3 + 1.5*IQR. Hereafter, we shall present our observations and missed connection analyses for different operational environments generated.

### A. EFFECT OF MCT ON MISSED CONNECTIONS

Figure 15 shows the connection time variation from 30 to 60 min on x-axis, with the box-plots (and averages) of the missed connection values on y-axis. It is observed that when the connections are tighter than 45 minutes, we observe some passengers missed connections. Specifically, for a connection time of 30 min an average of 12 (0.8%) passengers (refer table 2), out of a total of 1216 transfer passengers, miss their connections. This average drops to 4 passengers (approx.) for an MCT of 45 minutes. However, the average percentage of missed connections effectively decreases to zero for the connection time of 60 min. Overall, missed connections show a downward trend as MCT increases. It can therefore be inferred, from the passenger point-of-view, that in the present operational scenario, a minimum buffer time of 60 min should be maintained between connecting flights at Changi Airport terminal 4.

### B. EFFECT OF TURNAROUND TIME ON MISSED CONNECTIONS

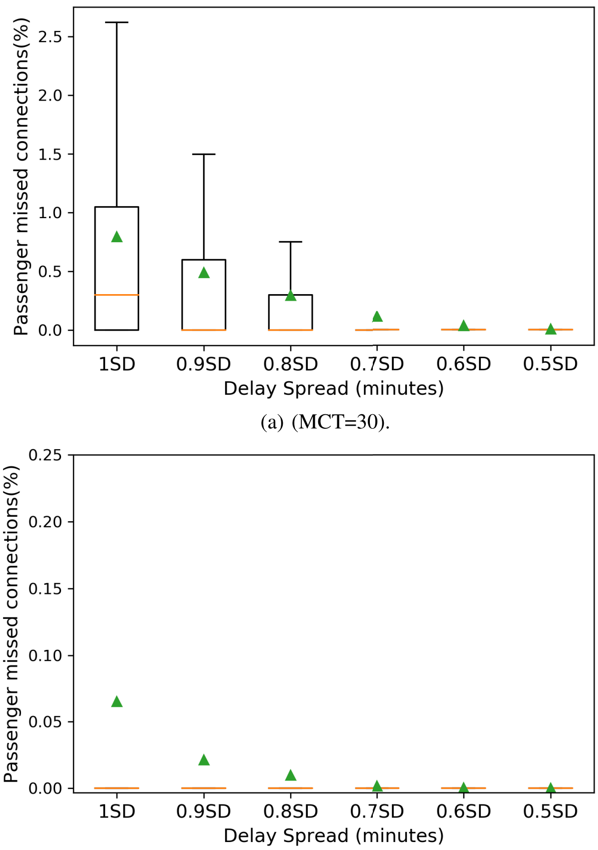
Figure 16 shows the TAT variation from 30 to 60 min on x-axis, with the boxplots (and averages) of the corresponding

**TABLE 2. Effect of minimum connection time (MCT) on missed connections.**

| MCT | Missed connections (nos.) Avg | Std | Median | Disrupted flight-gate (pairs) Avg | Std | Median | Missed connections (%) Avg | Std | Median |
|---|---|---|---|---|---|---|---|---|---|
| 30 min | 12 | 13.8 | 4 | 1.7 | 1.5 | 1 | 0.8 | 1 | 0.5 |
| 35 min | 6.8 | 1.8 | 0 | 0.8 | 1.1 | 0 | 0.5 | 0.9 | 0 |
| 40 min | 3 | 6.1 | 0 | 0.4 | 0.7 | 0 | 0.2 | 0.4 | 0 |
| 45 min | 3.9 | 6.4 | 0 | 0.6 | 0.9 | 0 | 0.2 | 0.4 | 0 |
| 50 min | 3.8 | 11.4 | 0 | 0.3 | 0.7 | 0 | 0.2 | 0.8 | 0 |
| 55 min | 2.7 | 10.7 | 0 | 0.2 | 0.5 | 0 | 0.2 | 0.8 | 0 |
| 60 min | 0.1 | 0.8 | 0 | 0 | 0.1 | 0 | 0 | 0 | 0 |

**TABLE 3. Effect of Turnaround time (TAT) on missed connections.**

| TAT | Missed connections: Missed connections (nos.) Avg | Std | Median | Disrupted flight-gate (pairs) Avg | Std | Median | Missed connections (%) Avg | Std | Median |
|---|---|---|---|---|---|---|---|---|---|
| 30 min | 3.4 | 12.3 | 0 | 0.17 | 0.4 | 0 | 0.2 | 1.0 | 0 |
| 35 min | 1.8 | 7.6 | 0 | 0.1 | 0.5 | 0 | 0.1 | 0.6 | 0 |
| 40 min | 0.8 | 3.0 | 0 | 0.1 | 0.5 | 0 | 0.0 | 0.2 | 0 |
| 45 min | 1.7 | 8.8 | 0 | 0.1 | 0.4 | 0 | 0.1 | 0.7 | 0 |
| 50 min | 1.1 | 4.2 | 0 | 0.2 | 0.6 | 0 | 0.0 | 0.3 | 0 |
| 55 min | 0.9 | 3.5 | 0 | 0.1 | 0.5 | 0 | 0.0 | 0.2 | 0 |
| 60 min | 0.1 | 0.6 | 0 | 0.0 | 0.1 | 0 | 0.0 | 0.2 | 0 |




(a) (MCT=30).



(b) (MCT=60).

**FIGURE 17. Effect of arrival delays on missed connections.**

missed connection values on y-axis (y-axis has been scaled up for clarity) for each case. These plots are obtained at MCT = 60 and it is seen in conformance with the earlier plot (refer Figure 15), that all the box plots converge to a line at 0 missed connections (i.e. 100 percentile of the missed

**TABLE 4. Effect of delay, MCT = 30min.**

| Delay spread | Missed connections (head count) Avg | Std | Median | Missed connections (%) Avg | Std | Median |
|---|---|---|---|---|---|---|
| 1 SD | 10.6 | 16.22 | 4 | 0.79 | 1.21 | 0.3 |
| 0.9SD | 6.52 | 11.61 | 0 | 0.49 | 0.87 | 0 |
| 0.8SD | 3.96 | 8.96 | 0 | 0.3 | 0.67 | 0 |
| 0.7SD | 1.52 | 5.1 | 0 | 0.11 | 0.38 | 0 |
| 0.6SD | 0.47 | 2.54 | 0 | 0.04 | 0.19 | 0 |
| 0.5SD | 0.08 | 1 | 0 | 0.01 | 0.08 | 0 |

connection data is contained around 0) at MCT = 60. However, due to missed connections observed in some scenarios due to higher delay values (right tail-end of Weibull) encountered, the average missed connections are greater than 0. This observation complements the stochasticity involved in these experiments, which also leads missed connections at TAT = 40 to be slightly lesser (0.1%) than those at TAT = 45. Overall, mean values show a downward trend in missed connections as TAT increases. It is therefore inferred from the above experiments that when the TATs increase, chances of passengers missing their connections gradually decrease. This can be attributed to the understanding that with higher TATs, aircraft stay longer on the ground and thus passengers find it easier to make connections. As the chances of making connections improve, the missed connection probability diminishes. Moreover for terminal 4, a TAT of 50 min (refer Figure 16) observes 0.1% missed connections and absorbs most of the stochastic delays calculated for Changi airport. Although marginal reduction in missed connections is further observed for TAT of 55 and 60 min, a TAT of 50 min can be considered reasonable by airlines operating at terminal 4 to reduce sensitivity of most transfer passengers to arrival delays.

### C. EFFECT OF ARRIVAL DELAYS ON MISSED CONNECTIONS

The stochastic nature of operational delays plays the most important role in determining the magnitude of missed

**TABLE 5. Effect of delay, MCT = 60min.**

| | Missed connections (head count) | | | Missed connections (%) | | |
|---|---|---|---|---|---|---|
| Delay spread | Avg | Std | Median | Avg | Std | Median |
| 1 SD | 0.79 | 4.18 | 0 | 0.06 | 0.34 | 0 |
| 0.9SD | 0.26 | 1.73 | 0 | 0.02 | 0.14 | 0 |
| 0.8SD | 0.12 | 2.05 | 0 | 0.01 | 0.17 | 0 |
| 0.7SD | 0.02 | 0.47 | 0 | 0 | 0.04 | 0 |
| 0.6SD | 0 | 0.09 | 0 | 0 | 0.01 | 0 |
| 0.5SD | 0 | 0 | 0 | 0 | 0 | 0 |

(a) Departure gates.

(b) Arrival gates

**FIGURE 18. Missed connection sensitivity of Terminal 4 gates for the flight schedule dated 8-Feb-2019.**

connections. To understand this behavior, delay values were randomly drawn from the arrival delay distribution by varying scale factor ($\beta$) of the Weibull distribution to change the standard deviation (SD) for different use cases. Reducing the SD implies a narrow spread of the delay distribution without changing the initial shape (given by $\alpha$). 1000 runs were run for each scenario. Figure 17a (MCT = 30 minutes; more tight connections) and Figure 17b (MCT = 60 minutes; less tight connections) show impact of varying delay spread on passenger missed connections. Refer tables 4 and 5 for exact numbers. It can be seen from the plots, that when passengers keep a minimum connection buffer of 60 minutes (refer Figure 17b; y-axis has been scaled up for clarity), all the box plots converge to a line at 0 missed connections (i.e. effectively 100 percentile of the missed connection data is contained around 0). However, when connections are tight (MCT = 30 minutes; refer Figure 17), missed connections box plots are observed until 0.7SD delay values. Generally, as delay spread widens, the overall missed connections increase. It can, therefore, be inferred from these results, that if the delays are reduced, missed connections would diminish consequently. Specifically, if delays are contained within 70% of the current delay spread, the missed connection occurrences would reduce sharply, even when the connections are as tight as 30 minutes.

### D. MISSED CONNECTION WITH OPTIMIZED OPERATIONAL PARAMETERS

When the TAT and MCT were kept at 50 and 60 min respectively, and arrival delay values were contained within 70% of the present delay deviation, only the departure flights in two gates (hot-spots in figure 18a) at terminal 4 witnessed missed connections over 100 scenario runs. These missed connections emanated from delayed arrival flights landing at the gate on the elbow end(hot-spot in figure 18b), out of a total of 21 gates. Hence, it can be argued that the choice of operational parameters significantly limited the missed connections.

## VIII. CONCLUSION

In this paper, we have proposed a passenger-centric analysis of stochastic delays on self-connecting transfer passengers in the context of LCC operations. Herein, we have considered effect of arrival delays, TATs and MCTs on passenger connections. We have used Singapore Changi Airport (Terminal 4), which serves budget carriers, as an example to study the impacts of operational uncertainties on the passenger connections, considering an optimum gate assignment of flights arriving and departing from the airport.

To achieve this, we have proposed a model for missed connection analysis, with its various sub-components and their interaction provided. The model consists of four key components: operations (variables), passenger flows (simulations), disruption patterns (historical data) and infrastructure (fixed). Three critical operational parameters- TAT, MCT and arrival delays are varied to analyze their interactions with one another. Finally, all these sub-components are integrated in an optimized gate allocation scenario using a heuristic Tabu-search algorithm, to analyze their impacts upon missed connections. The proposed model also incorporates reassignment of gates in the disrupted scenario to minimize spatial deviation from the optimized gate assignments.

Our results indicate that by increasing TAT and MCT and by reducing delays, the chances of missed connections can be significantly reduced. Specifically, by maintaining the flight TAT at 50 min, MCT at 60 min and by containing arrival delays within 70% of the current delay spread, transfer passenger missed connections can be prevented for almost all the flights. The proposed model and methodology are generic and can be applied to any budget terminal/airport to gain valuable insights for airport operation managers and LCC airlines for better schedule coordination and passenger-centric operations.

## IX. LIMITATIONS OF CURRENT STUDY

This study assumes self-connecting passengers moving, from one gate to another to transfer between connecting flights, at a rather conservative average speed $v_{avg}$. However, precise movement of different passengers may vary depending upon their age, gender, group, travel purpose (business or tourism) etc. Moreover, Terminal 4 has 8 remote stands that were not assigned flights in this pilot LCC study to keep the model complexity moderate. Also, gate re-assignment is done in a planning paradigm, based on anticipated arrival delays. However, in an operation paradigm, obtaining perfect arrival delay information may indeed be challenging. Further, we have assumed passengers travelling with only hand luggage that is usually observed in tighter connection time scenarios.

## X. SCOPE OF FUTURE WORK

We plan to simulate precise passenger movement inside a terminal and to employ different passenger mobility models to introduce variability into passenger dynamics and formation of queues at different gates/ service counters to obtain more reliable estimates of missed connections. Further, data will be collected on actual passenger itineraries and transfer information shall be used to predict missed connections in real time. We shall use this information to model more precise de-boarding and boarding times as a function of passenger itineraries. Also, it will be interesting to perform a detailed multivariate analysis upon the factors impacting missed connections at LCC airports. Passengers with check-in luggage may be considered in further study, as well.

## REFERENCES


[1] IATA. (2018). *IATA Forecast Predicts 8.2 Billion Air Travelers in 2037*. [Online]. Available: https://www.iata.org/pressroom/pr/Pages/2018-10-24-02.aspx

[2] ICAO. (2015). *Low Cost Carriers*. Accessed: Oct. 2, 2019. [Online]. Available: https://www.icao.int/sustainability/Pages/Low-Cost-Carriers.aspx

[3] ICAO. (2019). *Solid Passenger Traffic Growth and Moderate Air Cargo Demand in 2018*. [Online]. Available: https://www.icao.int/Newsroom/Pages/Solid-passenger-traffic-growth-and-moderate-air-cargo-demand-in-2018.aspx

[4] R. De Neufville, "Low-cost airports for low-cost airlines: Flexible design to manage the risks," *Transp. Planning Technol.*, vol. 31, no. 1, pp. 35–68, 2008.

[5] J. Y. Pan and D. Truong, "Passengers' intentions to use low-cost carriers: An extended theory of planned behavior model," *J. Air Transp. Manage.*, vol. 69, pp. 38–48, Jun. 2018.

[6] Changi Airport Singapore. (2018). *Terminal 4 Breaks New Ground for Changi*. [Online]. Available: http://www.changiairport.com/corporate/media-centre/resources/publication/issue-24/terminal-4-breaks-new-ground-for-Changi.html.

[7] R. De Neufville, A. G. De Barros, and S. C. Belin, "Optimal configuration of airport passenger buildings for travelers," *J. Transp. Eng.*, vol. 128, no. 3, pp. 211–217, 2002.

[8] Singapore Airport. *Singapore Airport Terminal*. [Online]. Available: https://www.singapore-airport.net/terminal-4.php

[9] X. Fageda, P. Suau-Sanchez, and K. J. Mason, "The evolving low-cost business model: Network implications of fare bundling and connecting flights in Europe," *J. Air Transp. Manage.*, vol. 42, pp. 289–296, Jan. 2015.

[10] F. Fichert and R. Klophaus, "Self-connecting, codesharing and hubbing among european lccs: From point-to-point to connections?" *Res. Transp. Bus. Manage.*, vol. 21, pp. 94–98, Dec. 2016.

[11] M. Alderighi, A. Cento, P. Nijkamp, and P. Rietveld, "Network competition—The coexistence of hub-and-spoke and point-to-point systems," *J. Air Transp. Manage.*, vol. 11, no. 5, pp. 328–334, 2005.

[12] M. Alderighi, A. Cento, P. Nijkamp, and P. Rietveld, "Assessment of new hub-and-spoke and point-to-point airline network configurations," *Transp. Rev.*, vol. 27, no. 5, pp. 529–549, 2007.

[13] A. E. Vanderboll, "Tarmac delay policies: A passenger-centric analysis," Ph.D. dissertation, Dept. Civil Environ. Eng., Massachusetts Inst. Technol., Cambridge, MA, USA, 2013.

[14] B. F. Santos, M. M. E. C. Wormer, T. A. O. Achola, and R. Curran, "Airline delay management problem with airport capacity constraints and priority decisions," *J. Air Transp. Manage.*, vol. 63, pp. 34–44, Aug. 2017.

[15] S. Bratu and C. Barnhart, "An analysis of passenger delays using flight operations and passenger booking data," *Air Traffic Control Quart.*, vol. 13, no. 1, pp. 1–27, 2005.

[16] C. Barnhart, D. Fearing, and V. Vaze, "Modeling passenger travel and delays in the national air transportation system," *Oper. Res.*, vol. 62, no. 3, pp. 580–601, 2014.

[17] J. F. O'Connell and G. Williams, "Passengers' perceptions of low cost airlines and full service carriers: A case study involving Ryanair, Aer Lingus, air Asia and Malaysia airlines," *J. Air Transp. Manage.*, vol. 11, no. 4, pp. 259–272, 2005.

[18] Y.-C. Chang, W.-H. Lee, and C.-H. Wu, "Potential opportunities for Asian airports to develop self-connecting passenger markets," *J. Air Transp. Manage.*, vol. 77, pp. 7–16, Jun. 2019.

[19] (2014). *Self Connectivity*. [Online]. Available: http://aviationfacts.eu/uploads/thema/file_en/57681a7970726f08b5000000/Self-connectivity_Fact_sheet.pdf/

[20] (2016). *Dublin Airport Tops European League For Self-Connecting Passengers*. [Online]. Available: https://www.routesonline.com/news/29/breaking-news/254313/dublin-airport-tops-european-league-for-self-connecting-passengers/

[21] M. Schultz, S. Lorenz, R. Schmitz, and L. Delgado, "Weather impact on airport performance," *Aerospace*, vol. 5, no. 4, p. 109, 2018.

[22] U. Dorndorf, A. Drexl, Y. Nikulin, and E. Pesch, "Flight gate scheduling: State-of-the-art and recent developments," *Omega*, vol. 35, no. 3, pp. 326–334, 2007.

[23] D. K. Chin, J. Goldberg, and T. Tang, "Airport surface delays and causes: A preliminary analysis," Tech. Rep., 1997.

[24] A. Cook, G. Tanner, S. Cristóbal, and M Zanin, "Delay propagation–new metrics, new insights," in *Proc. 11th USA/Eur. Air Traffic Manage. Res. Develop. Seminar (EUROCONTROL/FAA)*, 2015, pp. 1–11.

[25] Y. Wang, X. Xu, M. Hu, and J. Zhan, "The structure and dynamics of the multilayer air transport system," in *Proc. 12th USA/Eur. Air Traffic Manage. R&D Seminar*, Seattle, WA, USA, Jun. 2017, pp. 1–8.

[26] M. Schultz, C. Schulz, and H. Fricke, "Enhanced information flow and guidance in airport terminals using best passengers visual perception," in *Proc. 6th Eurocontrol Innov. Res. Workshop*, 2007, pp. 1–9.

[27] *Airport Development Reference Manual*, 11th ed., Int. Air Transp. Assoc., Montreal, QC, Canada, 2019.

[28] M. Schultz, T. Kunze, B. Oreschko, and H. Fricke, "Dynamic turnaround management in a highly automated airport environment," in *Proc. 28th Int. Congr. Aeronaut. Sci.*, 2012, pp. 1–10.

[29] A. Odoni and R. D. Neufville, *Airport Systems: Planning, Design, and Management*. McGraw-Hill, 2003.

[30] E. Mueller and G. Chatterji, "Analysis of aircraft arrival and departure delay characteristics," in *Proc. AIAA's Aircr. Technol., Integr., Oper. (ATIO) Tech. Forum*, 2002, p. 5866.

[31] J. Tang, S. Alam, H. Abbass, and C. Lokan, "Modelling and evolutionary multi-objective evaluation of interdependencies and work processes in airport operations," in *Proc. 1st ACM/SIGEVO Summit Genet. Evol. Comput.*, 2009, pp. 977–984.

[32] H. Vajjarapu, A. Verma, and S. Gulzar, "Adaptation policy framework for climate change impacts on transportation sector in developing countries," *Transp. Develop. Econ.*, vol. 5, no. 1, p. 3, 2019.

[33] (2018). *Airlines for America*. [Online]. Available: http://airlines.org/dataset/per-minute-cost-of-delays-to-u-s-airlines/
[34] M. Ball, C. Barnhart, M. Dresner, M. Hansen, K. Neels, A. Odoni, E. Peterson, L. Sherry, A. Trani, and B. Zou, "Total delay impact study: A comprehensive assessment of the costs and impacts of flight delay in the United States," OCLC no. 671248487, 2010. [Online]. Available: https://rosap.ntl.bts.gov/view/dot/6234
[35] M. Schultz and H. Fricke, "Managing passenger handling at airport terminals," in *Proc. 9th USA/Eur. Air Traffic Manage. Res. Develop. Seminar (EUROCONTROL/FAA)*, 2011, pp. 14–17.
[36] J. Xu and G. Bailey, "The airport gate assignment problem: Mathematical model and a tabu search algorithm," in *Proc. 34th Annu. Hawaii Int. Conf. Syst. Sci.*, Jan. 2001, pp. 1–10.
[37] C. Yu, D. Zhang, and H. Y. Lau, "MIP-based heuristics for solving robust gate assignment problems," *Comput. Ind. Eng.*, vol. 93, pp. 171–191, Mar. 2016.
[38] S. H. Kim, E. Feron, and J.-P. Clarke, "Gate assignment to minimize passenger transit time and aircraft taxi time," *J. Guid., Control, Dyn.*, vol. 36, no. 2, pp. 467–475, 2013.
[39] B. Oreschko, M. Schultz, J. Elflein, and H. Fricke, "Significant turnaround process variations due to airport characteristics," TU-Dresden, Dresden, Germany, Tech. Rep., 2010.
[40] M. Schultz, T. Kunze, B. Oreschko, and H. Fricke, "Microscopic process modelling for efficient aircraft turnaround management," *Air Transp. Oper.*, 2013.
[41] CAAS. (2018). *Aeronautical Information Publication and Amendment 2 of 2018*. [Online]. Available: https://www.caas.gov.sg/legislation-regulations/guidelines-advisory/air-navigation-services/aeronautical-information-publication-amendments
[42] ICAO. (2017). *The World of Air Transport in 2017*. [Online]. Available: https://www.icao.int/annual-report-2017/Pagesthe-world-of-air-transport-in-2017.aspx
[43] (2019). *FlightStats*. [Online]. Available: https://www.flightstats.com/v2/flight-tracker/search
[44] (2018). *Seatguru*. [Online]. Available: https://www.seatguru.com/
[45] M. Schultz, "Field trial measurements to validate a stochastic aircraft boarding model," *Aerospace*, vol. 5, no. 1, p. 27, Mar. 2018.
[46] M. Schultz, "The seat interference potential as an indicator for the aircraft boarding progress," SAE Tech. Paper 2017-01-2113, 2017.
[47] Changi Airport. (2019). [Online]. Available: http://www.changiairport.com/en/maps.html#18.5/1.3550017/103.9885069/-67
[48] H. Ali and A. K. Kar, "Discriminant analysis using ant colony optimization—An intra-algorithm exploration," *Procedia Comput. Sci.*, vol. 132, pp. 880–889, Jan. 2018.
[49] H. Ding, A. Lim, B. Rodrigues, and Y. Zhu, "The over-constrained airport gate assignment problem," *Comput. Oper. Res.*, vol. 32, no. 7, pp. 1867–1880, 2005.
[50] S. H. Kim, E. Feron, J.-P. Clarke, A. Marzuoli, and D. Delahaye, "Airport gate scheduling for passengers, aircraft, and operation," 2013, *arXiv:1301.3535*. [Online]. Available: https://arxiv.org/abs/1301.3535
[51] H. Fricke and M. Schultz, "Delay impacts onto turnaround performance," in *Proc. ATM Seminar*, 2009, pp. 1–10.
[52] S. H. Kim and E. Feron, "Robust gate assignment," in *Proc. AIAA Guid., Navigat., Control Conf.*, 2011, p. 6382.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