

Impact of Stochastic Delays, Turnaround Time and Connection Time on Missed Connections at Low Cost Airports

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Abstract—Low cost carriers usually operate from 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 transfer passengers. In this paper we propose a framework to analyze the effect of turnaround times, minimum connection times and stochastic delays on missed connections of self-connecting passengers. We use Singapore Changi Airport budget terminal as a case study to demonstrate the impact of operational uncertainties on these passenger connections, considering an optimal gate assignment and using heuristic search for both scheduled arrivals and departures. 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, transfer passenger missed connections can be prevented for almost all the flights. The gate assignment framework adopted in this study may also help to identify the gates which are more prone to missed connections given operational uncertainties and different flight scenarios.

I. INTRODUCTION

Low cost carriers (LCCs) have witnessed a continuous 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 [1]. 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 [2]. 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 [3]. 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 turnaround times. This leads to an interesting phenomena at LCC terminals/airports, when passengers flying on aggressive flight schedules, experience uncertainties that exist in the very nature of airport operations.

Uncertainties in airport and airline operations often manifests itself as delays which flights experience due to a host of reasons such as bad weather [4], gate or flight breakdowns [5], or runway excursions/incursions [6]. These delays, although generated at one airport have cascading effects which propagates across the global aviation network in a sinister fashion [7], [8]. 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. This problem is further compounded in the case of LCCs which uses point-to-point network and operate on much tighter schedules when compared with legacy carriers. Because of insufficient time buffers to absorb the delays, these are compounded due the very nature of point-to-point network. Thus, the self-connecting passengers who travel in a LCC network are more vulnerable to miss-connections in presence of flight delays.

In the point-to-point LCC network model, any disruption may easily translate to a number of missed connections. Missed LCC connections severely affect self-connecting passengers at an LCC airport since LCC airlines, in a point-to-point network, are not liable to passengers, who miss connecting flights. In this research we propose a passenger-centric framework to analyze the missed connections due to arrival delays, tighter turnaround time and minimum connection time in a gate optimized scenario (minimized transit time or transfer walking distance) at an LCC terminal. In this study, minimum connection time refers to the required connection time 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. As a case study, we perform the analyses over Singapore Changi Airport-Terminal 4, which is a dedicated low cost carrier terminal. Through this study, we also attempt to identify, for a given LCC terminal, the gate/s which are more likely to have missed connections given arrival

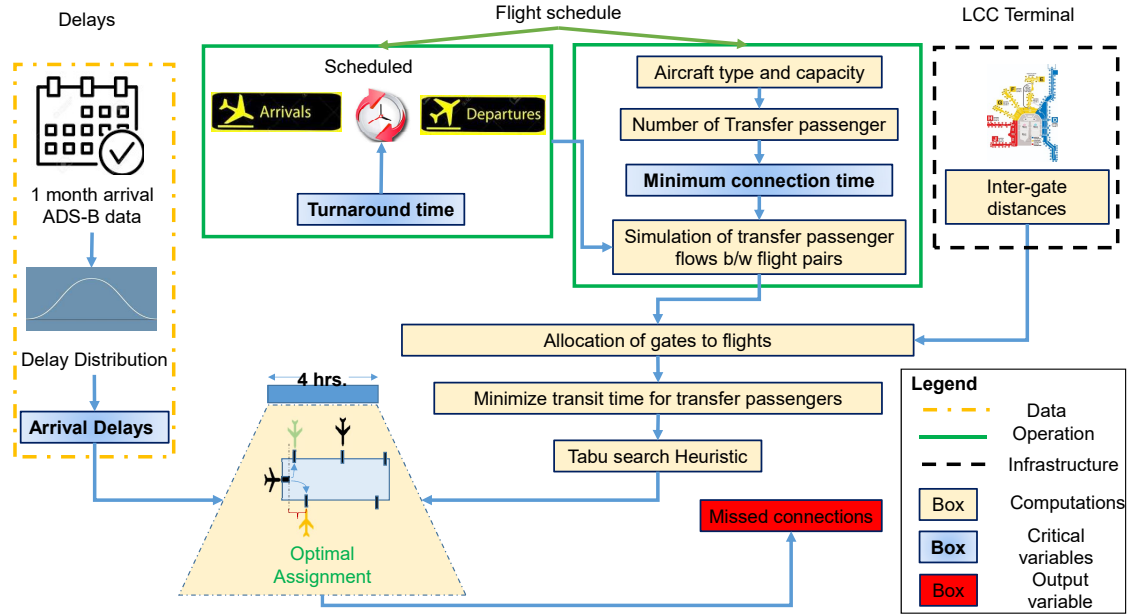


Figure 1. Proposed framework illustrating the interactions between the terminal infrastructure (inter-gate distances), operations (flight schedules and passengers distribution) and data (delay distribution) for missed connection analysis.

delay patterns, turnaround time and passenger connection time.

The remaining document is organized as follows. In section II, we provide the context of Singapore Changi airport Terminal 4 which is used as a case study, then in section III, we formulate the research problem and present the key factors that contributes to missed connections in a LCC terminal/airport. Then, the research methodology is elaborated in section IV with details of heuristic algorithm used for gate assignment such as to minimize the transit time of transfer passengers. Finally, in section V results are discussed along with analysis of gates where the possibility of missed connections is high. We conclude in section VI, with some insights and recommendations.

II. BUDGET TERMINAL AT SINGAPORE CHANGI AIRPORT

In South-East Asia, Singapore Changi airport has emerged as major LCC hub airport, with a dedicated low cost terminal - Terminal 4. Changi Airport has witnessed high traffic growth for the years 2004 and 2011 (refer figure 2). Specifically, the year 2004 saw an annual increase of almost 20 percent for arrivals and departures over the previous year due to arrival of two major low-cost carriers, Tiger Air and Jet Star, which started operations in 2003. Similar trend was observed in 2011, in the form of 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 as dedicated budget terminal, which is based on

linear configuration to facilitate quick passenger connectivity and shorter turnaround time [9]. The new terminal have 21 contact gates and can handle up to 16 million passengers per year.

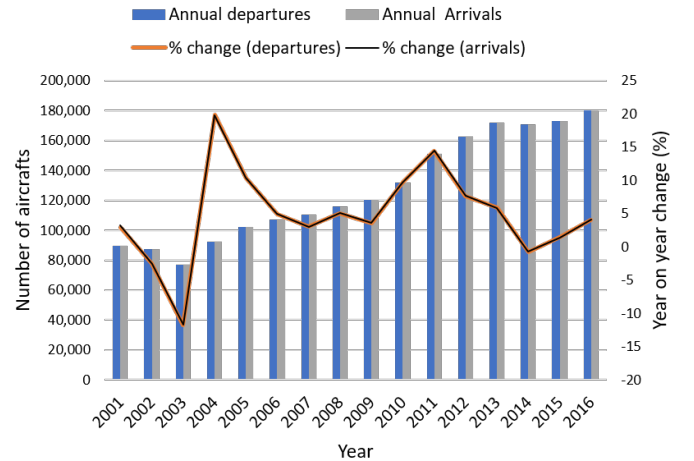


Figure 2. Aircraft departures and arrivals - year on year change at Singapore Changi Airport with spikes at 2003 and 2011 with introduction of new LCC carriers.

III. PROPOSED FRAMEWORK

In figure 1 we illustrates the proposed framework, for missed connection analysis, with its various sub-components and their interaction. The framework consists of three key components data (given), operations (variables) and infrastructure (fixed).

First component, the arrival delay distribution is derived using commercial ADS-B data sourced from FlightAware and thereafter arrival delay values are drawn from the distribution to introduce stochasticity into scheduled flight operations. The second component refers to the use of flight schedules and aircraft types, from Changi airport terminal 4 website, to derive information regarding arrival and departure flight sequence and the transfer passengers. The third 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) [10], [11].

Further three critical operational parameters turnaround time (TAT), minimum connection time (MCT) and arrival delays are varied to analyze their interactions with one another (cf. [12]). Finally all these sub-components are integrated in an optimized gate allocation scenario, to analyze their impacts upon missed connections.

IV. FACTORS IMPACTING MISSED CONNECTIONS

There are several factors, which impact the missed connections. These are delayed operations as well as the number and distribution of associated transfer passengers. We 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 [13]. 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. [14]–[16]. Among them passenger induced delay is a major concern. In US alone, the annual costs of delays (direct cost to airlines and passengers, lost demand, and indirect costs) in 2017 are estimated to be \$26.6 billion [17].

It has also been discussed in literature, that research on delay has remained airport-centric, lacking passenger-centric matrices to fully evaluate the system behavior [7]. 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 [7], [18], [19].

B. Transfer passengers

There are basically three kinds of passengers at every airport. Origin passengers who initiate their journeys, while destination passengers who terminate their journeys at an

airport. The third kind, who are called transfer passengers, arrive and depart from airports in their arrival and departure flights respectively, regularly transported by a full service airline. Transfer passengers account for a large share of flyers specially 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 [20]. 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 [21]–[23]. 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 quality of the solution generated depends on these underlying assumptions and inputs which 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. Turnaround time

Turnaround time (TAT) is defined as the period for which an aircraft occupies an apron or a gate position [24], [25]. Between positioning and removal of the wheel chocks (called as block in and block out), the turnaround is composed of unloading/loading of passengers and cargo, catering, cleaning and refueling of the aircraft. Shorter turnaround times mean lower occupancy at airport stands/gates which essentially mean lesser airline expenditure. Moreover, shorter turnaround times also enable longer time in the air which implies more trips between origin and destination airports, increasing the airlines revenue from the same 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 make the operational costs minimum. One obvious way to reduce operational costs is to keep turnaround time as low as possible and to fly more trips with the same aircraft.

V. METHODOLOGY

The objective of this research is to analyze the missed connections due to arrival delays, tighter turnaround time and minimum connection time in a gate optimized scenario (minimum transit time) at a LCC terminal. 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 3 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 viz. turnaround time and minimum connection time on missed passenger connections is analyzed. The following text details out each step of the methodological approach adopted in this study.

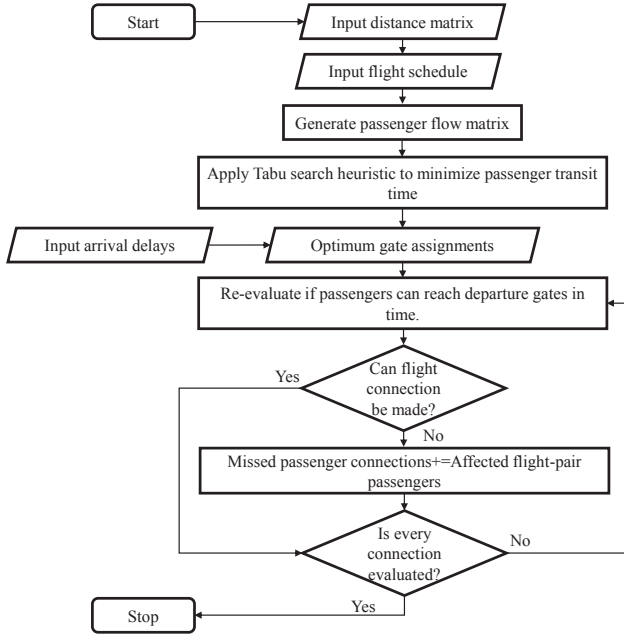


Figure 3. Flow of algorithmic logic to compute missed connections

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) [26]. 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. Fig. 4 shows the terminal 4 under consideration.

B. Importing flight schedule

In this study, flight arrival schedule are taken from Singapore Changi airport website for 20-Aug-2018. 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 [27]. To derive the aircraft seating capacities, aircraft type information is taken from the website flightStats.com [28]

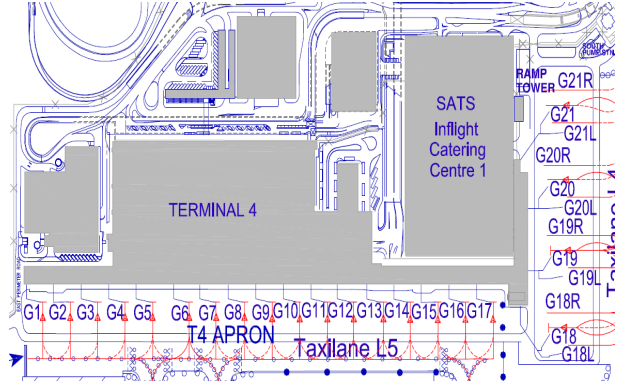


Figure 4. Terminal T4, Changi airport

and the aircraft seating capacity, for the given aircraft type, is obtained from seatguru.com website [29].

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) poison 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, \dots, X_n be the random numbers drawn from multinomial distribution, then X_1, X_2, \dots, X_n obey a probability function

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

where x_i are positive integers with θ_i being their respective probabilities such that

$$\sum_{i=1}^n x_i = N \quad (2)$$

$$\sum_{i=1}^n \theta_i = 1 \quad (3)$$

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

Case 1: All flights with uniform acceptance rate

$$\theta_i = \frac{1}{n_i} \quad (4)$$

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

Case 2: Flights with acceptance rate proportional to their respective capacities

$$\theta_i = \frac{C_i}{\sum_{i=1}^n C_i} \quad (5)$$

where C_i refers to seating capacity of flight i

2) *Poisson distribution*: 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 λ the Poisson distribution $f(k; \lambda)$ describes the probability of k arrival events occurring within the observed interval λ .

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

The Poisson distribution allows to model passengers transferring in groups from one aircraft to other available aircraft [30], [31]. Thus λ 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 (usually in bursts or groups) moving between aircraft. Poisson distribution in the figure 5 is shown as case III.

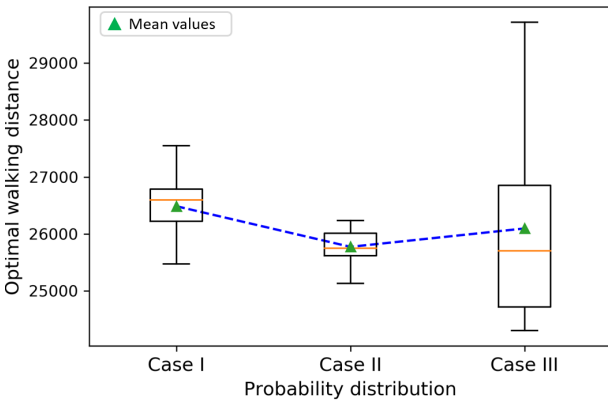


Figure 5. Effect of passenger distributions on the optimal walking distance

The above distributions are used to model the most likely passenger flows.

Connection feasibility- owing to the terminal 4 geometry which requires a minimum transit time of 16 min to move from one extreme to another- between different flights 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 (figure 5). It can be inferred that when passengers distribute according to multinomial distribution based on aircraft size, the walking distance shows least variation and is the most predictable. Also, it is found to replicate actual operations more reasonably as larger aircraft in reality service greater number of passengers (else airlines may replace them with smaller ones to function viably from an economic point of view) and often passengers board flights to highly frequented destinations (served by larger aircraft) and do not evenly distribute among available flight options as is assumed under case I. Moreover, Poisson distribution is found to be infeasible since it often generates passenger flows in which passenger traffic to some connecting flights exceed respective aircraft capacities due to the random behavior of Poisson distribution. Henceforth all experiments are performed on passenger flow matrix generated using Multinomial distribution with size based probabilities (Case II).

D. Gate allocation to flights to minimize transit time

Gate are assigned with an objective to minimize total transit times of all the transfer passengers inside a terminal. 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.

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

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 .

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

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 overlapping flights i and e can not be assigned to a single gate j

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

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

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

The arrival sequence of flights is first considered before allocating feasible gates. Feasibility is ensured when two (or more) flights with overlapping ground time are not assigned to the same gate. Further, optimization algorithm ensures that gates are so chosen that total transit time of all transit passengers is minimized. Since the gate assignment optimization problem is NP hard, the simplex branch and bound method does not converge to a solution in reasonable time. Since any analytical method essentially proves to be infeasible for minimizing transit times over multiple iterations for varied scenarios, we adopt a heuristic search algorithm (refer Algorithm 1) for our airport data, based on Tabu search [32], [33], to obtain optimum gate assignments that minimize passenger walking distance.

E. 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 the arrival delays. To derive a mathematical description of the arrival delay, three commonly used distribution functions are used to fit the measured data: Gamma (11), Weibull (12) and Log-Normal (13) distribution [24], [34], [35]. In (11)-(13), α is the shape and β is the scale parameter, μ is the expected value, σ is the standard deviation, and Δx is the data offset (set to $\Delta x = -20min$), since all functions are only defined with $x \in (0, +\infty)$.

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

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

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

To allow for an appropriate fitting, a χ^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 χ^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. Finally, the Weibull distribution is chosen for the following simulation experiments due to its better fit

Algorithm 1: Tabu search pseudocode to obtain optimum gate assignments that minimize passenger transit time

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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,  $iter_{max}$  to be  $150 * (\text{no. of gates}) - 400$ 
5 Set the insert and interval counters to be 0.
6 Set the tabu_memory as an empty dictionary, {}
7 while iteration in range(1,  $iter_{max}$ ) do
8   if (iteration is not a multiple of 5) and (insert counter is less than 50) then
9     Find feasible insert moves
10    if (insert move is possible) and (tabu_memory{insert move} < iteration) then
11      update the current assignment and cost to  $S_{candidate}$  and  $C_{candidate}$  respectively
12      if  $C_{candidate} < C_{best}$  then
13        update the best solution  $S_{best}$  and the least cost  $C_{best}$ 
14        update tabu_memory{insert move}
15      else
16        Increase insert counter by one
17      end
18    end
19  else
20    if (interval move is possible) and (tabu_memory{interval move} < iteration) then
21      update the current assignment and cost to  $S_{candidate}$  and  $C_{candidate}$  respectively
22      if  $C_{candidate} < C_{best}$  then
23        update the best solution  $S_{best}$  and the least cost  $C_{best}$ 
24        update tabu_memory{interval move}
25      else
26        Increase interval counter by one
27      end
28    end
29  end
30 end
31 if solution is not improved over  $10 * (\text{no. of gates})$  number of iterations then
32   break
33 end
34 increase iteration count by 1
35 end
Result: best assignment and least cost

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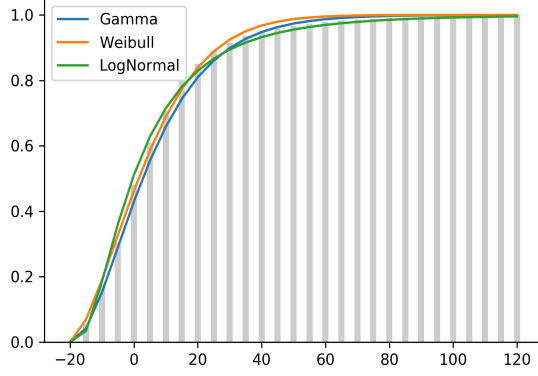


Figure 6. Arrival delays with fitted distributions - cumulative distribution function (CDF)

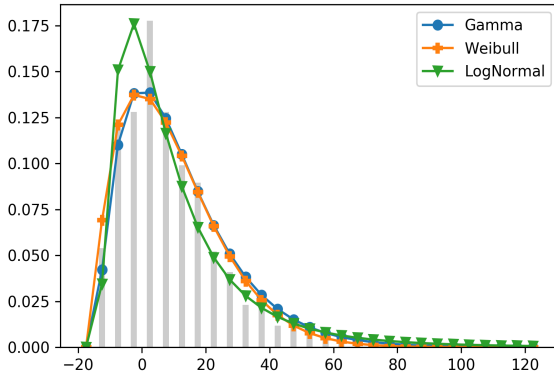


Figure 7. Arrival delays with fitted distributions - probability density function (PDF)

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.

$$a_{act} = a_{sch} + dl \quad (14)$$

Where,

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

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

Where,

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

F. 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 16.

$$a_{act_i} + db_i + tr_{i,j} > d_{sch_j} \quad \forall (i,j) \in f \quad (16)$$

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.
- $tr_{i,j}$ refers to transit time required by passengers to walk from arrival flight i to connecting flight j
- d_{sch_j} refers to the scheduled departure time of connecting flight j

G. Computing total missed connections

Passengers for whom equation 16 is violated are the ones who are deemed to have miss their connections. These passengers are then aggregated to arrive at the total head count of transfer passengers who missed their connecting flights.

H. Experimental design

The experiments are designed to analyze the effect of the chosen operational parameters on the missed connections. To replicate real airport operations, sufficient stochasticity is introduced into the problem design, by generating 30 scenarios to evaluate missed connections for every case. For CASE I, the TAT is varied from 30 to 60 min in steps of 5 min, keeping the minimum connection time fixed at 30 min. For each value of TAT, delay values are fed into the algorithm. Similarly, for CASE II, the minimum connection time is varied from 30 to 60 min, in steps of 5 min, keeping TAT constant at 45 min. In both CASE I and CASE II, the delay values are drawn from Weibull distribution and fed into the algorithm. To study the effect of delays in CASE III, TAT and MCT are kept 45 and 30 min respectively and the scale parameter β of the Weibull distribution is varied to limit the range of stochastic delays, from 27.15 min (original β value) to 13.57 min (50% of β value) in steps of 10 % decrements. The variation of β 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 18.

$$\sigma = \beta \sqrt{\Gamma\left(1 + \frac{2}{\alpha}\right) - 2\left(\Gamma\left(1 + \frac{1}{\alpha}\right)\right)^2} \quad (17)$$

$$\mu = \beta \Gamma\left(1 + \frac{1}{\alpha}\right) \quad (18)$$

	Parameters	
	Variable	Fixed
CASE I - Effect of turnaround time	TAT	Connection time
		Delay
CASE II – effect of connection time	Connection time	TAT
		Delay
CASE III – Effect of Delays	Delay	TAT
		Connection time

Figure 8. Experimental design

VI. RESULTS AND DISCUSSIONS

A. Effect of turnaround time on missed connections

Figure 9 shows the TAT variation from 30 to 60 min on x-axis, with the boxplots and trends of mean values of the corresponding missed connections on y-axis for each case. On average 19 passengers (1.4%) out of a total of 1,336 transfer passengers, missed their connections with a maximum of 47 passengers (3.4%) (TAT = 35 min). The trendline for the average values of missed connections shows a negative slope. It is therefore inferred from the above experiments that when the TATs increase, chances of passengers missing their connections gradually decrease. This can be partially 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 LCC terminal 4 at Changi airport, a TAT of 50 min absorbs most of the stochastic delays that Changi airport usually witnesses. A TAT of 50 min can therefore be considered reasonable by airlines operating at terminal 4 to reduce delays induced by most transfer passengers. The marginal increment in missed connections for TAT of 55 and 60 min can be attributed to larger disruptions in form of stochastic delay values that were witnessed in the respective algorithm runs.

B. Effect of delays on missed connections

The stochastic nature of operational delays play a substantial role in determining the magnitude of missed connections. To understand this behavior, delay values were randomly chosen from the arrival delay distribution with a varying scale factor (β) of the Weibull distribution to change the standard deviation (SD) for different use cases. Reducing the standard deviation implies a narrow spread of the delay distribution without changing the initial shape (given by α). Figure10 shows

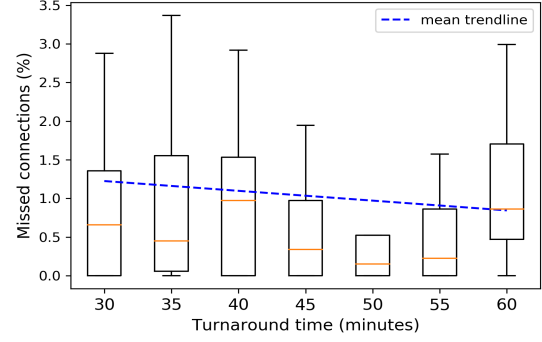


Figure 9. Effect of turnaround time on missed connections

the box plots for each case of SD and the average missed connections connected with a dashed line. It can be seen that for a SD of 27.15 min, an average of 1.02% of passengers miss their connections, which can be translated to 14 passengers out of a total 1,336 transfer passengers. A maximum of 80 passengers (3.7%) miss their connections in this case. The average value of missed connections decreases monotonically as the SD is reduced, with no passengers missing their flights for 0.7 SD. It can be inferred from the results, that if the delays are contained within 70% of the current delay spread, the missed connection occurrences would reduce sharply.

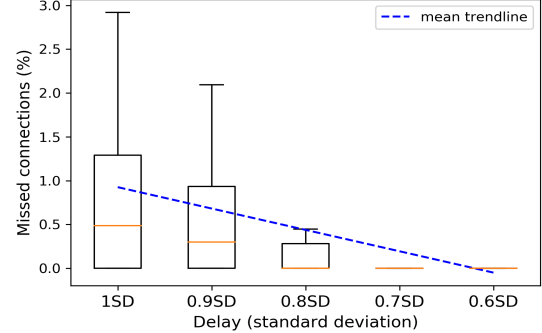


Figure 10. Effect of arrival delays on missed connections

C. Effect of minimum connection time on missed connections

Figure11 shows the connection time variation from 30 to 60 min, with the box-plots, and trends of mean values of the missed connections for each case. For a connection time of 30 min an average of 9 (0.7%) passenger out of a total of 1,216 transfer passengers, miss their connections with a maximum of 73 passengers among the cases for this connection time. Similar to the previous case of turnaround time variation, the trend line of the average values of missed connections on varying the minimum connection time shows a negative slope, implying a monotonic decrease in missed connections as the connection time is increased. The average percentage of missed connections decreases to zero for the

connection time of 60 min. It can therefore be inferred from the passenger point-of-view that in the present operational scenario, a minimum buffer time of 60 min must be maintained between connecting flights at Changi Airport terminal 4.

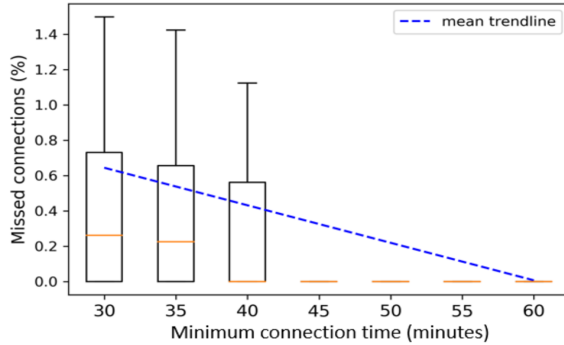


Figure 11. Effect of connection time on missed connections

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 12) at terminal 4 witnessed missed connections. These missed connections emanated from delayed arrival flight at one gate (hot-spot in figure 13) gate out of a total of 21 gates. Hence it can be argued that the choice of operational parameters, significantly limited the missed connections.

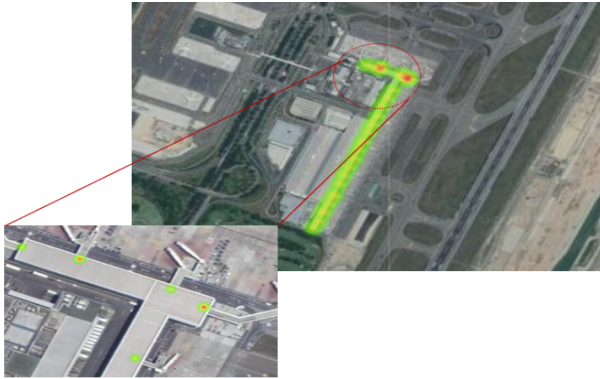


Figure 12. Missed connection sensitivity of T4 departure gates for the flight schedule dated 8-Feb-2018

VII. CONCLUSION

With our contribution we aim to provide a passenger-centric analysis of the effect of delayed turnaround times to self-connecting transfer passengers in the context of LCC operations. Herein, we consider stochastic arrival delays and minimum connection times, which may lead to missed connections. We used Singapore Changi Airport budget Terminal (Terminal 4) as an example to study the impacts of operational uncertainties on the passenger connections, considering an



Figure 13. Missed connection sensitivity of T4 arrival gates for the flight schedule dated 8-Feb-2018

optimum gate assignment of flights arriving and departing from the airport.

To achieve this we proposed a framework, for missed connection analysis, with its various sub-components and their interaction provided. The framework consists of three key components viz. data (given), operations (variables) and infrastructure (fixed). Three critical operational parameters turnaround time, minimum connection time 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, to analyze their impacts upon missed connections using a heuristic Tabu-search algorithm.

Our results indicate that by increasing turnaround time and minimum connection time and by reducing delays, the chances of missed connections can be significantly reduced. Specifically by maintaining the flight turn around time at 50 min, minimum connection time 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 framework 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.

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